

SP500 Forecast Based on ARIMA and ETS Models

Qihan Dong^{1, a, *}

¹ College of Management, Sichuan Agricultural University, Chengdu, China

a. email, 202203510@stu.sicau.edu.cn

*Corresponding author

Abstract: Prediction of stock price, as a core issue in the financial sector, is deeply affected by the Federal Reserve's interest rate decision. As an important engine of the world economy, the United States' economic policies and decisions undoubtedly play a pivotal role on the global economic stage. The Fed's rate cut had a profound impact on global capital markets. Under the current macro background of the US interest rate cut, it is particularly critical to study and build an effective stock price forecasting model. In this paper, ARIMA and ETS models are used to predict SP500, and the results show that the RMSE value of ETS model fitting is lower than that of ARIMA model fitting. The ETS model can provide better prediction results in predicting SP500. This paper combines ARIMA and ETS models to provide a new perspective for stock price forecasting and a new idea for stock price forecasting under the background of US interest rate reduction.

Keywords: Prediction, ARIMA, ETS, SP500.

1. Introduction

The accurate prediction of stock prices is crucial for individual and institutional investors. It can not only help them make more sensible investment choices and optimize risk management, but also have a profound impact on the strategic planning of enterprises, the effective allocation of resources, the improvement of market efficiency, the enhancement of consumer confidence and the formulation of economic policies by the government. In the meantime, it can also help maintain the stability of financial markets and promotes the healthy functioning of the entire economic system.

At present, the academic circle has done quite a lot of research on stock price forecasting, which can be divided into three types. The first is studying the impact of exogenous variables on asset prices, such as analyzing from the perspective of news sentiment and combining it with stock prices to make stock predictions [1], analyzing from the angle of investors' sentiments and using text extraction method to make stock prediction [2], making stock prediction based on sentiment analysis of stock social media [3]. The second is using machine learning for stock price forecasting, including establishing stock price prediction project based on deep learning [4], establishing convolutional neural network based on graph convolution features [5], predicting international carbon finance market based on particle swarm optimization and support vector machine [6], using deep learning neural network to make stock prediction [7], etc. The third is to build a model for asset price prediction through time series data of stock prices, including CNN-BiLSTM-AM method [8], CNN-LSTM-Based method [9], LSTM model [10], etc. However, these studies generally focus on the time before US rate cut. As a major economy in the world, the adjustment of the interest rate policy of the United

States will undoubtedly have a profound impact on the global capital market. The current research on the forecast of stock price trend in the US interest rate reduction cycle is still insufficient.

In this paper, ARIMA and ETS models are constructed to forecast the stock price of SP500's time series data. This paper uses data from 2015 to 2022 as the training set and data from 2023 to 2024 as the test set. This paper uses data from 2015 to 2022 as the training set and data from 2023 to 2024 as the test set. After fitting the data of the training set with ARIMA model and ETS model, the results show that both of the two models can predict the development trend of stock price correctly. Therefore, this paper further compares the RMSE index of the two models. The results show that the RMSE value of ETS model fitting results is smaller than that of ARIMA model fitting results, so this paper conclude that ETS model prediction results are more accurate.

ARIMA and ETS are both widely used models in time series data forecasting. This paper innovatively combines the two models and finally concludes that ETS model is more accurate, providing a new perspective for stock price forecasting. In addition, the research data is in the cycle of US interest rate reduction, and this study will provide a new idea for the stock prediction under the background of US interest rate reduction cycle.

2. Data

The SP500 is a fairly representative and authoritative stock index in the world today. The SP500 includes a total of 500 listed companies in different sectors. Compared to the Dow Jones Industrial Average, it includes more companies, spreads risk more widely and reflects broader market changes.

The SP500 data used in this article comes from FRED (<https://fred.stlouisfed.org/>). Due to the timeliness of the data, only daily data from January 2015 to August 2024 are taken in this paper. In addition, in order to improve the continuity of the data, the discrete daily data is processed into the monthly data with strong continuity by averaging. The SP500 index over the sample period is shown in Figure 1 below.

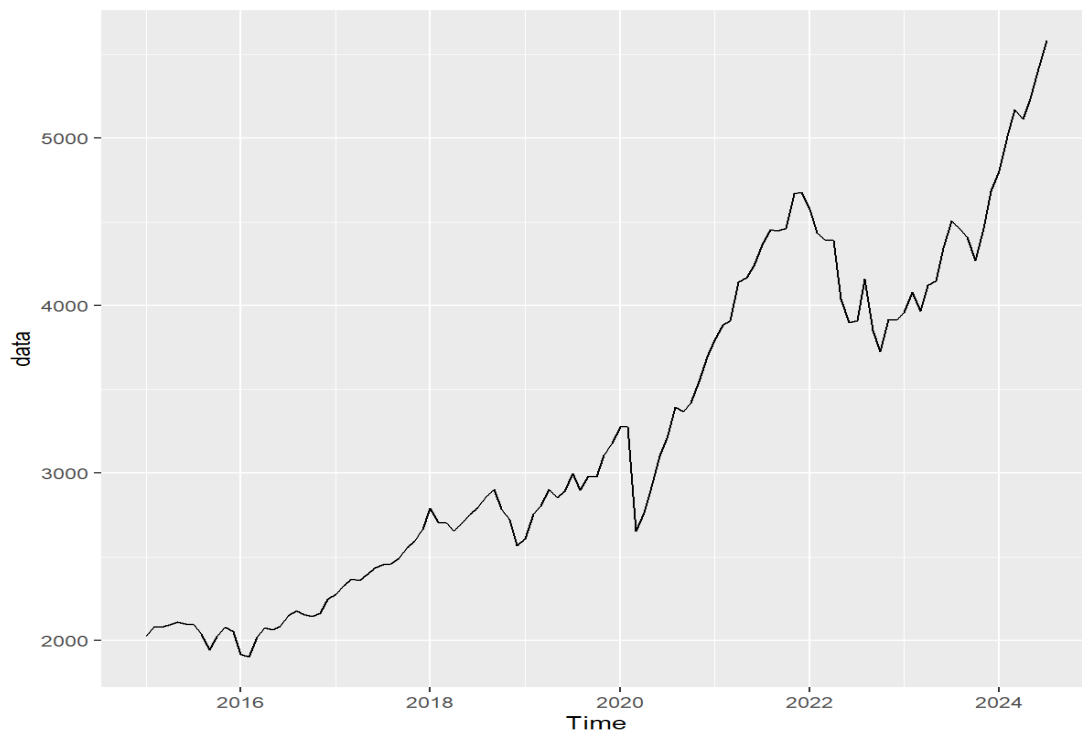


Figure 1: SP500

Figure 1 shows the trend of changes in the data. It is not difficult to find that, overall, the data shows a trend of rising volatility and does not have obvious seasonal characteristics. Growth in the index was relatively flat until 2020, but it saw rapid growth in both early 2020 and late 2022, peaking in August 2024. The basic descriptive statistical characteristics of the data in the selected sample period are shown in Table 1 below.

Table 1: Descriptive Statistics

	mean	SD	max	min	kurtosis	skewness
SP500	3251.13	982.14	5579.89	1904.42	-1.01	0.42

According to Table 1, it is not difficult to find that the maximum value of the data is 5579.89, the minimum value is 1904.42, the mean value is 3251.13, and the standard deviation is 982.14, which indicates that the data distribution is relatively dispersed and has great fluctuations. The kurtosis is -1.01, which is less than 0, indicating that the data distribution is relatively flat compared with the normal distribution and is the flat peak. The skewness is 0.42, which is greater than 0, indicating that the data distribution is more skewed to the right than the normal distribution.

3. Method

3.1. ARIMA

For time series data that do not have seasonal characteristics, ARIMA can play a very good forecasting effect. This is because ARIMA models capture and predict the dynamic behavior of data through three main components: First, the autoregressive part, which considers the relationship between the current value in the time series and its past value. By analyzing historical data points, the ARIMA model is able to identify autocorrelations in time series, that is, correlations between current values and past values. Second, the difference part, for non-stationary time series data, that is, the statistical properties of the data (such as mean and variance) change over time, the ARIMA model makes the series stable through differential operations. Differential means subtracting the current value in a sequence from the previous value, thereby eliminating the effects of trend and seasonality and keeping the statistical properties of the sequence stable. Third, the moving average section, which considers the relationship between the current values in the time series and past prediction errors. By analyzing past prediction errors, the model is able to predict future fluctuations in values. The specific formula is as follows:

$$Y_t = c + \sum_{i=1}^p \varphi_i Y_{t-i} + \sum_{i=1}^q \theta_i \epsilon_{t-i} + \epsilon_t \quad (1)$$

In this formula, Y_t is the SP500 this paper studies. φ_1 to φ_p are the parameters of the AR model. These parameters are used to describe the relationship between the current value and the value of the past p time points. θ_1 to θ_q are the parameters of the AR model. These parameters are used to describe the relationship between the current value and the error at q time points in the past. ϵ_t is the error term at time t . c is a constant term.

3.2. ETS

The ETS model is a time series prediction model used to analyze and predict time series data with trend, seasonality, and error components. The structure of the ETS model is relatively simple, which

means it is easy to understand and implement. It doesn't require complex math, making it easy for even non-expert users to get started quickly. This simplicity also means that the model has fewer parameters, which reduces the risk of overfitting and makes the model more stable and reliable. In addition, the ETS model allows users to select different trend and seasonal components based on the specific characteristics of the data, and this flexibility allows it to adapt to a wide range of different data types and forecasting needs.

The ETS model consists of three main components: First, errors, which represent random fluctuations in the data, that is, changes that cannot be explained by trends or seasonality. The trend component describes the long-term trend of a time series over time. Third, seasonality, the seasonal component reflects the regular changes in the data over a fixed period.

Figure 2 shows the flow of data processing by the ETS model. First, model identification is needed to perform, determine if there are trend and seasonal components in the time series data, and select the appropriate type of error (additive or multiplicative). Second, this paper needs to do model fitting, using historical data to estimate the model parameters, applying the estimated parameters to the model to fit the time series data. Third, this paper uses a well-fitted model to predict future values. Finally, this paper needs to evaluate the predictive performance of the model by calculating the prediction error and plotting the predicted value against the actual value.



Figure 2: Flowchart

4. Results

In this study, this paper uses data from 2015 to 2022 as the training set and data from 2023 to 2024 as the test set. The parameters obtained by fitting training set data are shown in Table 2 below.

Table 2: Parameter Fitting Results

	Parameter 1	Parameter 2	Parameter 3
ARIMA	0	1	0
ETS	M	A	N

As shown in Table 2, this paper chooses the ARIMA (0,1,0) and ETS (M, A, N) models respectively. For ARIMA (0,1,0), $p=0$ means that there is no autoregressive part, that is, the model does not use past values to predict the current value. $d=1$ means that the data needs a difference to reach a stationary state. This means that the model assumes that there are non-stationary trend or seasonal components in the data, and these non-stationarities can be eliminated by a first difference. $q=0$ indicates that there is no moving average part, that is, the model does not use past error terms to predict the current value. For the ETS (M, A, N) model, the first letter M represents the multiplication model applied to the error term. The second letter A represents the addition model applied to the trend term. The third letter N represents that the model does not have seasonal terms. The fitting results of ARIMA and ETS are shown in Figures 3 and 4, respectively.

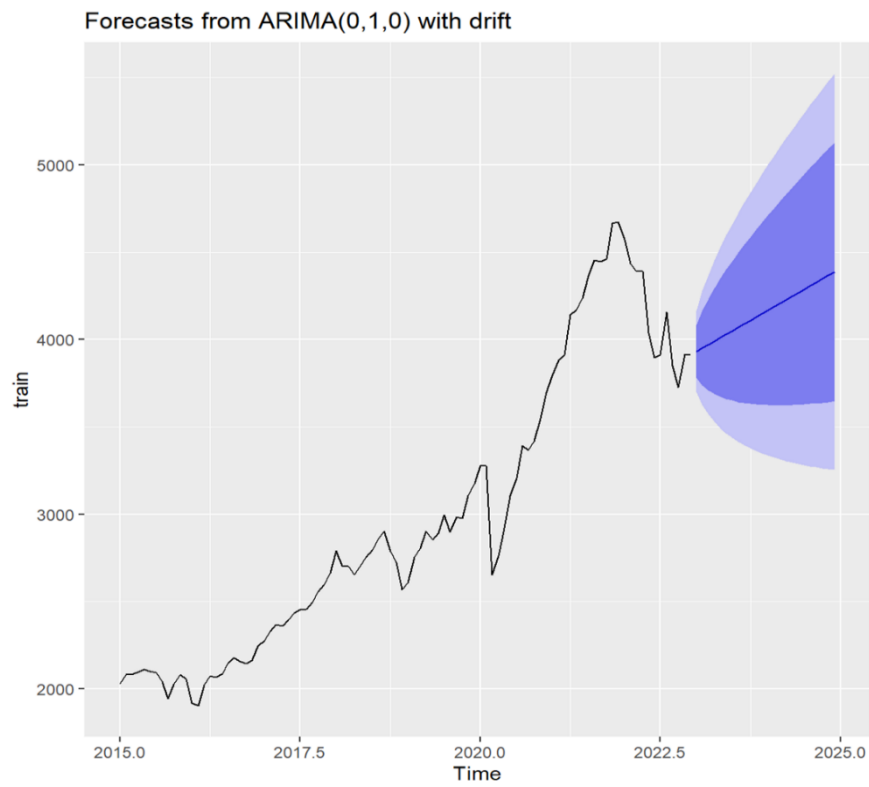


Figure 3:ARIMA Result

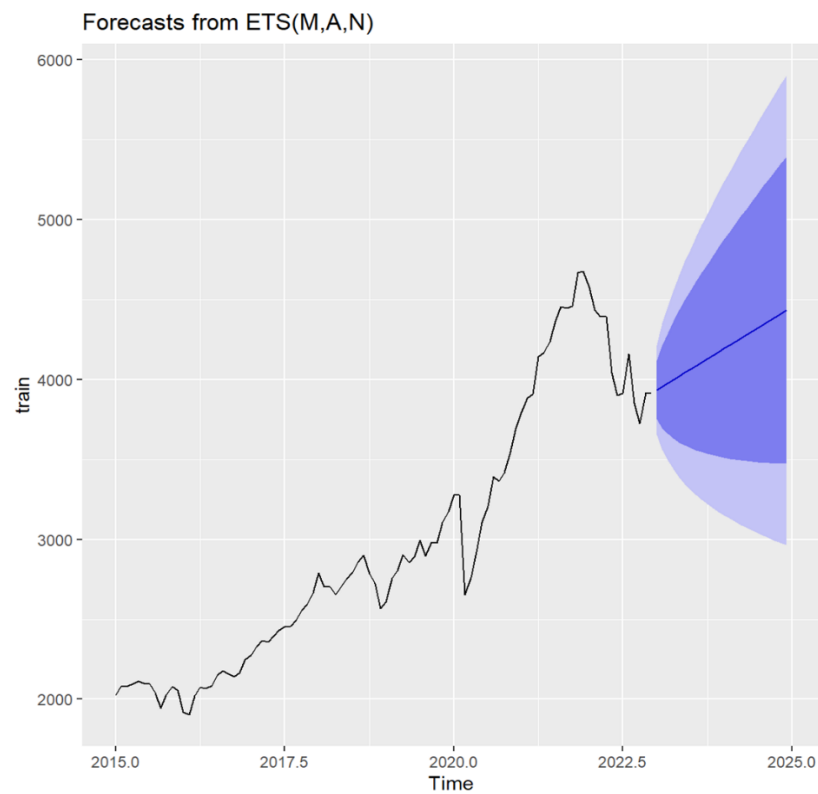


Figure 4: ETS Result

By comparing Figure 3 and Figure 4, it is not difficult to find that the ARIMA model and the ETS model have similar predictions for the SP500 index, and both have made upward predictions for its development trend, which is the same as the actual situation. In order to further compare the performance of the two forecasting stock indexes, this paper uses RMSE index to further compare the forecasting accuracy. Table 3 shows the accuracy of ARIMA and ETS model predictions.

Table 3: Comparison Results

Model	Rmse Results
ARIMA	639.0638
ETS	618.7069

By observing Table 3, it is not difficult to find that ETS model has lower Rmse value, which indicates that ETS model can better predict the development trend of stock index.

5. Conclusion

In the field of finance, stock price prediction has always occupied the core position, and the interest rate adjustment policy of the Federal Reserve has a non-negligible impact on the global capital market. Given that the US is currently in a rate reduction cycle, it is particularly important to develop and evaluate accurate asset price forecasting models. In this study, the prediction ability of ARIMA and ETS for SP500 is compared and analyzed, and the prediction accuracy of ETS model was better than ARIMA model. This paper expands the horizon of asset price forecasting and provides a new way of thinking for asset price forecasting in the US interest rate reduction cycle.

In the future research, researchers can deepen the exploration of the SP500 index forecast from two dimensions. On the one hand, it can broaden the time span of the research, allowing to analyze and forecast the SP500 index from a more macro perspective. On the other hand, it is possible to experiment with different forecasting models in order to discover the model that performs best in predicting the SP500 index. Through these methods, researchers are able to understand market dynamics more comprehensively, thus providing investors with more accurate asset price forecasts.

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