Research on the Impact of ARMA Model on Stock Price Prediction

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Abstract. Japanese government's first discharge of nuclear wastewater occurred on August 24, 2023. This study selects the closing prices of Guolian Aquatic Products (300094) over a period of 87 days from April 3 to August 13, 2023, as the sample. Using Stata 17 software and the ARMA model, the study forecasts the closing prices for the 14 days following August 13 and compares these predicted values with the actual stock prices during that period. The research finds that the error between the predicted and actual closing prices is relatively small before the discharge announcement, but increases significantly after the discharge. Additionally, Japan's discharge of nuclear wastewater has a short-term positive impact on the stock prices of the fishery sector. This indicates that the ARMA model can be effectively used for short-term stock price prediction with favorable results, and it also reflects the extent to which sudden events can influence stock prices.

Keywords: Time series, nuclear wastewater discharge, Autoregressive Moving Average Model, Stock price prediction.

1. Introduction

Time series is a chronologically ordered sequence of data exhibiting randomness while maintaining certain interdependencies. There are many types of time series data available in the financial market such as fluctuating stock prices and interest rates. Unlike cross-sectional data, there is an inherent pattern in time series models which can be discovered through systematic research. We can uncover these underlying patterns and make predictions about future trends, which proves crucial for financial professionals.

As an economic barometer, stock price forecasting mantains significant importance for both nations and investors. The ARMA (Autoregressive Moving Average) model stands as the most widely adopted approach for modeling stationary time series which effectively integrates two critical aspects in financial forecasting: temporal dependencies between market indicators and random noise interference. This dual consideration enables accurate short-term trend predictions. Moreover, the ARMA model boasts mature theoretical foundations, facilitating comprehensive statistical analysis and mathematical manipulation.

The Japanese government officially launched the Fukushima nuclear contaminated water discharge plan on August 24, 2023, and announced that the process will last for at least 30 years. The "Bad Events" caused a great deal of controversy in China and the impact of the event could be reflected through stock prices. Therefore, we want to discover the impact of this event on Chinese stock prices. Japan's discharge of nuclear wastewater is mainly for the ocean, and we would like to measure the impact of this event by selecting changes in the stock prices of listed companies related to the ocean. This article selects the closing prices of Guolian Aquatic Products (300094) for a total of 87 days from April 3 to August 13, 2023 as samples. Using Stata17 software and ARMA model, we predict the closing prices for the next 14 days based on August 13, and compare the predicted values with the actual stock prices during these days.

2. Literature Review

Similarly, Ren Min and others used the daily closing price of SSE Pharma four months before the COVID-19 to predict the impact of COVID-19, and found that the COVID-19 has a long-term and positive impact on the Chinese hospital sector. Xu Chenmeng used the ARMA model to predict the stock price of China Merchants Bank in the next three days, and found that the ARMA model had a small error between the predicted results and the actual values, making it a good tool for stock price prediction. Huang Shimin used the ARMA model to predict the stock price of China Merchants Bank, and also found that the predicted value of the ARMA model was close to the actual value, indicating that the model could predict the stock price well.

3. Introduction to ARMA Model and Its Modeling Design

3.1. ARMA model andvariable usage

ARMA (Auto-Regressive Moving Average) model is a fundamental approach in time series analysis, widely used for modeling and forecasting stationary time series. The model combines two components: AR (Auto-Regressive) and MA (Moving Average).

In the ARMA (p, q) model parameters, p represents the lag order of the autoregressive part, and q represents the lag order of the moving average part. The general form of an ARMA(p, q) model can be expressed as: ARMA(p, q) Model:

p: Lag order of the autoregressive (AR) part.

q: Lag order of the moving average (MA) part.

The ARMA model combines AR(p) and MA (q) components, typically written as:

$$X_t = \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \ldots \Phi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \tag{1}$$

Where θ and Φ are parameters and ε is white noise.

In this article, we use the price sequence of the closing price as the independent variable, so the independent variable is named Ps

3.2. Modeling Design Steps

(1) Data Preparation: Ensure the time series is stationary

(2) Model Identification: Determine AR (p) and MA (q) orders using ACF/PACF plots and criteria like AIC/BIC.

(3) Parameter Estimation: Fit the model using methods like maximum likelihood estimation.

(4) Model Validation: Check residuals for white noise properties.

(5) Once the ARMA (p, q) model is fitted and validated, it can be used to generate point forecasts and confidence intervals for future time points, helping to analyze the series' trend.

4. Empirical analysis

4.1. Stationarity test

Table 1. Dickey–Fuller test for unit root

Test	Dicker-Fuller ------critical value------		
Statistics	1%	5%	10%
Z (t) - 4.096	-3.548	-2.912	-2.591

MacKinnon approximate p-value for Z(t) = 0.0010.

Before applying the ARMA model to a set of time series data, it is necessary to test for stationarity. In this paper, the unit root test method was used. As shown in the table below, the p-value of the closing price (ps) sequence is 0.001, indicating that the selected data sequence is stationary under the original conditions and passes the stationarity test. Therefore, the original sequence does not require differencing, and in the ARIMA (p,d,q) model, the order of differencing d=0.

4.2. Parameter determination

After ensuring the stationarity of the time series, the next step is to determine the values of p and q in the ARMA model. The order selection is based on analyzing the Partial Autocorrelation (PACF) and Autocorrelation (ACF) plots.Based on the analysis of the Partial Autocorrelation (PACF) plot, a cutoff is observed at lag 1, indicating a p-value of 1. The Autocorrelation (ACF) plot shows a dragging-off pattern, where the q-value is determined as the lag at which the ACF line first exceeds the confidence interval (but not exceeding two standard deviations from the mean), minus 1. This suggests q could be 0, 1, or 2.

Therefore, three ARIMA model specifications are compared: ARIMA (1, 0, 0), ARIMA (1, 0, 1), ARIMA (1, 0, 2).

Among them, the MA(2) coefficient in ARIMA (1, 0, 2) is not significant and is therefore excluded. In the case where both ARIMA(1,0,0) and ARIMA (1, 0, 1) have coefficients that pass the significance test, the AIC criterion is further used to compare their AIC values, with the model having the smaller AIC value being considered superior.Based on the AIC criterion, the ARIMA (1, 0, 1) model with an AIC value of -77.4903 is superior to the ARIMA (1, 0, 0) model (-74.18636) and is therefore selected as the optimal model.

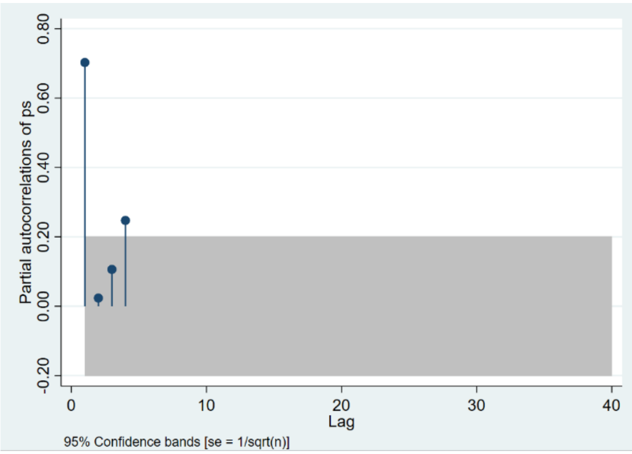

Figure 1. Partial correlation graph

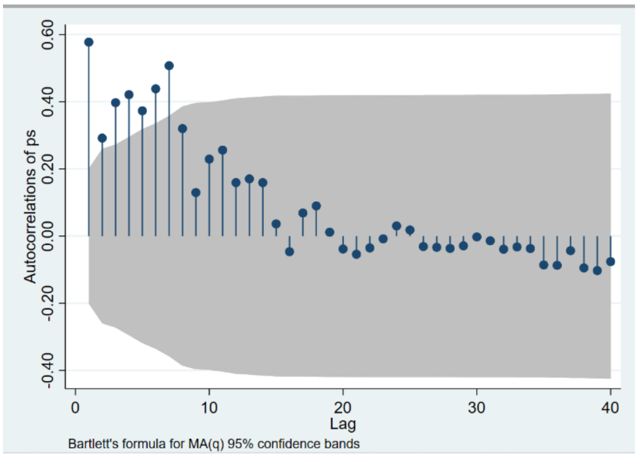

Figure 2. autocorrelogram

Table 2. AIC values table for ARIMA models

	AIC	BIC
ARIMA (1, 0, 0)	- 74.19	-66.52
ARIMA (1, 0, 1)	- 77.49	-67.27

4.3. Establishment of the Opening Price Sequence Model

According to Table 3, the equation of the ARIMA model can be derived as:

$$P_{S_t} = 5.06902 + 0.9265804 P_{S_{t-1}} + \varepsilon_t - 0.4387906 \varepsilon_{t-1} \quad (2)$$

Moreover, the p-values of all corresponding parameters in this model are below 0.05, indicating that the model is statistically significant and effective.where $\{\varepsilon_t\}$ denotes the residual sequence.

Table 3. The regression results of the ARIMA (1, 0, 1) model

		Opg				
Ps	Coefficient	std. err.	z	P>|z|	[95% conf.	interval]
Ps						
_cons	5.06902	.0983046	51.56	0.000	4.876346	5.261693
ARMA						
ar						
L1.	.9265804	.0460244	20.13	0.000	.8363742	1.016787
ma						
L1.	-.4387906	.176288	-2.49	0.013	-.7843088	-.0932725
/sigma	.1459497	.0049963	29.21	0.000	.1361571	.1557423

4.4. Residual diagnostic tests

After establishing the model, stationarity tests need to be performed on the residual terms. If the model is well-fitted, the residual series should approximate white noise, meaning it has a mean of zero, constant variance, and no autocorrelation or partial autocorrelation. Tools for residual diagnostics include residual time series plots, ACF (Autocorrelation Function), PACF (Partial Autocorrelation Function), Ljung-Box test, and the Portmanteau test.

Since white noise is a stationary series, and the model's residual series approximates white noise, a unit root test is conducted on the residual series to check for stationarity. According to the results in the table, the p-value is sufficiently close to zero, and the test statistic is smaller than the critical value at the 1% significance level. This indicates that the residual series is stationary, meeting the definition of an approximately white noise stationary series.

In addition to stationarity, the residual series must also be tested for autocorrelation. Therefore, the Portmanteau test is employed. The test results show that the p-value of the residual series under the Portmanteau test is greater than 0.05, leading to the rejection of the hypothesis that the residual series has autocorrelation. Thus, the residual series satisfies the assumption of no autocorrelation.

Table 4. Augmented Dickey-Fuller (ADF) test table for residual stationarity

	--------critical value---------			
	Statistic	1%	5%	10%
Z (t)	-9.195	-3.548	-2.912	-2.591

MacKinnon approximate p-value for Z(t) = 0.0000.

Table 5. Autocorrelation test results for the residual series

Portmanteau test for white noise
Portmanteau (Q) statistic = 16.1589
Prob > chi2(40) = 0.9997

4.5. Predictive analysis

Table 6. Stock Price Forecast Results Table

Date	real share price (yuan)	stock price prediction (yuan)	Difference	percentage
2023-08-14	5.0700	5.11584	-0.0458423	-0.90%
2023-08-15	5.0900	5.08387	0.0061252	0.12%
2023-08-16	5.0700	5.08592	-0.0159218	-0.31%
2023-08-17	5.1600	5.07684	0.0831595	1.61%
2023-08-18	5.1200	5.11690	0.0030949	0.06%
2023-08-21	5.1000	5.10841	-0.0084099	-0.16%
2023-08-22	5.3500	5.100284	0.249716	4.67%
2023-08-23	5.9400	5.097989	0.7140939	12.02%
2023-08-24	7.1300	5.095861	1.563957	21.93%
2023-08-25	7.0200	5.093891	0.7261657	10.34%
2023-08-28	7.3400	5.092065	0.78175	10.65%
2023-08-29	6.5600	5.090373	-0.2702671	-4.12%
2023-08-30	6.3200	5.088805	-0.2491215	-3.94%
2023-08-31	6.4600	5.087353	0.1225345	1.90%
2023-09-01	5.9800	5.086007	-0.3241078	-5.42%

Note: Difference = Actual Stock Price - Predicted Stock Price; Relative Prediction Error (%) = (Actual Stock Price - Predicted Stock Price) / Actual Stock Price * 100%.

According to the results in Table 5, before the statement about Japan's nuclear wastewater discharge was released on August 22, the stock price predictions from the 14th to the 21st were relatively accurate, with small differences and low relative error percentages, even reaching 0.06%. This indicates that, in the absence of major disruptive events, the model's predicted values were quite close to the actual stock prices.

However, on the day the statement was released (August 22), the impact on the company's stock price was unexpectedly positive, with an increase of 4.67%. The rise continued on the 23rd, reaching 12.02%, but the peak had not yet been reached. The initial surge was likely because some people believed seafood would become unsafe after the nuclear wastewater discharge and rushed to enjoy it one last time. The reason the peak was not yet reached might be that some anticipated global opposition to Japan's actions, leading to less concern.

On August 24, videos of Japan's nuclear wastewater discharge spread widely across major websites, making people realize the severity of the issue and that seafood would no longer be safe. This led to a surge in demand for existing edible seafood, causing the stock price to rise sharply by 21.93%. However, after the buying frenzy on the 24th, the stock price increases in the following days began to decline and even turned negative, reflecting diminishing public confidence in the seafood industry and expectations that stock prices would eventually return to normal levels.

In summary, the ARMA model performs well in predicting stock prices in the short term and under normal circumstances, with predictions closely matching actual values. However, when major disruptive events occur, stock price fluctuations deviate significantly from the normal range, leading to larger prediction errors. Overall, the ARMA model remains highly valuable for stock price forecasting.

5. Summary

Stock price prediction has always been a topic of great interest. This paper employs the ARMA model to forecast the closing price of Guolian Aquatic Products (300094), demonstrating the feasibility of time-series models for short-term stock price prediction. The model effectively extracts price information, exhibits good fitting performance, and yields relatively small errors between predicted and actual values. However, since the next period's prediction is calculated based on the previous period's forecast, the cumulative error will gradually increase. For long-term stock price forecasting, the ARMA model's predictive performance significantly declines. Moreover, long-term stock price trends are heavily influenced by political factors, industry policies, unforeseen events, and environmental conditions, whereas short-term predictions are less affected in the absence of major disruptions. Therefore, under normal circumstances, investors can use the ARMA model for short-term predictions as a reference for investment decisions.

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