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Stock Price Forecasting Using ARIMA: Evidence from Zijin Mining Group

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Abstract. As market conditions become increasingly volatile, stock price predictions are becoming more challenging for all investors and researchers. Therefore, using a suitable model structure for stock price forecasting is crucial. The ARIMA model is a classic stock price prediction model in time series analysis, capturing patterns in past price changes and the impact of past shocks. This article analyzes and predicts Zijin Mining's stock price based on this model, selecting the closing prices of trading days from 2021 to 2025. The model ARIMA(1,1,1), which showed the best fit and had all significant parameters, was selected to predict the next five trading days. The results indicate that the model's short-term predictive effect on Zijin Mining's stock price is only average, possibly because it did not take into account market sentiment and macroeconomic adjustments. In future research, a mixture model or the inclusion of some macroeconomic variables could be considered.

Keywords: ARIMA model, Stock price prediction, time series.

1. Introduction

The prediction of stock prices attracts investors' attention in the financial field. Investors want to seek extra and stable profit through forecasting price movement based on professional knowledge and stock analysis tools [1]. With the financial market becoming increasingly complex, unexpected risks and emergencies, quantitative forecasting models have become essential tools for analyzing stock price movements and supporting investment decision-making.

Among various forecasting models, time series models play an extraordinary role in financial prediction. This is because the stock prices have a strong temporal feature and are recorded in specific time units. By analyzing the characteristics of the past data, time series models can capture these specific changes to predict future values of the series [2]. Based on these advantages, Time Series Forecasting (TSF) has garnered growing attention, driven by the growing size of historical data and the rising demand for production prediction, which focuses on sequentially anticipating future values, particularly given the restrictions of conventional predicting approaches, for instance, high complexity and time-consuming routines [3]. As a type of time series data, stock prices embody inherent operational patterns. Analyzing these patterns enables trend forecasting for the stock market and provides valuable decision support for investors. Among the numerous time series forecasting models, the Autoregressive Integrated Moving Average (ARIMA) model has become one of the most widely applied approaches in financial time series analysis.

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The ARIMA model, also known as the Box-Jenkins model, is the most standard and common in time series forecasting, combining autoregressive (AR), differencing (I) and moving average (MA) [4]. ARIMA models rest on a basic intuition: past observations often carry lasting influence over current and future values [5]. Therefore, it can identify the change tendency to forecast the future price. Besides, the model is particularly well-suited for non-stationary time series. Through differencing operations to attain stationarity, ARIMA effectively captures temporal dependencies and uses them to model and forecast future trends [6]. Due to these advantages, the ARIMA model is highly favored in price prediction. However, although ARIMA has been widely applied in financial time series forecasting, its effectiveness in capturing the price dynamics of commodity-related stocks remains insufficiently explored.

Zijin Mining Group stands as one of the world's leading multinational metal mining companies, with operations spanning the exploration and extraction of various mineral resources including gold, copper, zinc and lithium. It is among the world's top mining companies in terms of both financial strength and annual mineral output [7]. Due to its strong linkage with the global precious metals market, the stock price of Zijin Mining often exhibits significant fluctuations with the continuously rising metal prices, making it an interesting case for stock price forecasting using time series models.

This paper has mainly focused on the accuracy of forecasting single stock prices of Zijin Mining, compared with the realistic price data. This study follows the time series forecasting framework, covering model identification, parameter estimation, and diagnostic testing, to select a suitable ARIMA model for forecasting short-term price movements. The results are expected to deepen the understanding of financial time series forecasting and offer empirical support for the effectiveness of ARIMA in forecasting the prices of commodity-related stocks.

2. Methodology

2.1. Data source

The data of Zijin Mining Group is obtained by the Eastmoney Choice, and covers a series of time from January 4th, 2021, to December 31st, 2025. The sample consists of stock prices from all trading days of Zijin Mining Group starting in 2021. Since the observations are arranged chronologically over time, the dataset forms a typical financial time series.

2.2. Indicator selection

The information about observations is composed of 4 portions: open price, low price, high price and close price, respectively. The closing price was chosen as a metric for the company's price forecasting. It was selected because it comprehensively reflects trading activities of the index throughout a single trading day, especially the overall market evaluation of a stock during that day. Besides, the changes in closing price are allowed to capture fluctuations and movements in the stock market and reflect the managing and operating performance of the company. And the change of closing price in the sample can be observed in Figure 1.

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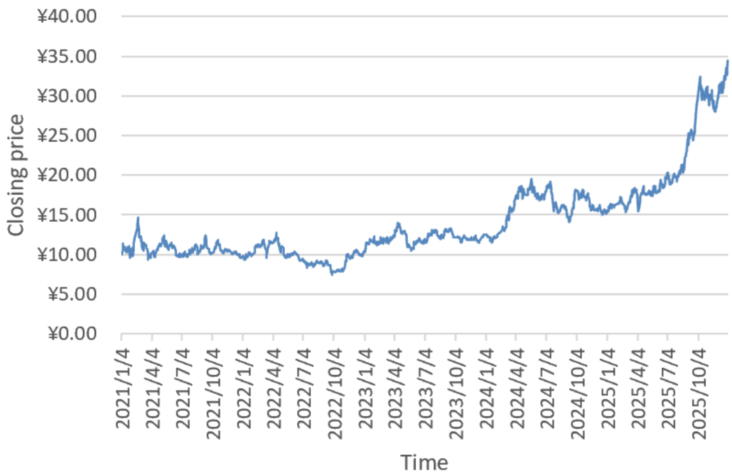

Figure 1. Sequence diagram of Zijin Mining Group stock closing price (picture credit: original)

2.3. Model introductiono

The Autoregressive Integrated Moving Average (ARIMA) model evolved from the standard adjustment of the Autoregressive Moving Average (ARMA) model. And this model is generally expressed as ARIMA(p, d, q), where p and q represent the number of autoregressive and moving average components, and d refers to the order of differencing needed to render the time series stationary.

The ARIMA (p, q) formulation is generalized as:

$$u_t = \phi_0 + \phi_1 u_{t-1} + \cdots + \phi_p u_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \tag{1}$$

In equation (1), $\{ \varepsilon_t \}$ is a sequence of white noise, with p and q being non-negative values. Besides, both the AR and MA models are special cases of ARIMA (p, q). When q=0, ARIMA(p, 0) = AR(p); when p=0, ARIMA(0, q) = MA(q).

To make sure the time series is stationary, the primitive sample is subjected to the Augmented Dickey-Fuller (ADF) Test. If the test result shows that the series is non-stationary, it is necessary to make the series meet the stationarity condition through differencing, identifying the number of d. After achieving stationarity, the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) are employed on the final time series data to decide appropriate values of p and q. However, the combination of the values of p and q could yield a multitude of distinct models. Several candidate models usually need to be estimated and compared before selecting the best model. Therefore, through Bayesian or Schwarz Information Criterion (BIC) and other methods, these models identify the one with the relatively smallest numerical value [5,8]. Then, a white noise test is conducted by analyzing the residuals of the model. If the residuals show no significant autocorrelation, the model is considered suitable for forecasting future values of the time series. Finally, a diagnostic analysis is performed to evaluate model validity, and the predicted results are compared with actual observations to assess accuracy [9]. This study utilizes the EViews software for parameter calculation and validation purposes to evaluate the ARIMA model for Zijin Mining Group.

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3. Result and discussion

3.1. Stationarity test and data transformation

Before constructing the ARIMA model, it is essential to test the original data. From Figure 1, it is found that the closing price exhibits a significant fluctuation during the selected sample period, meaning that the data constitutes a non-stationary time series. However, this is merely a preliminary inference, and further scientific verification is required. Therefore, the Augmented Dickey–Fuller (ADF) test is applied to determine whether units exist in the original data. The null hypothesis assumed that the original closing price contains a unit root. Table 1 shows that the value of the T-statistic is 1.8828, while the corresponding p-value is 0.9998, vastly exceeding the significant levels of 1%, 5% and 10%. Hence, there is insufficient evidence to reject the null hypothesis, meaning that the original data was a non-stationary time series. As a result, the differencing method is utilized into the initial series, and a line graph is presented in the new data (Figure 2, where there is no obvious upward or downward trend.

Table 1. ADF test results of the original data

Project	T-Statistic	Probability
ADF test statistic	1.8828	0.9998
Critical value: 1% level	-3.4356	
Critical value: 5% level	-2.8637	
Critical value: 10% level	-2.5680	

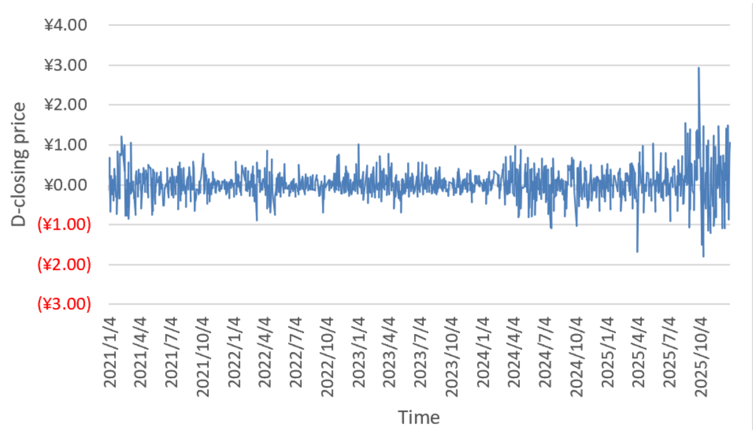

Figure 2. Sequence diagram after first difference (picture credit: original)

3.2. Model identification

When the primary sequence has undergone a process of differentiation, the next step is to determine the appropriate ARIMA model based on the ACF and PACF to determine the values of p and q.

The ACF and PACF plots of the differencing sequence are obtained through EViews (Figure 3). According to the observation method, the model parameters are estimated as p=2 and q=2. However, the veracity of the model is not certain and convincing because it is only observed by the eyes. Therefore, further evaluation must be made through adjusting R-square, AIC and BIC.

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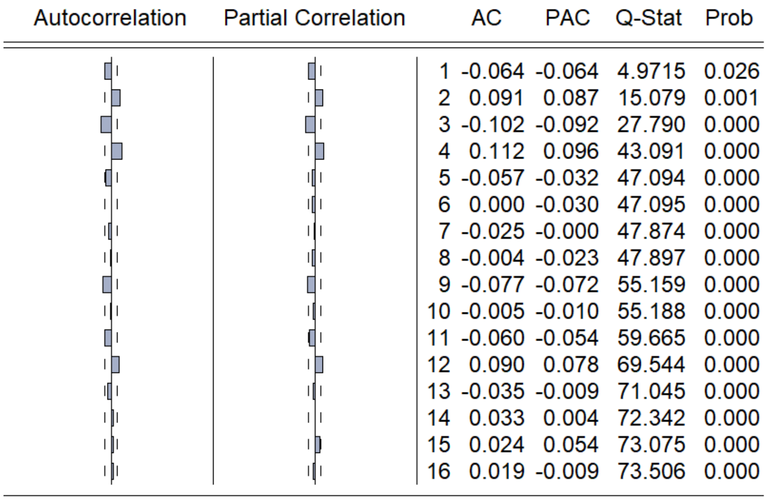

Figure 3. ACF and PACF plot after first difference (picture credit: original)

Because the p and q values are observed to be both 2 as only a rough estimate, a range of plus or minus one unit of fluctuation is needed to test, compared to which one has the most optimal fitting results. Therefore, seven different ARIMA models are established equations to obtain adjusted R-squared, AIC and BIC (Table 2).

Table 2. Adjusting R^2, AIC and BIC values of various models

	Adjusting R^2	AIC	BIC
ARIMA (2,1,2)	0.0268	0.8074	0.8327
ARIMA (2,1,1)	0.0237	0.8097	0.8308
ARIMA (1,1,2)	0.0238	0.8097	0.8307
ARIMA (1,1,1)	0.0231	0.8095	0.8264
ARIMA (3,1,2)	0.0279	0.8071	0.8366
ARIMA (3,1,3)	0.0259	0.8100	0.8437
ARIMA (2,1,3)	0.0277	0.8073	0.8368

As shown in Table 2, although ARIMA (1,1,1) has the least adjusting R-square, its BIC is also the least and AIC is relatively small. Because BIC and AIC have stronger reference significance than adjusting R-square and BIC penalizes model complexity more strictly, ARIMA(1,1,1) is selected as the optimal model.

When the values of the ARIMA model are confirmed, it is necessary to test the parameter significance. Table 3 shows that the coefficients of AR(1) and MA(1) are significant at the 1% level, and the constant term is also statistically significant at the 5% level with a p-value of 0.0477. Accordingly, the model can be expressed as:

$$y_t = 0.0202 - 0.9123 y_{t-1} + \varepsilon_t + 0.8457 \varepsilon_{t-1} \tag{2}$$

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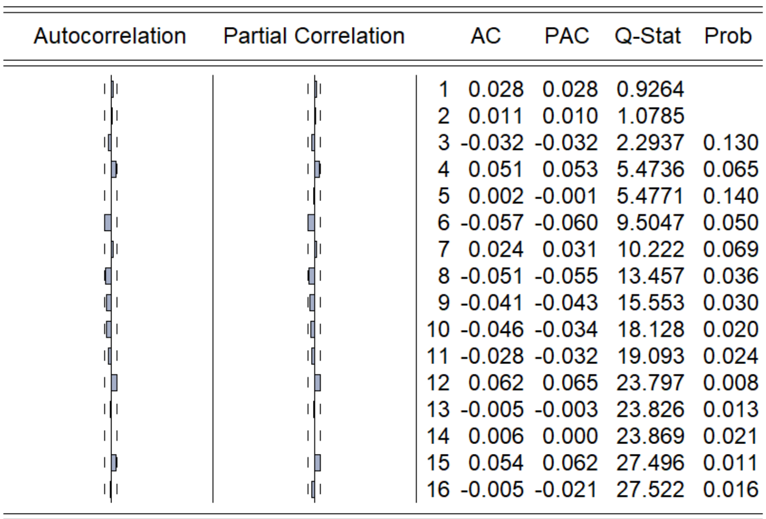
Table 3. Model building and parameter estimation

Variable	Coefficient	Std. Error	T-statistic	Prob.
C	0.0202	0.0102	1.9817	0.0477
AR(1)	-0.9123	0.0263	-34.716	0.0000
MA(1)	0.8457	0.0346	24.412	0.0000

3.3. Residual test

After estimating parameters, diagnostic checking is conducted to examine whether the residuals behave as white noise. This is an important step to make sure the model has captured the main information and patterns.

In Figure 4, most of the correlograms of the residuals are located within the confidence interval, while the p-values generally exceed 0.05 at the lower lags. It indicates that there is not sufficient proof to refuse null hypothesis, meaning that model residuals can be treated as white noise. The ARIMA (1,1,1) model is a fit and reasonable method to forecast the future price.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.028	0.028	0.9264	
		2	0.011	0.010	1.0785	
		3	-0.032	-0.032	2.2937	0.130
		4	0.051	0.053	5.4736	0.065
		5	0.002	-0.001	5.4771	0.140
		6	-0.057	-0.060	9.5047	0.050
		7	0.024	0.031	10.222	0.069
		8	-0.051	-0.055	13.457	0.036
		9	-0.041	-0.043	15.553	0.030
		10	-0.046	-0.034	18.128	0.020
		11	-0.028	-0.032	19.093	0.024
		12	0.062	0.065	23.797	0.008
		13	-0.005	-0.003	23.826	0.013
		14	0.006	0.000	23.869	0.021
		15	0.054	0.062	27.496	0.011
		16	-0.005	-0.021	27.522	0.016

Figure 4. Residual examination (picture credit: original)

3.4. Forecast evaluation

The ARIMA (1,1,1) model is employed to predict the closing price for the next trading week of the Zijin Mining Group, compared with the true values as shown in Table 4.

Table 4. The stock closing price prediction of Zijin Mining Group

Date	Predicted value	Actual Value	Error
2026/1/5	33.6225	35.3	1.6775
2026/1/6	33.5312	36	2.4688
2026/1/7	33.6532	37.6	3.9468
2026/1/8	33.5806	36.2	2.6194
2026/1/9	33.6855	36	2.3145

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It can be observed that the forecasting error between the real value and forecasting value is very large, from 1.6775 to 3.9468, indicating there is an obvious deviation between them. The large error may be attributed to the fact that the model does not consider the market sentiment and macroeconomic conditions, especially the price of the commodity. Because Zijin Mining Group sells and processes gold, copper, and other precious metals. In recent years, the price of gold and copper has been highly volatile and subject to sharp fluctuations [10,11]. And the model does not include this information and unexpected news. Therefore, the model may fail to reflect the rapid price movement.

Overall, while the ARIMA(1,1,1) model provides a basic indication of stock price movements, it struggles to capture sudden market changes. Therefore, its forecasting results should be interpreted with caution [12].

4. Conclusion

Forecasting the stock market is a challenge for investors. Although a variety of new methods have emerged in recent years, traditional time series models such as ARIMA are still widely used in stock price forecasting. This paper selects Zijin Mining Group as the research object and takes the ARIMA model as the predictive model.

However, even though comparing different parameters in the model to choose the best one - ARIMA (1,1,1), the error between the predicted value and the actual value is very huge for the next few days. It indicates that when the sample fluctuates vastly, the prediction accuracy is not guaranteed, especially with the profundity of the external factors.

To sum up, the ARIMA (1,1,1) model provides a limited prediction for the short-term stock price due to complex and rapid market conditions. Future research may consider incorporating external variables or combining ARIMA with other models to improve forecasting accuracy.

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