Research on Early Warning of Extreme Price Fluctuations in Technology Stocks Based on the ARIMA Model

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Abstract: With the continuous digitalization of capital markets, technology stocks have gradually become a major focus for investors and financial regulators due to their strong growth potential, high valuation flexibility, and significant market attention. However, the prices of technology stocks are often influenced by multiple factors, including the macroeconomic environment, industrial policy changes, corporate innovation capability, market sentiment, and unexpected external events. As a result, sharp price swings may occur within a short period, sometimes even leading to extreme market risks. To improve the identification of abnormal price movements and enhance risk warning capability, this study takes the time series of technology stock prices as the research object and introduces the ARIMA model to analyze and forecast stock price trends. Meanwhile, an early warning mechanism for extreme price fluctuations is constructed by combining forecasting errors, volatility thresholds, and abnormal deviation levels. Through stationarity testing, differencing, model identification, parameter estimation, and forecasting analysis of historical price data, the applicability of the ARIMA model in short-term prediction and abnormal fluctuation identification for technology stock prices is verified. The results indicate that the ARIMA model can effectively capture trend changes and short-term volatility characteristics in technology stock price series, providing quantitative support for investor risk management, market supervision, and financial technology applications.

1. Introduction

In recent years, the rapid growth of emerging industries such as artificial intelligence, semiconductors, cloud computing, big data, and new energy vehicles has significantly increased the influence of technology-related companies in capital markets. Compared with traditional industry stocks, technology stocks are more sensitive to technological innovation, policy changes, market expectations, and investor sentiment. As a result, their prices often experience substantial short-term fluctuations, sometimes leading to extreme volatility. Extreme price fluctuations in technology stocks not only affect investors' returns, but may also increase overall market risk. When market expectations become overly optimistic, stock prices may rise rapidly beyond fundamental values. Conversely, policy tightening, disappointing corporate performance, or changes in market sentiment may trigger sharp price declines. Therefore, developing effective quantitative methods to predict price movements and provide early warning signals before abnormal fluctuations occur has become an important issue in financial risk management and investment analysis. Existing stock price forecasting methods mainly include technical analysis, machine learning approaches, and time series models. Among them, the ARIMA model is widely used because of its clear structure, strong interpretability, and effectiveness in short-term forecasting. By combining autoregressive, differencing, and moving average processes, the ARIMA model can effectively capture dynamic changes in financial time series. Based on this background, this study applies the ARIMA model to technology stock price forecasting and extreme fluctuation warning analysis. Through stationarity testing, model identification, and forecasting error analysis, an early warning mechanism for abnormal price fluctuations is constructed to support investment risk control and financial market monitoring.

2. Theoretical Basis and Literature Review

2.1. Characteristics of Technology Stock Price Fluctuations

Technology stocks are generally characterized by strong growth potential and expectation-driven pricing mechanisms. Their price movements depend not only on current corporate profitability, but also on future technological pathways, industry expansion prospects, capital preference, and macroeconomic changes. Compared with traditional industry stocks, the valuation of technology stocks is more heavily based on expectations of future growth. Therefore, when the market reassesses a company’s technological breakthroughs, commercialization capability, or competitive position, stock prices often undergo substantial adjustments[1]. This sensitivity and amplification effect make technology stocks more likely to experience extreme price volatility. From the perspective of influencing factors, technology stock price fluctuations are driven by multiple sources. As shown in Figure 1, the main factors affecting technology stock volatility include technological innovation, policy changes, macroeconomic conditions, market sentiment, earnings volatility, high valuations, trading activity, and external shocks. Among these, technological innovation is a major source of value changes in technology stocks. New product launches, core technological breakthroughs, or R&D failures may significantly alter investor expectations regarding corporate growth potential. Policy changes influence market expectations through industry regulation, data security requirements, antitrust rules, and industrial support policies. Meanwhile, macroeconomic changes affect capital costs, risk preferences, and overall market liquidity, thereby further influencing technology stock valuations[2].

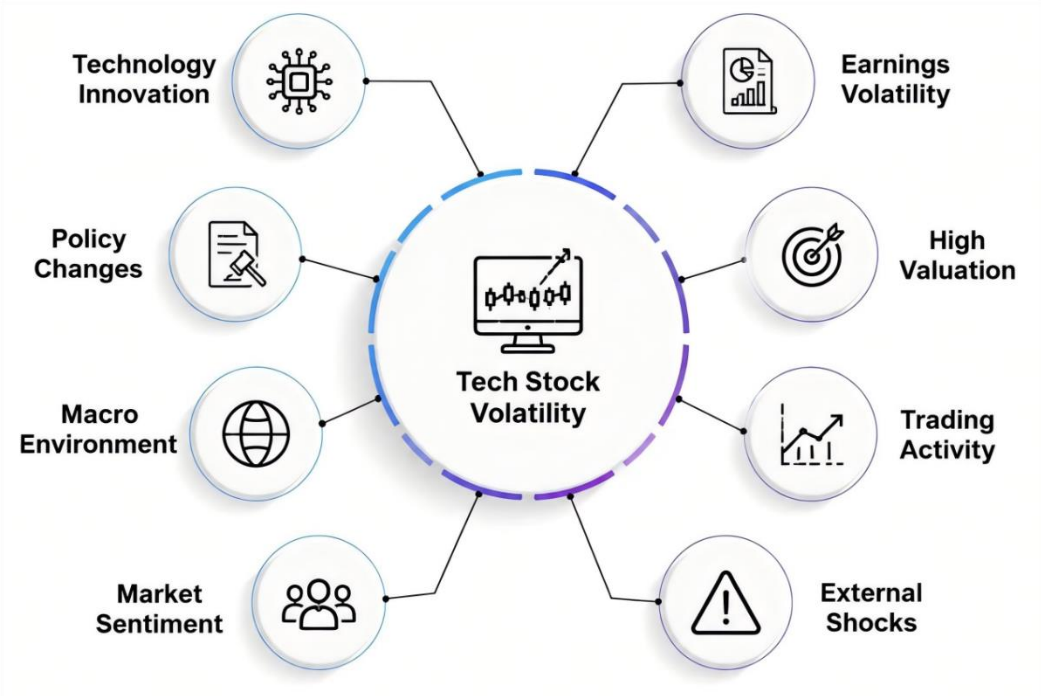

Figure 1. Main Influencing Factors of Technology Stock Price Fluctuations

In addition, technology stock prices are highly sensitive to market sentiment and trading behavior. When market sentiment is optimistic, investors are often willing to pay higher premiums for future growth, driving stock prices upward rapidly. Conversely, when external shocks occur, earnings disappoint expectations, or macroeconomic uncertainty increases, highly valued stocks may face stronger valuation corrections[3]. The earnings volatility, high valuation levels, and trading activity illustrated in Figure 1 also indicate that short-term technology stock prices are not determined solely by fundamentals, but rather by the combined effects of fundamental expectations, capital flows, and investor behavior. As a result, technology stock price series often exhibit non-stationarity, trending behavior, abrupt changes, and high volatility, providing a theoretical basis for subsequent differencing, trend forecasting, and extreme volatility warning using the ARIMA model[4].

2.2. Current Research on Early Warning of Extreme Price Fluctuations

Early warning of extreme price fluctuations is an important part of financial risk management. Its main purpose is to identify possible risk signals before asset prices rise or fall sharply. Existing studies generally suggest that extreme stock price movements are not completely random. Instead, they are often related to changes in market liquidity, investor sentiment, macroeconomic policy, trading behavior, and corporate fundamentals[5]. Therefore, early warning research usually focuses on extracting abnormal signals from price series, returns, trading volume, volatility, and market sentiment, and then converting them into measurable risk indicators. In terms of research methods, earlier studies mainly used technical indicators and statistical tools, such as moving averages, relative strength indexes, Bollinger Bands, historical volatility, and threshold-based rules. These methods are easy to understand and apply, but their ability to capture complex and nonlinear market fluctuations is limited. Later, econometric models such as GARCH, VaR, and time series forecasting models were introduced to measure volatility risk. Among them, the ARIMA model is useful because it can describe trend changes and short-term dependence based on historical price information. Recently, machine learning and deep learning models, including support vector machines, random forests, LSTM networks, and hybrid models, have also been applied to stock volatility warning. Although these methods can handle complex variables, they often require large datasets and have weaker interpretability. In contrast, the ARIMA model has a clearer modeling process and stronger explanatory value. Therefore, this study applies ARIMA to technology stock price forecasting and builds an interpretable warning mechanism based on deviations between actual and predicted prices[6].

3. Construction of the Early Warning Model for Technology Stock Price Fluctuations

3.1. Data Sources and Indicator Selection

This study uses historical trading data of technology stocks as the foundational dataset for model construction, with particular attention paid to the variation patterns and abnormal deviation characteristics of stock price series[7]. Since the ARIMA model is mainly designed for univariate time series analysis, the closing price is selected as the core modeling variable. At the same time, opening price, highest price, lowest price, trading volume, percentage price change, and return indicators are incorporated to assist in identifying fluctuation conditions in stock prices. The data may be collected from financial databases such as stock exchanges, Wind, Eastmoney, Yahoo Finance, or Tonghuashun. Representative technology-listed companies or technology stock indices can be selected as samples, while daily trading data are adopted to ensure continuity and suitability for time series modeling[8].

Table 1 Selection of Early Warning Indicators for Technology Stock Price Fluctuations

Indicator Category	Indicator Name	Description	Role in the Model
Price Indicator	Opening Price	Opening trading price of the stock	Reflects market opening expectations
Price Indicator	Highest Price	Highest trading price during the day	Measures intraday upward fluctuation
Price Indicator	Lowest Price	Lowest trading price during the day	Measures intraday downward fluctuation
Core Variable	Closing Price	Daily closing trading price	Main forecasting target of the ARIMA model
Trading Indicator	Trading Volume	Daily stock trading quantity	Assists in evaluating market activity
Volatility Indicator	Percentage Change	Daily price change relative to the previous trading day	Measures short-term price fluctuation intensity
Return Indicator	Logarithmic Return	Logarithmic form of price change between adjacent trading days	Reflects direction and magnitude of price changes
Warning Indicator	Forecast Error	Deviation between actual and predicted prices	Identifies abnormal fluctuations and triggers warnings

As shown in Table 1, the closing price serves as the core variable of the ARIMA model because it reflects the final trading outcome and the comprehensive judgment of investors during a trading day, making it highly representative. Although opening price, highest price, and lowest price are not directly used as the main input variables of the ARIMA model, they can still be employed to analyze intraday fluctuation ranges and determine whether abnormal upward surges or rapid declines occur. Trading volume reflects the degree of market participation. When sharp price changes are accompanied by a significant increase in trading volume, it often indicates substantial changes in market sentiment or trading behavior[9].

In terms of data processing, the original price data are first cleaned by removing suspended trading records, missing values, and abnormal observations, and then sorted according to trading dates. The closing price series is subsequently used as the input of the ARIMA model, and stationarity testing is conducted to determine whether differencing treatment is required. After model forecasting is completed, the forecast error between actual closing prices and predicted closing prices is calculated. Combined with percentage price change and logarithmic returns, extreme price fluctuations can then be identified. When the forecast error exceeds a predefined threshold or when returns deviate significantly from the historical normal fluctuation range, the technology stock is considered to have abnormal fluctuation risk, thereby triggering the corresponding warning signal[10].

3.2. Principles and Modeling Procedure of the ARIMA Model

The ARIMA model is a classical forecasting model for non-stationary time series and is suitable for handling technology stock closing prices that exhibit trending behavior, randomness, and short-term dependency characteristics. Since technology stock prices are easily influenced by market sentiment, industrial policies, corporate performance, and external shocks, the original price series is usually non-stationary[11]. Therefore, data cleaning, stationarity testing, and differencing processing are required before model construction. As illustrated in Figure 2, the modeling framework in this study mainly consists of four stages: data processing, model construction, price forecasting, and risk warning. In other words, the original technology stock price data are first transformed into a model-ready sequence, then future prices are forecasted through the ARIMA model, and finally extreme fluctuation warnings are generated according to forecasting deviations[12].

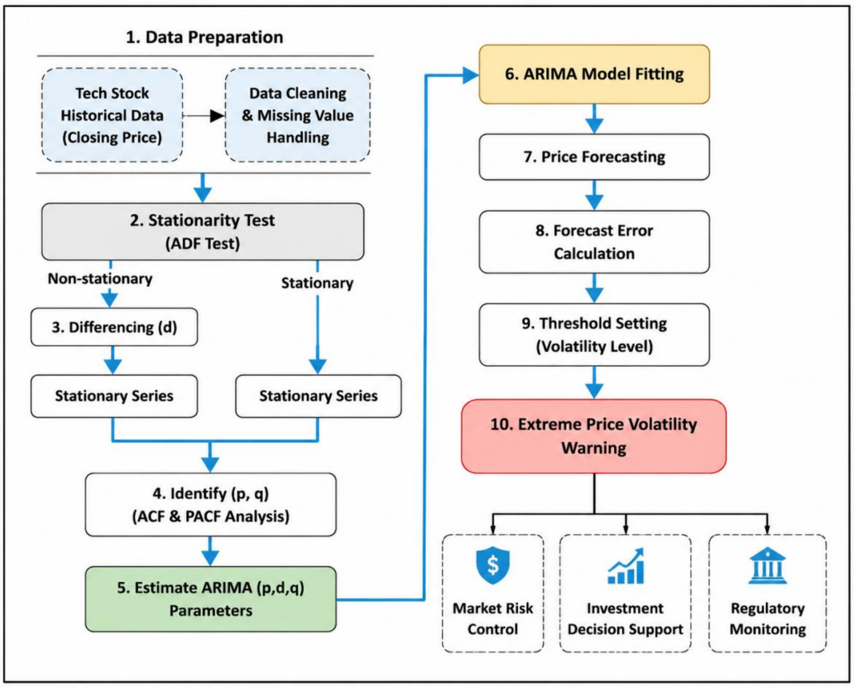

Figure 2. ARIMA Modeling and Early Warning Process

First, the original closing price sequence is differenced to eliminate trend components and non-stationary characteristics. The calculation formula is given as shown in Formula 1:

$$Y_t = \nabla^d P_t = (1 - B)^d P_t \tag{1}$$

where P_t represents the closing price of the technology stock on trading day t, B denotes the lag operator, d is the differencing order, and Y_t is the stationary sequence after differencing. When d=1, first-order differencing is adopted, meaning that price fluctuations are represented by the difference between the current closing price and the previous closing price. This step corresponds to the stationarity testing and differencing stage in Figure 2 and forms the basis for effective ARIMA modeling. After obtaining a stationary sequence, the ARIMA (p,d,q) model is constructed. Its general expression is shown as shown in Formula 2:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \phi_j \varepsilon_{t-j} \tag{2}$$

where c is the constant term, p is the autoregressive order, q is the moving average order, ϕ_i represents the autoregressive coefficient, ϕ_j denotes the moving average coefficient, ε_t is the current random disturbance term, and ε_{t-j} refers to historical error terms. Through historical price movements and past forecasting errors, the model characterizes the short-term dynamic relationships of technology stock prices. This process corresponds to the model identification, parameter estimation, and model fitting stages shown in Figure 2.

After model fitting is completed, the ARIMA model is used to obtain the predicted closing price of technology stocks. The deviation between actual prices and predicted prices is then calculated using the following warning as shown in Formula 3:

$$R_t = \frac{|P_t - \hat{P}_t|}{\hat{P}_t} \times 100\% \tag{3}$$

where R_t denotes the forecast error rate on trading day t, P_t is the actual closing price, and $\hat{P}_t$ is the predicted closing price generated by the ARIMA model. When (R_t<5%), the price fluctuation is considered normal; when (5%leqR_tt<8%), a general warning is triggered; when (8%leqR_t<10%), a moderate warning is generated; and when ($R_t$geq10%), a high-level warning is issued. This procedure corresponds to the forecasting, error calculation, and extreme fluctuation warning stages in Figure 2. Therefore, the ARIMA model can not only be applied to short-term prediction of technology stock prices, but can also transform abnormal fluctuations into identifiable warning signals through forecast error analysis[13].

4. Empirical Analysis

4.1. Stationarity Testing and Model Identification

To verify the applicability of the ARIMA model in early warning of extreme technology stock price fluctuations, this study selects the daily closing price data of a technology stock index as the research object and conducts stationarity testing and model identification analysis on the time series[14]. Since the ARIMA model requires the input sequence to satisfy stationarity conditions, it is necessary to first examine whether the original price sequence contains trends or unit root characteristics before model construction. In this study, the Augmented Dickey-Fuller (ADF) test is applied to analyze the stationarity of the technology stock closing price series, while differencing results are further used to determine whether the sequence meets the modeling requirements[15].

Table 2 presents the ADF test results of the technology stock closing price series under both the original state and the differenced state. As shown in the table, the ADF statistic of the original price sequence is greater than the critical value at the 5% significance level, and the corresponding p-value is significantly higher than 0.05. This indicates that the original sequence contains a unit root and belongs to a non-stationary time series. The result suggests that technology stock prices exhibit obvious trend movements and persistent volatility. Direct ARIMA modeling on the original sequence may therefore lead to large forecasting deviations. Consequently, first-order differencing is further applied to eliminate trend effects and random drift.

Table 2. ADF Stationarity Test Results of Technology Stock Price Series

Sequence Type	ADF Statistic	5% Critical Value	P-value	Test Result
Original Closing Price Series	-1.842	-2.871	0.362	Non-stationary
First-Order Differenced Series	-5.974	-2.871	0.000	Stationary
Logarithmic Return Series	-6.418	-2.871	0.000	Stationary

According to Table 2, the ADF statistic after first-order differencing is significantly lower than the critical value, while the p-value approaches zero, indicating that the differenced price series satisfies the stationarity requirement. In addition, the logarithmic return series also demonstrates strong stationarity. Therefore, the differenced closing price series can be used as the input variable of the ARIMA model. Based on the stationarity testing results, the differencing order is determined as (d=1).

After the stationary transformation is completed, the autoregressive order (p) and moving average order (q) of the ARIMA model must be further determined. In this study, the autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs are used for preliminary judgment, while AIC and BIC information criteria are employed to compare different model structures in order to identify the model with the best overall fitting performance. Table 3 presents the parameter identification results and model evaluation indicators of different ARIMA models.

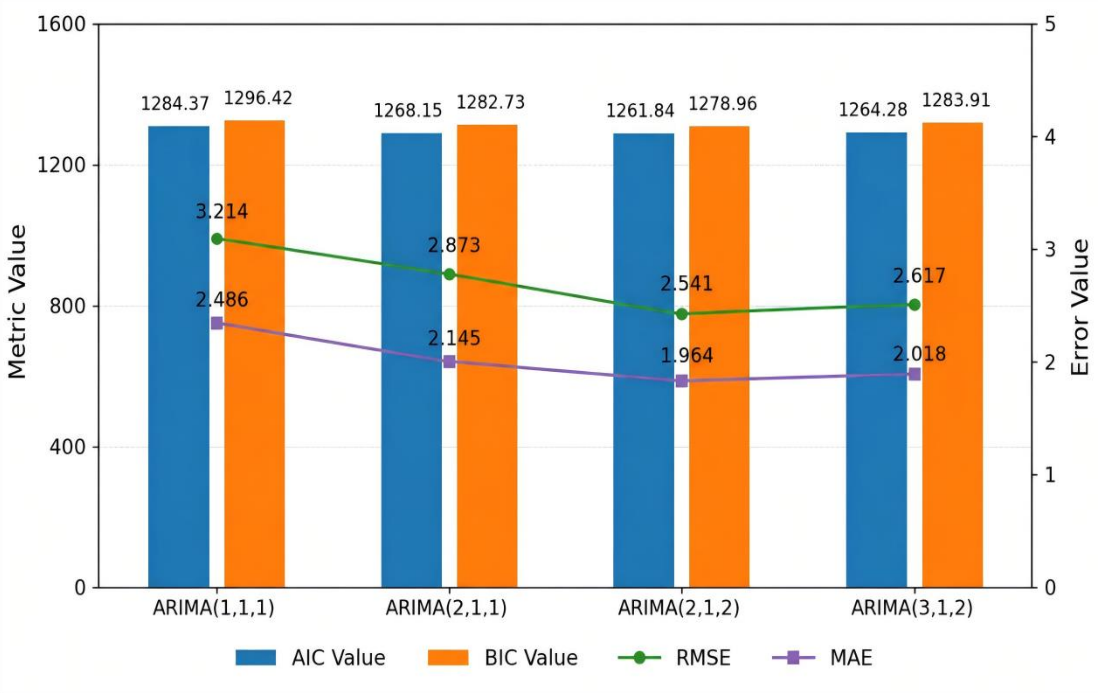

Figure 3. Comparison of Parameter Identification Results for Different ARIMA Models

As indicated in Figure 3, the ARIMA(2,1,2) model achieves relatively lower AIC and BIC values, while also producing better RMSE and MAE results than the other models. This demonstrates that the ARIMA(2,1,2) model performs better in terms of fitting accuracy and forecast error control. Therefore, the ARIMA(2,1,2) model is ultimately selected as the forecasting model for technology stock price fluctuations, and subsequent extreme price fluctuation warning analysis is conducted based on this model.

4.2. Evaluation and Comparative Analysis of Model Performance

To further verify the effectiveness of the ARIMA model in early warning of extreme price fluctuations in technology stocks, this study evaluates the model from multiple perspectives, including forecasting accuracy, error control capability, and warning identification performance. At the same time, in order to improve the reliability of the results, the ARIMA model is compared with the Moving Average (MA) model and the Exponential Smoothing (ES) model to examine its advantages in forecasting technology stock prices.

First, regarding forecasting accuracy evaluation, indicators such as RMSE, MAE, MAPE, and directional prediction accuracy are adopted to compare different models. RMSE reflects the overall magnitude of forecasting errors, while MAE measures the average absolute deviation between predicted values and actual values. MAPE represents the relative error level, and directional prediction accuracy is mainly used to evaluate whether the model can correctly identify the direction of stock price movements. The comparative results of different forecasting models are shown in Figure 4.

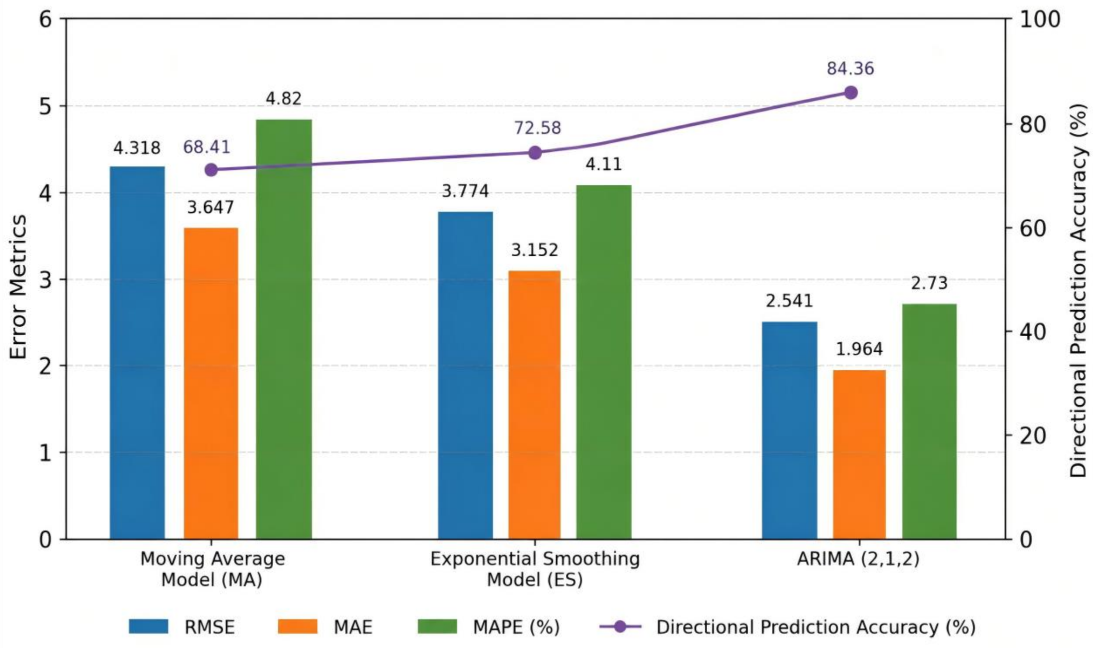

Figure 4. Comparison of Different Forecasting Models

As indicated in Figure 4, the ARIMA(2,1,2) model performs better across all evaluation indicators. In particular, its RMSE and MAE values are significantly lower than those of the MA and ES models, suggesting that the ARIMA model can more accurately capture changes in technology stock price trends and reduce forecasting deviations. Meanwhile, the MAPE value of the ARIMA model is only 2.73%, indicating a relatively low level of forecasting error. In terms of directional prediction accuracy, the ARIMA model achieves 84.36%, which is substantially higher than the two traditional forecasting methods. This demonstrates that the ARIMA model can not only fit the magnitude of price fluctuations effectively, but can also more accurately identify the future direction of stock price movements. Therefore, it is more suitable for short-term fluctuation forecasting and risk warning of technology stocks.

Beyond forecasting accuracy, the key value of an extreme price fluctuation warning model also lies in its risk identification capability. Accordingly, this study further evaluates the model from perspectives such as the number of warning triggers, effective warning ratio, false alarm rate, and missed warning rate. Situations where actual abnormal fluctuations occur and are successfully identified by the model are defined as effective warnings, whereas cases where warnings are triggered despite no obvious abnormal fluctuation are regarded as false alarms. The related results are shown in Table 3.

Table 3. Analysis of Warning Identification Performance of the ARIMA Model

Indicator	Value
Actual Number of Abnormal Fluctuation Events	28
Successfully Identified Events	24
Effective Warning Rate / %	85.71
Number of False Alarms	5
False Alarm Rate / %	17.86
Number of Missed Warnings	4
Missed Warning Rate / %	14.29
Average Early Warning Time (days)	2.4

As shown in Table 3, the ARIMA model can effectively identify abnormal fluctuation events in technology stock prices. Among the 28 actual abnormal fluctuation events, the model successfully identified 24 cases, resulting in an effective warning rate of 85.71%, which demonstrates strong risk identification capability. In addition, the model can issue warning signals approximately 2.4 days in advance on average, providing investors and regulators with a certain amount of response time. Although some forecasting errors still exist, both the false alarm rate and the missed warning rate remain at relatively low levels, indicating that the ARIMA model maintains good stability while preserving high warning sensitivity.

Overall, the results presented in Figure 4 and Table 3 suggest that the ARIMA model outperforms traditional statistical forecasting approaches not only in forecasting accuracy, but also in identifying and warning against extreme price fluctuations. Particularly in the highly volatile and sensitive environment of technology stocks, the ARIMA model can more accurately capture price trend changes and abnormal deviations, thereby providing relatively reliable quantitative support for market risk control, investment decision-making, and financial market supervision.

5. Risk Prevention and Control Strategies for Extreme Price Fluctuations in Technology Stocks

Technology stocks usually have high growth potential, high valuations, and strong sensitivity to market sentiment. Therefore, their prices may fluctuate more sharply than those of traditional industry stocks, especially when policy changes, international events, industry competition, or corporate risks occur. To reduce the impact of extreme price movements on investors and market stability, a more systematic risk prevention mechanism is needed.First, dynamic monitoring and early warning systems should be improved. Since the ARIMA model can identify trend changes and abnormal price deviations, it can be integrated into market risk monitoring systems. By tracking closing prices, returns, trading volume, and forecast errors in real time, the system can detect abnormal signals and issue warnings when forecast errors expand or returns move beyond normal historical ranges. Second, investors should make more rational decisions and avoid blindly chasing rising prices or panic selling. Technology stock prices are often affected by short-term market themes and emotional trading. Therefore, investors should focus more on corporate fundamentals, R&D capability, earnings quality, and long-term competitiveness. Portfolio diversification, stop-loss rules, and position control can also help reduce losses caused by sharp price swings. Third, listed technology companies should improve information disclosure and operational stability. Timely disclosure of business performance, R&D progress, and potential risks can reduce information asymmetry and prevent unnecessary market speculation. Stronger profitability and cash flow management can also improve investor confidence. Finally, regulators should strengthen supervision of abnormal trading and speculative behavior. Big data analysis, time series models, and intelligent warning systems can be used to monitor high-frequency volatility and concentrated speculation. In the future, ARIMA models can also be combined with machine learning, sentiment analysis, and multi-source data fusion to build a more accurate and real-time risk warning system for technology stocks.

6. Conclusion

This study focuses on the issue of early warning for extreme price fluctuations in technology stocks and constructs a price forecasting and risk identification framework based on the ARIMA model. The results show that technology stock prices exhibit strong non-stationarity and high volatility, while differencing treatment can effectively satisfy the modeling requirements of the ARIMA framework. Empirical findings indicate that the ARIMA(2,1,2) model can effectively fit short-term changes in technology stock prices and identify abnormal fluctuation risks through indicators such as forecast errors, returns, and trading volume. Overall, the proposed approach demonstrates good interpretability and practical application value, providing useful references for investor risk management, market supervision, and technology stock price monitoring.

References

[1] Bagalkot, Sneha S., Dinesha H. A., and Veeresh G. Kasabegoudar. "Novel grey wolf optimizer based parameters selection for GARCH and ARIMA models for stock price prediction." PeerJ Computer Science 10 (2024): e1735.

[2] Mutinda, John K., and Alex K. Langat. "Stock price prediction using combined GARCH-AI models." Scientific African 26 (2024): e02374.

[3] Lahboub, Kamal, Youssef El Amrani, and Mohamed El Bouhaddioui. "Assessing the predictive power of Transformers, ARIMA, and LSTM in stock price forecasting." Journal of Risk and Financial Management 17.7 (2024): 293.

[4] Wang, Pan, Yuhao Zhang, and Jiaqi Li. "Stock prediction based on TCN-ARIMA-GARCH model." Proceedings of the 2024 International Conference on Computer Science and Artificial Intelligence 2024 (2024): 241-247.

[5] Zhou, Haoran, Yuxuan Liu, and Minghao Chen. "Research on stock price prediction based on time series analysis." Proceedings of the 2024 International Conference on Data Economy and Artificial Intelligence 2024 (2024): 242-248.

[6] Xu, Xinyue, Zihan Wang, and Yuchen Li. "Empirical analysis of stocks based on ARIMA-GARCH-M model." Proceedings of the 2024 International Conference on Economic Management and Big Data Applications 2024 (2024): 176-182.

[7] Zhang, Jing, Xiaohui Li, and Wei Chen. "A hybrid approach of wavelet transform, ARIMA and LSTM for share price index futures forecasting." Applied Soft Computing 149 (2024): 110966.

[8] Wang, Jujie, Jing Liu, and Weiyi Jiang. "An enhanced interval-valued decomposition integration model for stock price prediction based on comprehensive feature extraction and optimized deep learning." Expert Systems with Applications 243 (2024): 122891.

[9] Pan, Haoyu, Xinyi Zhang, and Ming Li. "A stock index futures price prediction approach based on GARCH-family models and deep learning." Mathematics 12.11 (2024): 1677.

[10] Mei, Xiaoxiao, Yifan Zhang, and Rui Wang. "Forecasting stock volatility using time-distance weighting based GARCH-MIDAS model." International Review of Economics & Finance 93 (2024): 102-116.

[11] Alaminos, David, Alejandro Salas, and Manuel Ángel Fernández-Gámez. "Hybrid ARMA-GARCH-neural networks for intraday financial forecasting." Pattern Recognition 149 (2024): 110236.
[12] Yang, Zihan, Haoyu Chen, and Yilin Wang. "Research on stock price prediction based on the ARIMA model." Proceedings of the International Conference on Economic Management and Intelligent Computing 2025 (2025): 315-321.
[13] Khang, Vo Hoang, Nguyen Duc Thuan, and Tran Minh Quan. "Forecast of stock prices with ARIMA, rolling forecast and GARCH models." Journal of Internet, Hardware and Mobile Systems 16.3 (2025): 74-86.
[14] Ghosh, Raj Kumar, Anirban Chakraborty, and Suman Banerjee. "Deep learning-based hybrid model with multi-head attention for stock price prediction." Journal of Risk and Financial Management 18.10 (2025): 551.
[15] Vo, Minh, Thanh Nguyen, and Hoang Pham. "Stock market volatility forecasting: Exploring the power of deep learning methods." Forecasting 4.4 (2025): 61.