Predictive analysis of US inflation, unemployment, and interest rates using ARIMA, Holt-Winter's Exponential Smoothing, and Extreme Gradient Boosting.

By Nnaemeka Newman Okereafor

Abstract:

This research scrutinizes the application and performance of three forecasting models—ARIMA, Exponential Smoothing, and XGBoost (extreme gradient boosting)—in the predictive analysis of U.S. economic indicators: inflation, unemployment, and interest rates. The purpose of the study is to discern which model most accurately forecasts these vital economic measures. Drawing upon datasets spanning from 1995 to 2020, from the Federal Reserve Economic Data (FRED) and the Bureau of Labor Statistics (BLS), the methodology includes a rigorous data transformation process to normalize and detrend the data to make it suitable for predictive modeling. The transformations applied include log transformation, Box-Cox transformation, and twelve-order differencing to address seasonality, ensuring the data's appropriateness for the advanced analytical techniques employed.

The study's findings are a testament to the varying strengths of the models: XGBoost performs exceptionally in forecasting inflation rates, as evidenced by the lowest MAPE (2.79%) and RMSE (0.0769%), while ARIMA demonstrates relative accuracy in predicting unemployment rates, particularly under the rolling forecast origin method. In forecasting interest rates, ARIMA and Exponential Smoothing exhibit comparable performance, with ARIMA showing a slight edge. The paper's conclusion underscores the efficacy of XGBoost in handling complex, nonlinear relationships between variables, thereby providing accurate inflation predictions. Meanwhile, ARIMA's robustness is highlighted in its capacity to forecast unemployment rates effectively through a rolling forecast origin approach, suggesting this method's advantage in reflecting real-world scenarios where economic data evolves.

The research emphasizes the potential of integrating these models to harness their collective strengths, especially considering the complexity and non-linearity inherent in economic data. In conclusion, the study sheds light on the comparative accuracy of traditional and machine learning methods and paves the way for future research to explore hybrid models, combining the predictive power of statistical techniques with machine learning innovations for enhanced economic forecasting.

Literature Review:

Predictive analytics has become an essential tool in economic forecasting, leveraging historical data to predict future trends. This literature review examines the utilization of AutoRegressive Integrated Moving Average (ARIMA), XGBoost, and exponential smoothing models in predicting US unemployment, interest, and inflation rates using a dataset spanning 25 years. These methodologies have been pivotal in offering insightful forecasts that assist policymakers, economists, and businesses in strategic decision-making.

1. ARIMA Model:

The ARIMA model, a cornerstone in time series forecasting, has been extensively applied to economic data due to its flexibility in handling data of a non-stationary nature. Notably, Box and Jenkins (1976) introduced the methodology of ARIMA, providing a systematic approach to identifying, estimating, and checking models for time series data. In the context of forecasting economic indicators, Pankratz (1983) provided a detailed application of ARIMA models for economic data, outlining their efficacy in handling the dynamic nature of economic cycles.

Recent studies, such as those by Tiao and Tsay (1989), have advanced the application of ARIMA models to multivariate time series, relevant for analyzing the interrelations between unemployment, interest, and inflation rates. These studies highlight that ARIMA models, especially when combined with seasonal adjustments, can adeptly capture the underlying patterns in economic data.

2. XGBoost (extreme gradient boosting):

XGBoost, a more recent addition to the predictive analytics toolkit, offers a gradient-boosting framework that has been successful in various forecasting competitions. Chen and Guestrin (2016) describe XGBoost as an optimized distributed gradient boosting system designed to be highly efficient, flexible, and portable. Researchers have found that XGBoost performs exceptionally well in scenarios where interactions among variables are complex and non-linear.

A noteworthy application of XGBoost in economic forecasting is detailed by Friedman (2001), who explored stochastic gradient boosting, a precursor to the algorithms used in XGBoost. More specifically, studies like those by Natekin and Knoll (2013) demonstrate how boosting techniques can improve prediction accuracy in economic indicators by handling large datasets and accommodating numerous predictor variables, thereby capturing intricate relationships within the data.

3. Holt Winter's Exponential Smoothing:

Exponential smoothing techniques are crucial for making forecasts on time series data, particularly when the series exhibits a trend or seasonal patterns. The seminal work by Holt (1957) and Winters (1960) established the foundation for exponential smoothing methods, which have been enhanced and widely applied in economic forecasting.

When a dataset contains level, trend, and seasonality components, we utilize Triple Exponential Smoothing, also known as the Holt-Winters method. It builds on the Double Exponential Smoothing method by adding a seasonal parameter, gamma (γ). In the Holt-Winters method, there are three smoothing parameters: alpha (α) for level, beta (β) for trend, and gamma (γ) for seasonality.

Hyndman et al. (2008) extended these methods by incorporating a state space model approach in the 'forecast' package for R, which allows for automatic model selection and has proven effective in predicting economic time series. This approach is particularly effective in capturing the seasonality and trend of economic indicators such as unemployment, interest, and inflation rates.

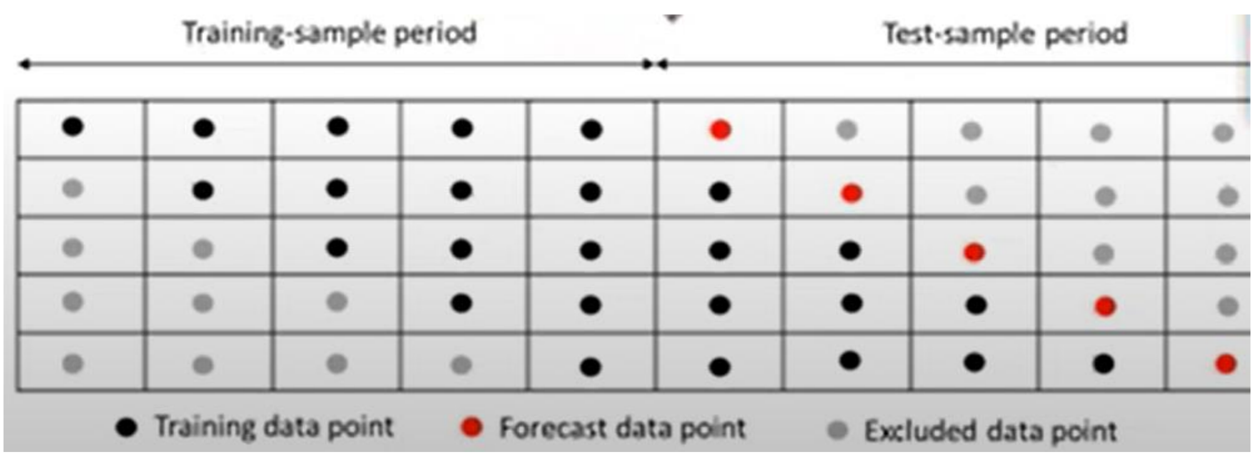
Synthesis and Comparative Analysis

Comparing these methodologies, ARIMA models are highly valued for their robustness and extensive applicative background in traditional economic time series analysis. However, they sometimes fall short in capturing sudden, non-linear shifts as compared to machine learning methods like XGBoost, which excels in handling complex, non-linear interactions between variables. Exponential smoothing models, on the other hand, provide a more intuitive approach to forecasting by smoothing out irregularities, making them ideal for data with trends and seasonal patterns but less effective in scenarios involving abrupt economic shocks.

Rolling Forecast Origin:

The rolling forecast origin, commonly known as walk-forward testing, is a critical method used in time series forecasting that assesses how well a predictive model performs over time by simulating a real-world scenario where predictions are continually updated with new data. This technique is particularly useful for models as the underlying data patterns shift over time. It provides a more realistic evaluation of a model's predictive accuracy and adaptability.

In the rolling forecast origin approach, the data set is divided into a training set where the model is initially trained, and a test set where the model's predictions are evaluated. The key aspect of this method is the continuous shifting of the training and test sets as new data becomes available, mimicking the process of making predictions in a dynamic, real-life environment. However, from a basic perspective, the rolling forecast origin method predicts one month at a time. After each month, it uses the actual data from that month to improve the next month's prediction. This continues to enhance accuracy over time.



Methodology:

For this study, comprehensive datasets were compiled from two primary sources. Interest rate and inflation data were extracted from the Federal Reserve Economic Data (FRED), a well-regarded repository managed by the Federal Reserve Bank of St. Louis. This dataset provides a detailed, consistent, and reliable measure of economic indicators such as interest rates and inflation, which are crucial for evaluating economic health and monetary policy impacts. Unemployment data, critical for assessing labor market conditions and economic cycles, was sourced from the Bureau of Labor Statistics (BLS). The BLS offers precise monthly unemployment statistics, which are essential for understanding the employment landscape.

The data spans a significant period from 1995 to 2020, encompassing various economic conditions, including periods of rapid growth, recession, and recovery. This 25-year timeline offers a rich temporal framework to observe and analyze long-term trends and cycles in the economic indicators. Such a comprehensive dataset not only allows for an in-depth analysis of historical patterns but also facilitates the exploration of potential predictors that may influence these economic variables. By examining monthly readings of each indicator, researchers can perform a robust analysis, identifying nuances and subtleties in economic shifts that might be overlooked in less detailed datasets. This extensive and meticulously compiled data thus serves as the foundation for a thorough and nuanced exploration of the interplay between interest rates, inflation, and unemployment rates over a quarter of a century.

Data Transformation:

Given the complexity and nature of economic data, several transformations were necessary to make the data suitable for predictive modeling:

Log Transformation: The initial step involved applying a log transformation to each time series data. This transformation is crucial for stabilizing the variance across the data. By converting the data into a logarithmic scale, the effects of any exponential trends are mitigated, which helps in normalizing the distribution of the values.

Box-Cox Transformation: To further stabilize the variance and address any asymmetry in distribution, a Box-Cox transformation was applied post-log transformation. This transformation, parameterized by λ (lambda), transforms the data to make it approximate normality, enhancing the homoscedasticity of the variance across the time series.

Twelve-Order Differencing: To stabilize the mean of the datasets and to eliminate seasonality and trends, a twelve-order differencing was employed. This method subtracts the value at a previous time step from the current value, repeated over twelve periods. This level of differencing was particularly chosen to account for annual cyclical effects in the data, as it removes patterns associated with yearly cycles commonly present in economic indicators.

Result:

The different statistical or machine learning models used for predictions include ARIMA, Exponential Smoothing, and XGBoost. Each model has results reported in the following format:

MAPE (Mean Absolute Percentage Error): This metric measures the accuracy of the forecasts. A lower MAPE value indicates better predictive accuracy.

RMSE (Root Mean Square Error): This measures the differences between values predicted by a model and the values observed. Lower RMSE values are preferable as they indicate higher accuracy.

Indicator	ARIMA				Holt Winter's Exponential Smoothing				XGBoost	
	Single Split CV		Rolling Forecast Origin		Single Split CV		Rolling Forecast Origin			
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
Inflation Rate	8.610%	0.2077%	4.300%	0.1077%	7.360%	0.2375%	8.400%	0.2329%	2.790%	0.0769%
Interest Rate	5.970%	0.3837%	2.980%	0.1796%	48.220%	3.0671%	20.550%	1.9044%	11.770%	0.6745%
Unemployment Rate	6.270%	0.2615%	2.990%	0.1516%	37.170%	2.1279%	30.020%	1.3595%	3.820%	0.1783%

Table 1. Prediction Results.

The results are provided under the "Single Split CV" (Cross Validation) and "Rolling Forecast Origin", indicating different approaches to training, and validating the models. XGBoost seems to perform best for predicting the Inflation Rate with the lowest MAPE and RMSE at 2.79% and 0.0769% respectively. For the interest rate and unemployment rate, ARIMA with rolling forecast origin appears to be relatively more accurate compared to Exponential Smoothing, and XGBoost. However, XGBoost still shows a good performance in terms of MAPE at 3.82% in forecasting unemployment.

The ARIMA model with rolling forecast origin predicted the trailing twelve (12) months of USA unemployment precisely at 2.99% MAPE and 0.1516% RMSE. The rolling forecast was more accurate and realistic because instead of predicting 12 months of the data, the model predicted just one month and then considered the real value of that month, and then predicted the next month, and so on so that a better prediction is made. Figure 1(i(c)) shows the actual unemployment data represented with a blue line and the predicted unemployment shown in dark-orange color. The residual of the prediction is represented in Figure 1(i(d)) shows a better and less biased distribution than Figure 1(i(b)) which most of the points are skewed towards the positive region (above the zero-line margin).

Figure 1. Prediction of unemployment rate using ARIMA model, i(a); Twelve (12) months prediction of unemployment rate, i(b); distribution of residuals from twelve (12) months prediction of unemployment rate, i(c); prediction of unemployment rate using rolling forecast origin, i(d); distribution of residuals from prediction of unemployment rate using rolling forecast origin.

Figure 1. i(a) compares the actual unemployment rate with the ARIMA model's predictions from 2020 to 2024, showcasing a dramatic decline after an initial peak, with the model closely tracking the actual rate. Figure 1. i(b) presents the residuals, or forecasting errors, from the ARIMA model, which fluctuate around the zero line, indicating varying degrees of over- and underestimation by the model. Figure 1. i(c) offers a detailed view of the actual and predicted unemployment rates around the onset of the COVID-19 pandemic, highlighting the model's response to the crisis. Lastly, chart i(d) features the rolling forecast residuals, emphasizing the model's short-term prediction errors, which seem to correct themselves over time without showing a systematic bias.

The USA inflation rate is better predicted using the XGBoost model with rolling forecast origin. The machine learning model performed at high accuracy with a balanced distribution of prediction errors (see Figure 2(ii(d)). The MAPE of the prediction is 2.79% while the RMSE is at 0.0769%.

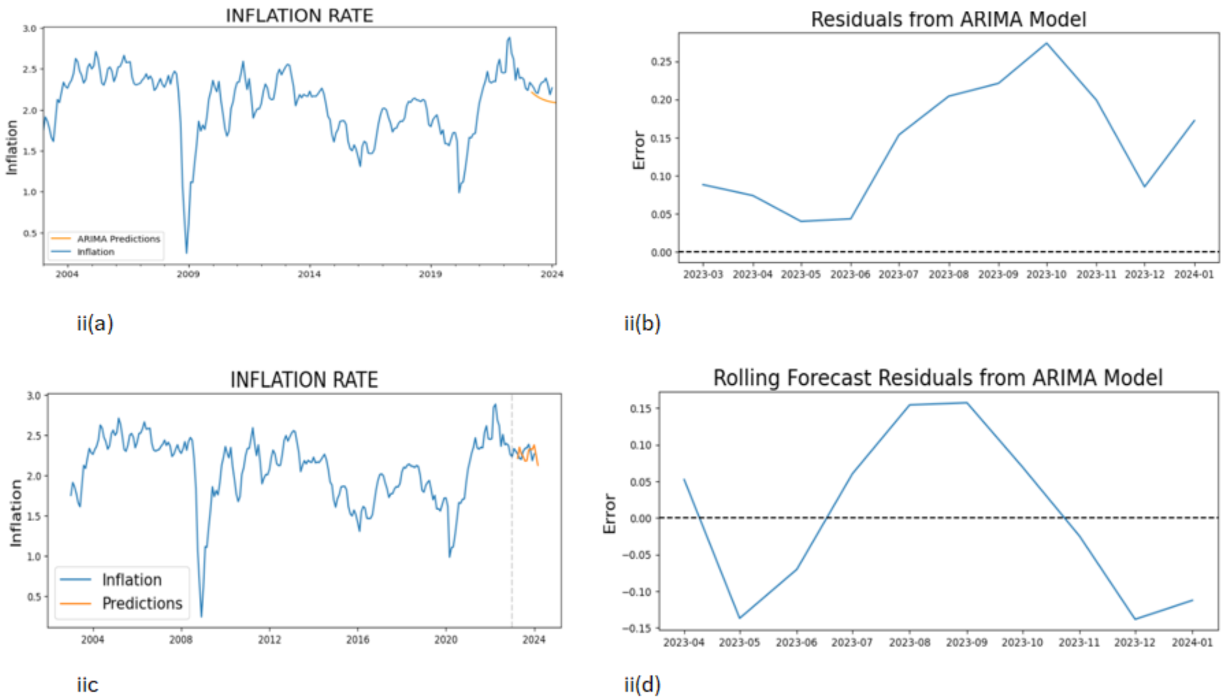


Figure 2. Prediction of inflation rate using ARIMA model, i(a); Twelve (12) months prediction of inflation rate, i(b); distribution of residuals from twelve (12) months prediction of inflation rate, i(c); prediction of inflation rate using rolling forecast origin, i(d); distribution of residuals from prediction of inflation rate using rolling forecast origin.

Figure 2. ii(a) illustrates the actual inflation rate over two decades with ARIMA model predictions, highlighting a recent uptick in inflation that the model forecasts will level off. Figure 2. ii(c) also shows the inflation trend with a segment of model predictions that slightly diverge from recent actual rates, suggesting a possible overestimation. Figure 2. ii(b) displays residuals from the ARIMA model for a specific period, showing a trend of increasing prediction error over time. In contrast, Figure 2. ii(d) shows rolling forecast residuals that demonstrate variability in the model's prediction accuracy, with errors swinging above and below zero but with a tendency to return toward zero, indicating no significant bias over time.

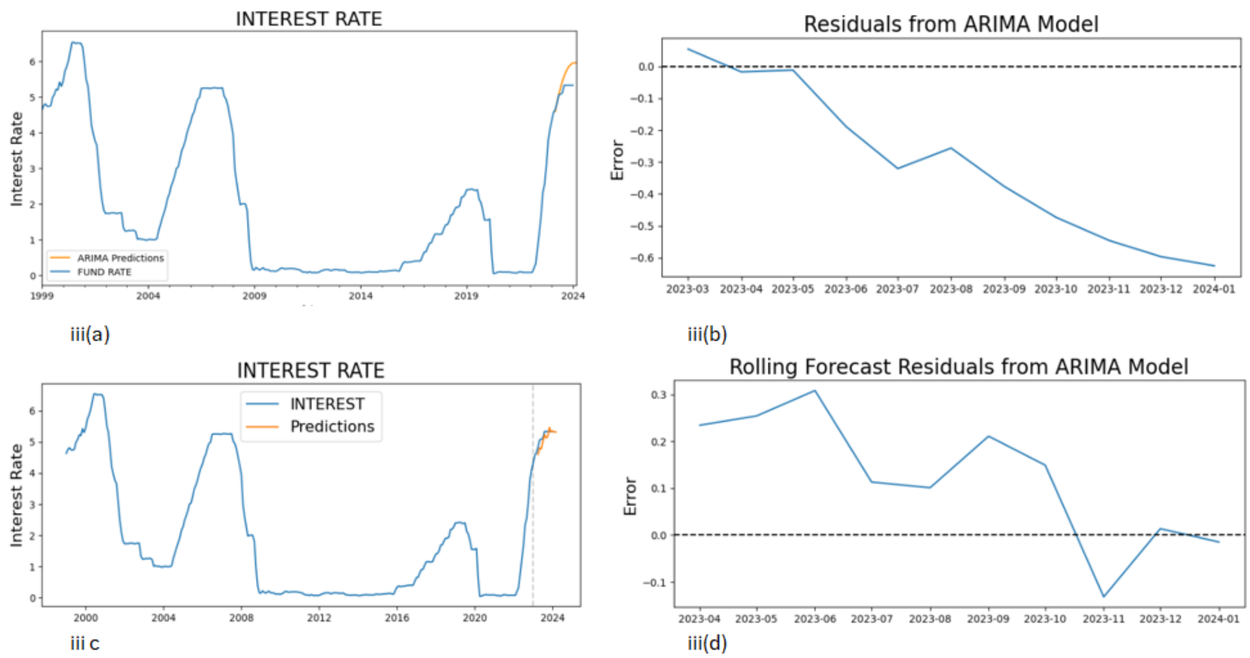


Figure 3. Prediction of interest rate using ARIMA model, iii(a); Twelve (12) months prediction of interest rate, iii(b); distribution of residuals from twelve (12) months prediction of interest rate, iii(c); prediction of interest rate using rolling forecast origin, iii(d); distribution of residuals from the prediction of interest rate using rolling forecast origin.

Figure 3. iii(a) displays the historical interest rates alongside the ARIMA model's predictions, showing a recent sharp increase in the rate, marked by an orange line that suggests a forecast. Figure 3. iii(c) mirrors the interest rate trend but explicitly marks the predicted portion in orange, indicating an expected continuation of the upward trend. Figure 3. iii(b) and iii(d) present residuals from the ARIMA model's predictions, with iii(b) showing a consistent underestimation over time and iii(d) displaying rolling forecast errors that fluctuate around the zero line, indicating variable prediction accuracy over the short term. The interest rate forecasts signal rising borrowing costs, while the residuals indicate areas where the ARIMA model's predictions could be refined.

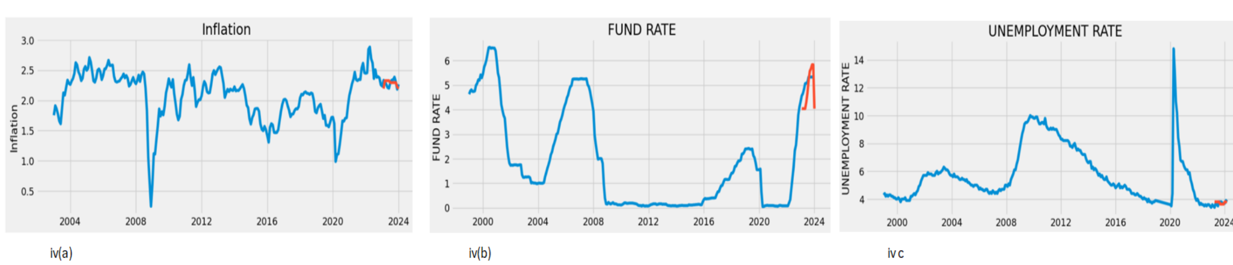


Figure 4. Prediction economic indicators using XGBoost model - iv (a) Twelve (12) months prediction of the inflation rate, iv(b); Twelve (12) months prediction of the unemployment rate, iv(c) Twelve (12) months prediction of interest rate.

Figure 4. displays historical trends of key economic indicators in the United States over two decades. Figure 4. i(a) shows the inflation rate with periodic fluctuations, peaking at times of economic stress such as the Great Recession and the COVID-19 pandemic. Figure 4. ii(b) illustrates the Federal Funds rate, with notable dips during recessions as a monetary policy response to stimulate the economy, and a red highlighted area indicating a forecast. Lastly, Figure 4 iii(c) portrays the unemployment rate, which also peaks during recessions and sharply increased during the COVID-19 pandemic, with a subsequent rapid decline, possibly indicating recovery or policy interventions.

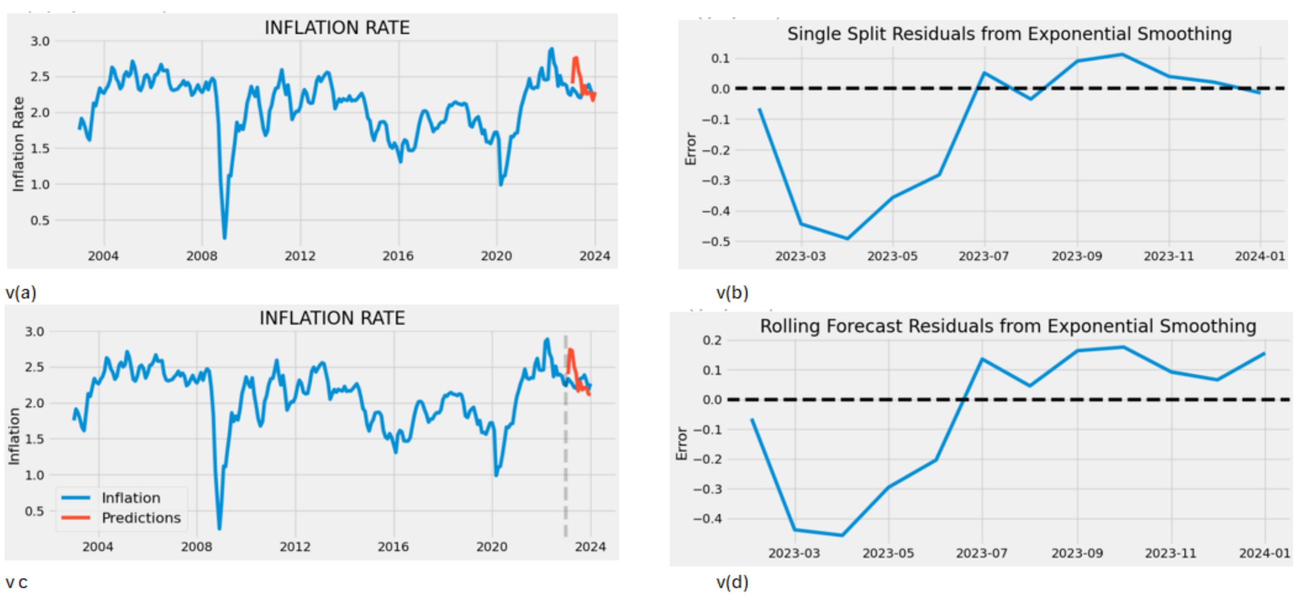
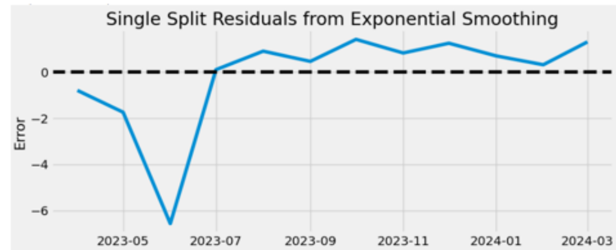


Figure 5. Prediction of inflation rate using Holt Winter's exponential smoothing model – v(a); Twelve (12) months prediction of inflation rate, v(b); distribution of residuals from twelve (12) months prediction of inflation rate, v(c); prediction of inflation rate using rolling forecast origin, v(d); distribution of residuals from the prediction of inflation rate using exponential smoothing and rolling forecast origin.

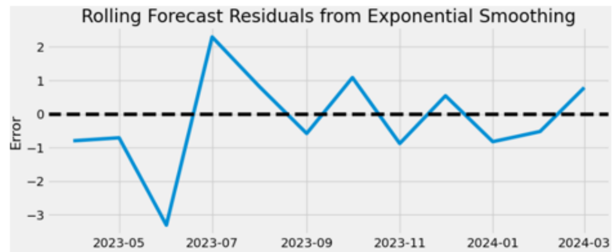
Figure 5. v(a) traces the historical inflation rate, showing its fluctuations with a recent downward trend and a red marker that indicates a forecasted decrease. Figure 5. v(c) similarly charts inflation over time but includes a prediction line in red that closely follows the actual rate, diverging slightly at the end. Figure 5. v(b) and v(d) represent the residuals from Exponential Smoothing forecasts, with v(b) illustrating a single prediction error over a period and v(d) showing rolling forecast errors, both indicating how the model's predictions differ from the actual rates, with errors oscillating above and below zero. The presence of red in v(a) and v(c) suggests attention to a significant change or area of interest where the model's prediction is less certain or diverges from historical trends.

vi(a)



vi(b)

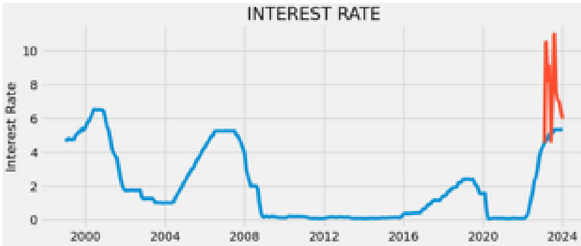
vi c



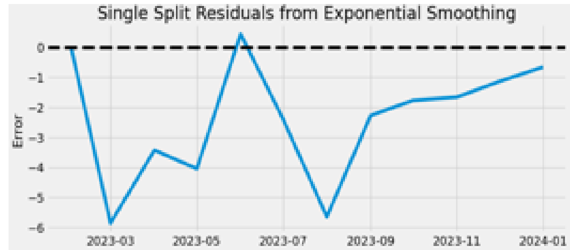
vi(d)

Figure 6. Prediction of unemployment rate using exponential smoothing model – v(a); Twelve (12) months prediction of unemployment rate, v(b); distribution of residuals from twelve (12) months prediction of unemployment rate, v(c); prediction of unemployment rate using rolling forecast origin, v(d); distribution of residuals from the prediction of unemployment rate using exponential smoothing and rolling forecast origin.

Figure 6. vi(a) shows the historical trend of the unemployment rate with peaks during recessions and a significant spike during the COVID-19 pandemic, followed by a rapid decrease and a red section indicating forecasts made using exponential smoothing. Figure vi(c) overlays predictions on the actual unemployment rate, with the red section suggesting forecasted data deviating from past trends. Figure vi(b) and vi(d) display the errors between actual data and Exponential Smoothing model predictions, with errors in vi(b) being higher, indicating a single split (perhaps a one-time prediction), and vi(d) showing a more varied error pattern, which could indicate rolling or sequential forecasts.

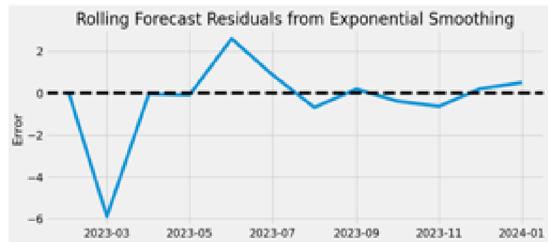


vii(a)



vii(b)

vii c



vii(d)

Figure 7. Prediction of interest rate using exponential smoothing model – v(a); Twelve (12) months prediction of interest rate, v(b); distribution of residuals from twelve (12) months prediction of interest rate, v(c); prediction of interest rate using rolling forecast origin, v(d); distribution of residuals from the prediction of interest rate using exponential smoothing and rolling forecast origin.

Figure 7. vii(a) depicts the historical interest rates with a notable increase in recent years, highlighted in red, indicating a projection. Figure 7. vii(b) and vii(d) compare the actual interest rates to those predicted by an Exponential Smoothing model, with the residuals indicating the prediction errors, which show some variance but no clear bias over the observed period.

Projections in 2024										
Model	**Indicator**	**4/1/2024**	**5/1/2024**	**6/1/2024**	**7/1/2024**	**8/1/2024**	**9/1/2024**	**10/1/2024**	**11/1/2024**	**12/1/2024**
ARIMA	**Inflation**	**2.27**	**2.236**	**2.1806**	**2.1844**	**2.3163**	**2.3292**	**2.3228**	**2.3785**	**2.2529**
	Interest	**5.1969**	**5.1245**	**5.0407**	**4.9466**	**4.8432**	**4.7317**	**4.613**	**4.4881**	**4.358**
	Unemployment	**3.4973**	**3.3948**	**3.7025**	**3.5999**	**3.4976**	**3.8046**	**3.8045**	**3.8044**	**3.7021**
Exponential Smoothing	**Inflation**	**2.2091**	**2.1648**	**2.1586**	**2.2304**	**2.2689**	**2.2616**	**2.2934**	**2.2119**	**2.0939**
	Interest	**6.4475**	**6.8049**	**6.1889**	**4.1732**	**4.0952**	**4.2057**	**4.2008**	**4.4119**	**4.573**
	Unemployment	**5.1392**	**9.3003**	**3.4849**	**2.7435**	**3.1525**	**2.2014**	**2.7113**	**2.3179**	**2.9735**
XGBoost	**Inflation**	**2.2781**	**2.2434**	**2.2595**	**2.2595**	**2.2595**	**2.2595**	**2.2595**	**2.2208**	**2.2772**
	Interest	**4.5842**	**4.7293**	**4.7762**	**5.3174**	**5.3391**	**5.4389**	**5.4087**	**5.38**	**5.4087**
	Unemployment	**3.8887**	**3.8715**	**3.8004**	**3.7277**	**3.5937**	**3.5272**	**3.5138**	**3.5135**	**3.4687**

Table 2. 2024 Economic Forecast: Monthly Projections of Inflation, Interest Rates, and Unemployment by Model

The attached table contains projections for various economic indicators in 2024, provided by three forecasting models: ARIMA, Exponential Smoothing, and XGBoost. It lists monthly predictions for inflation, interest rates, and unemployment rates from April to December. The ARIMA model presents a gradual increase in inflation rates, peaking in November, while interest rates show a consistent decrease throughout the year. Similarly, unemployment rates peak in September and then level off. The Exponential Smoothing model also forecasts inflation, showing a gradual increase and then a decrease towards the end of the year. However, the XGBoost model's projections for 2024 illustrate subtle fluctuations in inflation, with rates hovering around 2.25%, dipping slightly in November, and then returning to early-year levels by December. Interest rates are expected to show a more pronounced upward trend, starting at 4.5842% in April and gradually increasing to peak around 5.44% in September, maintaining near this level through the end of the year. Meanwhile, unemployment rates are forecasted to decline modestly from an initial 3.8887% in April to 3.4687% by December, indicating a slight improvement in employment conditions across the year. Each model offers a slightly different perspective, highlighting the variability and complexity of economic forecasting.

Summary:

The research targets precision in forecasting pivotal economic indicators such as inflation, unemployment, and interest rates. These indicators are crucial for policymakers, economic planners, and investors in crafting strategies that align with anticipated economic conditions. By analyzing and comparing the efficacy of three distinct forecasting models—ARIMA, Exponential Smoothing, and XGBoost—the study not only sheds light on which models excel under specific conditions but also identifies their limitations. Such insights are invaluable as they enhance the understanding of economic dynamics and refine the tools available for economic forecasting.

This study's significance also lies in its potential to improve economic preparedness. The demonstrated prowess of XGBoost in forecasting inflation and ARIMA's accuracy in predicting unemployment rates suggest that different models may be optimized for different economic variables. This specialization can lead to more precise forecasts, enabling more effective responses to economic challenges. Furthermore, the comparative analysis of these models helps in validating and enhancing economic theories and their practical applications, ensuring that economic predictions are as robust and reliable as possible.

To further enhance the quality and applicability of this research, several improvements can be considered. Incorporating additional variables such as geopolitical developments, fiscal policies, and global economic trends could provide a more comprehensive data set, leading to improved model accuracy. Extending the analysis to include data beyond 2020 would allow researchers to capture the economic impacts of recent significant global events, such as the COVID-19 pandemic. There is potential merit in developing hybrid models that integrate the statistical techniques of ARIMA and Exponential Smoothing with the machine learning capabilities of XGBoost, exploiting the strengths of each method for superior predictive performance. Testing these models against real-time data would help assess their effectiveness and flexibility in responding to rapid economic changes. Additionally, applying the models to economic data from various countries could broaden the understanding of how regional economic environments influence forecasting accuracy, enriching the global applicability of these models.

References:

1. Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis: Forecasting and control*. Holden-Day.

2. Pankratz, A. (1983). *Forecasting with univariate Box-Jenkins models: Concepts and cases*. Wiley.

3. Tiao, G. C., & Tsay, R. S. (1989). Model identification in time series. *Journal of the Royal Statistical Society. Series B (Methodological)*, 51(2), 157-213.

4. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785-794).

5. Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *The Annals of Statistics*, 29(5), 1189-1232.

6. Natekin, A., & Knoll, A. (2013). Gradient boosting machines, a tutorial. *Frontiers in Neurorobotics*, 7, 21.

7. Holt, C. E. (1957). Forecasting seasonals and trends by exponentially weighted moving averages. *ONR Research Memorandum*, Carnegie Institute of Technology, Pittsburgh USA.

8. Winters, P. R. (1960). Forecasting sales by exponentially weighted moving averages. *Management Science*, 6(3), 324-342.

9. Hyndman, R. J., Koehler, A. B., Ord, J. K., & Snyder, R. D. (2008). *Forecasting with exponential smoothing: The state space approach*. Springer.

10. De Livera, A. M., Hyndman, R. J., & Snyder, R. D. (2011). Forecasting time series with complex seasonal patterns using exponential smoothing. *Journal of the American Statistical Association*, 106(496), 1513-1527.

Appendices:

Project Codes:

- **Jupyter notebooks for predicting economic indicators with Holt Winter's exponential smoothing:**
  - I. https://github.com/nnaemeka-git/CUNY-MSDS/blob/main/DATA%20698/ExponentialSmoothing_Inflation.ipynb
  - II. https://github.com/nnaemeka-git/CUNY-MSDS/blob/main/DATA%20698/ExponentialSmoothing_Interest.ipynb
  - III. https://github.com/nnaemeka-git/CUNY-MSDS/blob/main/DATA%20698/ExponentialSmoothing_Unemployment.ipynb
- **Jupyter notebooks for predicting economic indicators with ARIMA:**
  - I. https://github.com/nnaemeka-git/CUNY-MSDS/blob/main/DATA%20698/USA_Inflation_ARIMA.ipynb
  - II. https://github.com/nnaemeka-git/CUNY-MSDS/blob/main/DATA%20698/USA_Interest_ARIMA.ipynb
  - III. https://github.com/nnaemeka-git/CUNY-MSDS/blob/main/DATA%20698/USA_Unemployment_ARIMA.ipynb
- **Jupyter notebooks for predicting economic indicators with XGBoost:**
  - IV. https://github.com/nnaemeka-git/CUNY-MSDS/blob/main/DATA%20698/XGBoost_Economic_Indicators.ipynb