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SSEC Forecast Based on ARIMA and ETS Models

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Abstract: Stock price forecasting is the main concern of the financial industry, which is affected by many macroeconomic variables. The Shanghai Securities Composite Index (SSEC), as a representative index of the Chinese stock market, provides an overall overview of the performance of the Chinese capital market. China's economic policy changes, especially the adjustment of monetary policy, have had a significant impact on the stock market. In this paper, ARIMA and ETS models are used to forecast SSEC under the current macroeconomic environment. The results show that the root mean square error (RMSE) value of ETS model is lower than that of ARIMA model, indicating that ETS model is more accurate in SSEC prediction. In addition, the ETS model is particularly suitable for stock market forecasting due to its ability to account for exponential trends. In order to provide a new perspective for predicting the Shanghai Stock Composite Index and provide guidance for stock market forecasting under complex economic environment, the ARIMA and ETS models are analyzed in this study.

Keywords: Forecasting, ARIMA, ETS, Shanghai Composite Index, SSEC.

1. Introduction

Proper stock price prediction is crucial for both individual and institutional investors. It not only helps them make better investment choices and better manage risks, but it also has a big impact on government policymaking, company strategy, resource allocation, market efficiency, and consumer confidence. Furthermore, stock price forecasting facilitates the seamless functioning of the larger economic system and helps to maintain the stability of financial markets.

Currently, a substantial body of research on stock price forecasting exists within academic circles, and it can generally be classified into three categories. The first category is sentiment analysis. For example, predicting stock prices from the perspective of news sentiment analysis, predicting the stock price from the angle of social media, predicting stock prices by embedding the enterprise knowledge graph, considering various business relationships between listed stocks [1-3]. In the second category, machine learning is used to forecast stock prices. This includes using neural network and regression models to analyze stock market data, hybrid models that combine decision trees and artificial neural networks (ANN), and genetic algorithms to forecast stock prices [4-6]. The third category is using time series analysis model to predict the stock price, such as CNN-BiLSTM-AM method, CNN-LSTM model, LSTM model [7-9]. Certainly, there are also approaches that integrate different categories, such as combining LSTM models with social media sentiment for the purpose of

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predicting stock market movements [10]. However, as a major global economy and a representative of emerging countries, research on asset price prediction in China is still relatively scarce.

In this paper, ARIMA and ETS models are constructed to forecast the stock price of SSEC's time series data. The data from February 2011 to February 2021 is used as the training set, and the data from March 2021 to September 2024 is used as the test set. After fitting the data with ARIMA and ETS models, the results show that both models can accurately predict the stock price trend. Thus, the RMSE indicators of the two models are further compared in this work. The findings suggest that the ETS model yields more accurate predictions than the ARIMA model since its fitting results have a lower RMSE.

2. Data

The Shanghai Composite Index is a stock index compiled by the Shanghai Stock Exchange in China, which reflects the performance of 2000 stocks. The market performance of every firm listed on the Shanghai firm Exchange is weighted averaged to create the Shanghai Composite Index, which represents the overall performance of the Shanghai stock market. Meanwhile, the Shanghai Composite Index has been compiled since December 19, 1990, and is one of the Chinese stock market's most representative indices, used to gauge the performance of the country's stock market.

The closing price time series data from February 2011 to September 2024 is displayed in Figure 1. February 2021 is indicated with a red dashed vertical line. The training set is represented by the data on the left of the dashed line (2011.2 to 2021.2), and the test set is represented by the data on the right of the line (2021.3 to 2024.9). Significant variations may be seen in the training set, including a peak around 2015 and a few minor variations until 2021. The test set spans the years following 2021 and continues with mild variations until around 2024.

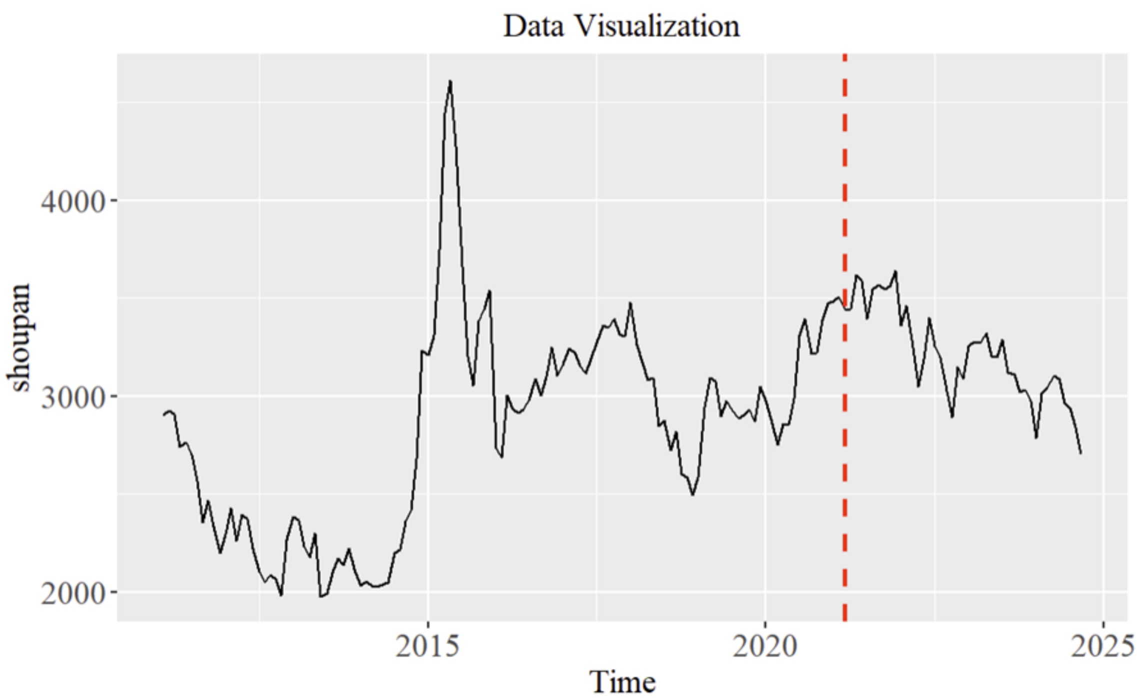

Figure 1: closing price of SSEC from 2011.2 to 2024.9

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3. Method

In this research, two models are required to fit the data which are the ARIMA model and the ETS model.

3.1. ARIMA Model

For time series data without seasonal patterns, ARIMA is a good forecasting model. It works by capturing the relationship between current and past value, stabilizing the data through differencing, and accounting for past prediction errors using the moving average component. These components work together, giving ARIMA model the ability to forecast trend and fluctuations with accuracy. A simple form of the ARIMA model is ARIMA (0, 1, 1), which involves no autoregressive terms, uses first-order differencing to make the series stationary, and includes a moving average term. The model can be expressed in Equation (1).

$$Y_t - Y_{t-1} = \theta_1 \epsilon_{t-1} + \epsilon_t \tag{1}$$

where Y_t is the current value of the time series, Y_{t-1} is the previous value, ϵ_t is the current error term, and θ_1 is the coefficient for the previous error term.

3.2. ETS Model

Based on exponential smoothing techniques, the ETS model is another popular model for time series forecasting. It can be applied to time series with different trends and seasonal patterns since it breaks the series down into three parts: Error, Trend, and Seasonality. A simple form of the ETS model is ETS (M, N, N), which includes an additive error component, no trend, and no seasonality. The model can be written in Equation (2).

$$Y_t = l_{t-1} + \epsilon_t \tag{2}$$

Where Y_t is the observed value at time t; l_{t-1} is the smoothed value from the previous period. ϵ_t is the multiplicative error term, which is a proportion of the level.

4. Result

This paper uses data from 2011.2 to 2021.2 as the training set and data from 2021.3 to 2024.9 as the test set. During the modeling process, the training data is used to fit the parameters. The fitting results are shown in Table 1 below.

Table 1: ARIMA and ETS model parameters

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

As shown in table, this paper chooses the ARIMA (0,1,1) and ETS (M, N, N) models. For ARIMA (0, 1, 1), p equals to 0 means that there is no autoregressive term and the model does not rely on previous values to predict the current value; d equals to 1 means the data is non-stationary and needs a difference to reach a stationary state; q equals to 1 means that there is one moving average term, which requires past forecast errors to adjust the current prediction. For the ETS (M, N, N) model, the first parameter multiplicative error (M) means that the error size depends on the value of the series.

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The second parameter no trend (N) suggests the model assumes no consistent trend over time. The third parameter no seasonality (N) implies no repeating seasonal patterns in the data.

Next, using the fitted ARIMA model and ETS model to forecast the data for the 43 months from March 2021 to September 2024, and compare the results with the actual data. As shown in the figure below, Figure 2 presents the comparison between the ARIMA forecast and the actual values, while Figure 3 presents the comparison between the ETS forecast and the actual values.

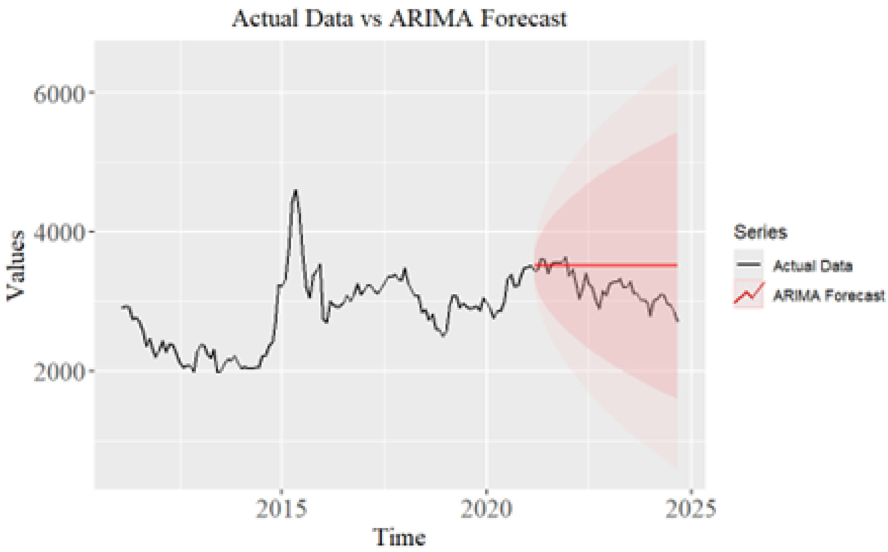

Figure 2: Forecast of ARIMA model

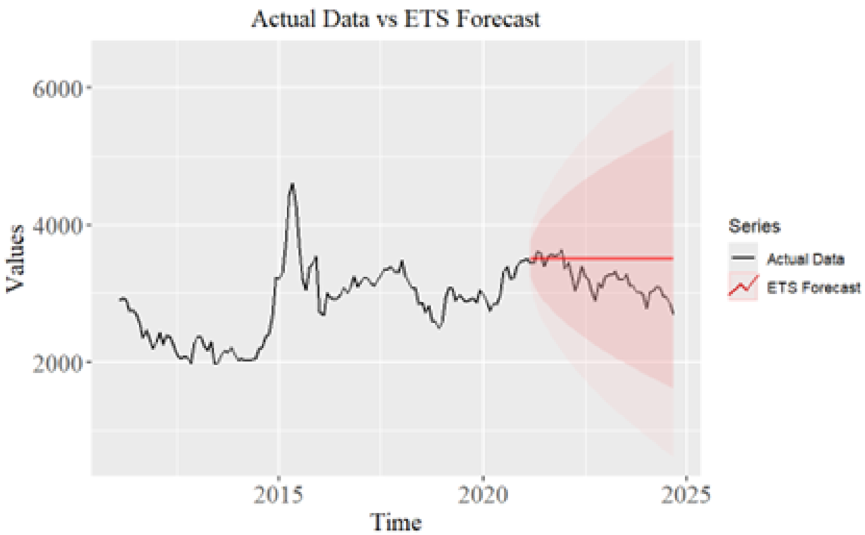

Figure 3: Forecast of ETS model

By comparing Figure 2 and Figure 3, it is not difficult to find that the ARIMA model and the ETS model have similar predictions for the SSEC, 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 (See Table 2).

Table 2: RMSE of ARIMA model and ETS model

Model	RMSE Result
ARIMA	382.6656
ETS	376.8132

Comparing the evaluation indexes of the two models, it is found that The RMSE of ARIMA model is 382.6656 and the RMSE of the ETS model is 376.8132, which shows ARIMA Model has a greater RMSE. Therefore, the ETS model is better than the ARIMA model.

5. Conclusion

In the finance field, stock price prediction is a core issue that is influenced by various macroeconomic factors. The Shanghai Composite Index, which is a representative index of the Chinese stock market, provides an overall picture of the country's capital markets' performance. Developing and evaluating asset price forecasting models is particularly important. In this study, the predictive ability of ARIMA and ETS models for SSEC is compared and analyzed, with the results showing that the ETS model has better predictive accuracy than the ARIMA model. This paper broadens the perspective of asset price forecasting and provides insights for predicting China's stock market in a complex economic environment.

In future research, researchers can investigate the Shanghai Composite Index (SSEC) projection from two perspectives. On the one hand, the time span of the research can be expanded. On the other hand, it is possible to test various models in order to determine which one is most suited for SSEC prediction. 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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