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U.S. Dollar Activeness Forecasting: Application of the Seasonal ARIMA Model

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Abstract: This article selects the US Dollar Activeness as the research object, and through the study, it predicts the US Dollar Activeness 12 months later. It also attempts to analyze the reasons for the fluctuations of the US Dollar Activeness at different stages. The US Dollar Activeness holds a high position in the international currency market, and its fluctuations can reflect the strength or weakness of the US dollar and the health of the economy. In the prediction process, this article introduces the ARIMA model to predict the future trend of the US Dollar Activeness and tries to identify its influencing factors. By using the seasonal ARIMA model, a forecast chart of the US Dollar Activeness for the next 12 months was obtained. The US Dollar Activeness is likely to maintain its strength in the short term, but there are still uncertainties. Predicting the US Dollar Index can influence future exchange rate fluctuations and monetary policy formulation, as it reflects the value of the dollar against a basket of foreign currencies, exerting a broad impact on global financial markets and economic activities.

Keywords: US Dollar Activeness, ARIMA model, Forecast.

1. Introduction

1.1. Research Background and Motivation

The U.S. dollar activeness serves as a crucial metric for evaluating the comparative value of the U.S. dollar in relation to a selection of foreign currencies [1]. Since the late 1970s, the U.S. dollar has appreciated, and the substantial purchase of U.S. securities by foreign investors has led to a shift from U.S. goods exports to securities exports. This transition marked the change from a trade surplus to a deficit in the early 1980s, with the deficit now accounting for nearly 4% of U.S. GDP [2]. These changes reveal that the role of the U.S. economy in the global economy is evolving, and they also highlight the importance for the U.S. to continuously adjust its economic strategies to address domestic and international economic challenges. Based on this, since time series models are widely used to predict the behavior of phenomena in many economics, the purpose of this paper is to identify the most suitable ARIMA model for predicting the U.S. dollar. The data selected for this study spans from 2016 to 2024 in order to achieve the most accurate forecast.

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1.2. Literature Review

In a globalized economic system, the value and activity of money are the key indicators to measure a country's economic strength and international influence. Especially for the United States, a country which occupies the core position in the global economy, the activity of the US dollar is not only the focus of financial markets, but also an important factor affecting the global economic dynamics. In the past decades, time series forecasting has played an important role in a wide range of domains including next-day electricity prices, financial market analysis and stock price prediction [3-5]. ARIMA model has become an effective tool for predicting financial time series such as US dollar index because of its advantages in processing non-stationary time series, capturing trends and seasonal patterns, and parameter optimization. In practice, an ARIMA model suitable for the dollar index prediction can be constructed through appropriate data preprocessing, model identification, parameter estimation and model testing steps.

Upon examining the historical patterns of the US dollar's exchange rate during each of the previous global economic crises, it has been observed that significant fluctuations in the value of the US dollar index are invariably linked to the improvement or deterioration of the global economy [6]. An in-depth analysis of the interplay between stock market returns, interest rates, and the US Dollar Index is conducted through a series of financial analyses, including time series examination, stationarity tests, Vector Auto Regression (VAR) modeling, and Granger causality tests. The findings revealed a mutual influence among the variables under investigation [7]. Also, the trend of the US dollar activeness is influenced by a multitude of factors, including the fundamentals of the US economy, interest rate policies, government attitudes, and the international economic environment. Forecasting its future trajectory requires a comprehensive consideration of the interplay and potential changes of these factors [8].

1.3. Research Contents

The main research content involves an in-depth analysis of the historical cyclical trends of the US dollar activeness and attempts to predict its trajectory over the next 12 months. The core of the research is to identify and analyze the key factors affecting the dollar activeness' volatility, including the fundamentals of the US economy, interest rate policy, government attitudes, and the international economic environment. Additionally, the study focuses on how the dollar activeness reflects the value of the dollar relative to a basket of foreign currencies and how such fluctuations impact global financial markets and economic activities.

Researcher selected data from 2016 to 2024 for their analysis. The research approach begins with historical data, employing time series analysis and stability tests to capture the time series characteristics of the US dollar activeness through the ARIMA model, including its trend, seasonal patterns, and non-stationarity. The paper also examines the historical performance of the dollar activeness during various global economic crises and its interactions with other macroeconomic variables to support the analysis and forecasting.

2. Methodology

2.1. ARIMA

The ARIMA model is a very popular and powerful tool in time series forecasting. The ARIMA (p,d,q) model, which stands for Autoregressive Integrated Moving Average, is a statistical model used for time series forecasting. It combines Autoregressive (AR), Integration (I), and Moving Average (MA) methods to process and predict data. The AR part uses previous values of the time series to predict the current value, the I part transforms a non-stationary time series into a stationary one, and the MA part uses past values of the stochastic disturbance terms of the time series to predict the current value.

$$y'_t = c + \varphi_1 y'_{t-1} + \cdots + \varphi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \quad (1)$$

Before applying the ARIMA model, appropriate parameters p, d, and q are identified using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, where p is the order of the autoregression, d is the order of differencing, and q is the order of the moving average. After parameter determination, parameter estimation is performed using maximum likelihood estimation or other optimization techniques.

2.2. Data Selection and Processing

This paper chooses the monthly change of the US dollar activeness as an indicator, with data sourced from the Federal Reserve. To assess the stationarity of the data, a second-order difference test was conducted, followed by the ADF test (see Table 1), which confirmed stationarity with a p-value significantly less than 0.05. A randomness test using the Ljung-Box test indicated that the data was not purely white noise, as evidenced by a p-value less than 0.05, suggesting the presence of non-white noise characteristics. Thus, the next step would be to construct the ARIMA model. The results indicate acceptance of the null hypothesis, which states that the sequence is white noise. This test also provided insights into the optimal ARIMA order for the model.

Table 1: The ADF test results

P-value in ADF test	0.010	Stationary
P-value in random test	0.003	Non-white noise

3. Empirical Analysis

3.1. Model Selection

During the model optimization process, this paper selects the Akaike Information Criterion corrected (AICc) as the reference criterion. In the model fitting process, by comparing the seasonal ARIMA model with the ARIMA (0, 1, 0) model, it is observed that the values of AIC, Bayesian Information Criterion (BIC), and AICc in the seasonal ARIMA model are all smaller than those in the ARIMA (0, 1, 0) model (see Table 2). Consequently, the paper concludes that the seasonal ARIMA model is more suitable for forecasting.

Table 2: The related parameter results

	AIC	AICc	BIC
Seasonal ARIMA (0,1,0)(0,0,1)	412.04	412.17	417.17
ARIMA (0,1,0)	416.04	416.08	418.60

Expanding on this, the AICc is a modification of the AIC that adjusts for the number of estimated parameters in the model, making it a more robust measure for model selection, especially when the sample size is small. The lower AICc values in the seasonal ARIMA model suggest that it provides a better fit to the data with a more parsimonious model, thus making it a preferable choice for predictive purposes. Seasonal ARIMA models are particularly effective in capturing the periodic patterns in time series data, which is often a key feature in many real-world datasets. By incorporating

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seasonal components, these models can more accurately reflect the underlying structure of the data and enhance the predictive accuracy of the forecasts.

During the optimization phase, the most effective parameter set for the model was identified, leading to the belief that the optimal configuration had been achieved. A significance test, with p-values above 0.05, confirmed the statistical significance of the model.

3.2. Results

After ensuring the absence of white noise, the model was fitted using the ARIMA function. The seasonal ARIMA model outperformed the non-seasonal ARIMA (0,1,0) model, as indicated by the lower AIC, AICc, and BIC values.

Following the seasonal ARIMA model, the subsequent phase involves the construction of a U.S. Dollar Activeness model. By employing the forecast function, the final predictive model is illustrated in Figure 1. This methodology entails fitting the seasonal ARIMA model to the historical data of the U.S. Dollar Index, which accounts for its inherent seasonal patterns and non-stationary behavior. The application of the seasonal ARIMA model allows for forecasting the U.S. dollar's activity for the next 12 months. This model provides a reliable foundation for future economic predictions and strategic decision-making.

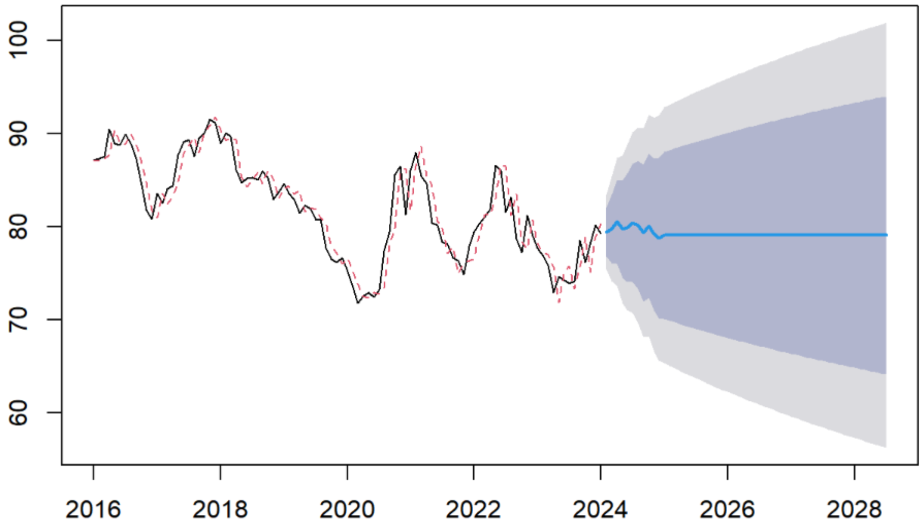

Figure 1: Forecasts from ARIMA (0,1,0)(0,0,1) [12]

4. Discussion

In summary, the reason why this model can only predict the U.S. Dollar Activeness data for the next 12 months is due to the use of the seasonal ARIMA model. Since the ARIMA (0, 1, 0) model is essentially a random walk model, the results obtained from the forecast may have certain limitations. The seasonal ARIMA model, while effective in capturing seasonal fluctuations, may not fully account for all underlying dynamics in the financial markets, which are influenced by a myriad of factors such as economic policies or market sentiment. Therefore, the predictions are inherently bounded by the assumptions and parameters set within the model. To enhance the accuracy and robustness of the forecasts, it is advisable to consider additional variables and models that could capture a broader spectrum of market influences, and to continually update the model with new data to reflect the most current market conditions.

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Given that Seasonal ARIMA models are mainly suitable for short-term forecasting, their long-term predictive capabilities may be limited. Although the forecast results in the report can provide valuable information for policymakers and investors, the uncertainty of the model's predictions and other market dynamics should be considered in practical applications. Firstly, in conjunction with the trend of the US dollar index, After the short-term market risk sentiment is released, there is room for a rebound; however, volatility is likely to remain high. It is still recommended that investors temporarily avoid risks [9]. Investors and policymakers should closely monitor economic data and market sentiment over the next 12 months to respond quickly to market changes. Secondly, implement risk management strategies to reduce potential losses. In addition, it is recommended to diversify investments, including different currencies and asset classes, to reduce dependence on the trend of a single currency. At the same time, continue to pay attention to macroeconomic factors affecting the US dollar, such as interest rate changes, inflation rates, and trade policies.

The enhanced precision of the SARIMA model over the ARIMA model is attributed to the incorporation of seasonal elements, such as trends and seasonality, which were previously omitted in ARIMA. This inclusion allows for a more accurate forecast by accounting for these patterns in the valid data [10]. However, regarding the predictive power of the model, since the seasonal ARIMA model can only forecast the dollar activity data for the next 12 months, this may imply that the model is more effective for short-term predictions but may have limited long-term predictive capabilities.

The predictive results of the report can provide valuable information for policymakers and investors, helping them make decisions. However, when applying it in practice, it is also necessary to consider the uncertainty of the model's predictions and other market dynamics

5. Conclusion

This paper utilizes the seasonal ARIMA model to forecast the trend of the US dollar index over the next 12 months, based on an in-depth analysis of historical data. The study's findings indicate that the dollar index is anticipated to maintain relative strength in the short term; however, its volatility is expected to persist due to the uncertainties inherent in the global economic environment. The predictive model employed in this paper demonstrates high accuracy in capturing the seasonal patterns and non-stationarity of the dollar index, offering valuable insights for investors and policymakers.

Regarding model selection, the seasonal ARIMA model outperforms the traditional ARIMA model in forecasting the US dollar index. This superiority is primarily attributed to its ability to account for seasonal fluctuations in the data, thereby providing a more precise reflection of market dynamics. Nevertheless, the model's predictive capabilities are constrained by its dependence on historical data and its limited capacity to anticipate potential nonlinear market changes and unforeseen events.

The conclusions drawn from this study are significant for comprehending the volatility of the US dollar index and for forecasting its future trajectory. Investors are advised to exercise caution in the short term and to closely monitor global economic indicators and policy shifts to promptly adapt their investment strategies. Policymakers can benefit from a clearer understanding of how exchange rate movements impact economic policies, enabling them to more effectively assess and mitigate potential market risks when devising relevant strategies.

For future research, there are several avenues for exploration: first, incorporating additional macroeconomic indicators into the model could enhance the accuracy and robustness of predictions; second, integrating advanced prediction methods, such as those involving machine learning and artificial intelligence, could be explored; and finally, the model's long-term predictive capabilities could be further validated and refined by incorporating more extensive historical data and cross-

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market information. These efforts could lead to a more practical and effective model, thereby offering stronger support for research and practical applications in related domains.

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