ACADEMIA International Journal for Social Sciences
Volume 4, Issue 3, 2025 ISSN-L (Online): 3006-6638

Nexus of Univariate and Multivariate Models for Forecasting Interest Rates in USA

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Received: 16-05-2025 **Revised:** 15-06-2025 **Accepted:** 17-07-2025 **Published:** 29-07-2025

ABSTRACT
Purpose *– This study examines the effectiveness of univariate and multivariate forecasting models for interest rate prediction, emphasizing the benefits of model combination techniques to enhance predictive accuracy. The research aims to provide a robust framework for policymakers, investors, and financial analysts to improve decision-making in macroeconomic forecasting.*
Design/methodology/approach *– Using secondary data from the IMF and World Bank (1990–2023), this study applies Naïve Forecasting, Exponential Smoothing, ARIMA (2,1,1), and NARDL models to predict interest rates. Statistical validation is performed using unit root tests (ADF and PP), normality checks, serial correlation tests, heteroskedasticity assessments, and model specification tests. To further improve forecasting accuracy, the study implements Equal Weight Averaging (EWA) and Cumulative Sum (CUMSUM) methods, assessing the effectiveness of two-way, three-way, and four-way model combinations.*
Findings *– The results reveal that NARDL and ARIMA models outperform other individual models, effectively capturing both short-term fluctuations and long-term trends. Among the combination models, the ARIMA + NARDL approach demonstrates the lowest forecasting errors, proving its reliability in interest rate prediction. The findings confirm that model combination significantly enhances forecasting accuracy, improving predictive stability and reducing errors.*
Originality/value *– This study contributes to the field of macroeconomic forecasting by demonstrating the effectiveness of combining traditional econometric models with advanced model averaging techniques. The research provides a practical framework for forecasting interest rates, which can be utilized by policymakers, financial analysts, and researchers. Future research should explore hybrid forecasting approaches integrating machine learning techniques and dynamic model averaging methods to further enhance predictive precision.*
Keywords: *Interest rate forecasting, ARIMA, NARDL, model combination, macroeconomic forecasting, financial modeling*

INTRODUCTION

Interest rate predictions form the foundation of financial decision-making processes while impacting all economic activities from individual monetary choices to international market performance. This process requires analysts to estimate how central banks will adjust their interest rates in future periods and is essential for businesses and investors to make informed decisions. Forecasts that accurately predict economic conditions enable central banks to direct monetary policy which regulates inflation and ensures growth and employment stability to maintain overall economic balance. A rapid increase in inflation causes central banks to elevate interest rates as a measure to temper spending and borrowing activity whereas reduced rates during economic downturns help to boost financial activity. Forecasting enables policymakers to schedule economic adjustments at the right moments which helps prevent sudden economic disruptions (Bernanke, 2020). Interest rate forecasts play a crucial role for investors when they strategize their asset allocation decisions. Interest rate forecasts allow investors to anticipate market movements and adjust their asset positions to both increase gains and lower exposure to risk in bonds, equities, real estate, and currency markets (Bianchi, Büchner, & Tamoni, 2021). Businesses require these forecasts to develop strategic plans which include assessing capital expenditure financing costs, changing pricing strategies, handling debt management and optimizing supply chains (Brogaard, & Pan, 2022). Interest rate forecasts provide consumers with valuable information for making important financial decisions like home purchases, mortgage refinancing, and retirement planning. Fluctuations in interest rates strongly influence borrowing expenses and savings returns while affecting consumer confidence levels which makes forecasting vital for personal financial strategy development (Mian & Sufi, 2021). International markets benefit from interest rate forecasting as it reduces risks especially for emerging economies that experience capital flight and currency weakening when advanced economies increase their rates (Miranda-Agrippino & Rey, 2022). The practice assists in grasping how exchange rates move and how these movements influence trade and investment patterns. Interest rate forecasting serves academic research and economic modeling functions which expand our macroeconomic knowledge and propel predictive analytics innovation. Innovations in machine learning and artificial intelligence now enable higher precision in interest rate predictions while delivering new analytical resources for researchers and practitioners (Masini, Medeiros, & Mendes, 2023). Reliable interest rate forecasts stand as essential instruments for decision-making that allow both individuals and institutions to effectively handle complex environments by navigating through uncertainties and capitalizing on opportunities. From policymakers managing national economies to investors chasing alpha and business leaders plotting growth routes as well as consumers devising financial plans, interest rate forecasting stands as a crucial tool for success in a fast-evolving economic world.

Interest rates have a major influence on consumer spending patterns. Forecasts show U.S. consumer spending will grow by 2.8% in 2025 after rising 2.4% in 2024 (Deloitte, 2025). The accuracy of these projections depends heavily on interest rate patterns because a rise in rates usually results in more expensive mortgages and loans that can suppress consumer spending. The Federal Reserve increased the federal funds rate from close to zero in early 2022 until it reached approximately 5.5% by late 2023 which led to decreased retail sales growth along with declining non-farm payrolls according to SHS Web of Conferences (2024).

According to statistical models by Deloitte (2025), inflation could reach a maximum of approximately 3.7% in 2026 if interest rates stay high or increase before beginning to decrease gradually. The Federal Reserve needs to manage a careful equilibrium between regulating inflation and encouraging economic growth. The Federal Reserve's interest rate decisions play a crucial role because they determine credit costs which then shape business investment strategies. The Federal Reserve might start reducing interest rates in 2025 with the goal of establishing a new target range between 3.75% and 4% according to a Capital.com report from 2024. These changes play a vital role in activating economic growth while avoiding recessionary conditions. Financial markets experience significant effects from interest rate predictions. Stock and bond markets tend to experience volatility when the Federal Reserve indicates potential shifts in its monetary policy direction. The Dow Jones Industrial Average and S&P 500 indices have historically shown sharp movements after Federal Reserve announcements about possible interest rate changes (Deloitte, 2025). Investor sentiment about forthcoming economic conditions determines how capital is distributed among different market sectors.

LITERATURE REVIEW

NAÏVE Model

As a basic method in time series prediction, the naïve forecasting model serves as a standard against which more advanced models are tested. This approach assumes that the forecast for an upcoming period matches the last observed data point. The straightforward nature and simple implementation process of this model establish it as a commonly selected benchmark in forecasting research. The naïve method stands out because it performs well across datasets with minimal pattern structures since it does not depend on assumptions about trends or seasonality according to Makridakis et al. (1998) and Hyndman and Athanasopoulos (2016).

The naïve model has found application in multiple disciplines including finance as well as agriculture and public health sectors. Dhakal and Shahi (2023) applied the naïve model for predicting rice production in Nepal in agriculture and measured its accuracy against a multiple regression model. The regression model yielded superior Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) results compared to the naïve method but the research demonstrated the significance of the naïve approach for benchmarking forecasting precision. In financial markets simple naïve models remain popular for stock and cryptocurrency price predictions because they offer straightforward methods for generating initial forecast estimates. Rao et al. (2023) developed a new hybrid method that merges naïve forecasts with movement prediction techniques to enhance financial market trend prediction accuracy.

The naïve forecasting model demonstrates weaknesses when handling datasets characterized by clear trends or seasonality patterns. The naïve forecasting model overlooks trends in data such as upward or downward movements which results in inaccurate forecasts for these scenarios. The straightforward nature of the model becomes beneficial for analyses of unstable or unpredictable datasets because complex models often over fit or deliver no valuable insights. New research shows that this model remains essential for benchmarking purposes and serves as an initial platform for creating sophisticated forecasting approaches.

Exponential Smoothing

Exponential smoothing stands as a prominent forecasting technique because it offers both straightforward application and the ability to adjust to dynamic data patterns. The development of exponential smoothing is based on foundational research conducted by pioneers such as Robert G. Brown. Brown and Charles C. The work of Holt during the 1950s and 1960s paved the way for exponential smoothing to become a collection of models including simple exponential smoothing (SES), Holt's linear trend method and Holt-Winters seasonal models which address different characteristics in time series data like trends and seasonality (Hyndman et al., 2021). Exponential smoothing operates on the principle of applying exponentially decreasing weights to past data points so that newer observations carry more significance. The method is ideal for short-term prediction due to its focus on recent data trends that have greater predictive power compared to older information. Latest developments have widened its use by combining exponential smoothing with machine learning and optimization methods to improve accuracy and reliability.

Recent studies have shown exponential smoothing is extensively applied across multiple fields such as economics and energy, healthcare and supply chain management. Wang, Gurmani, Tao, Liu and Chen (2024) performed an extensive review of exponential smoothing models which revealed their better performance in electricity demand forecasting against traditional statistical methods. The research showed that Holt-Winters models with trend and seasonality components produced substantially reduced mean absolute percentage errors in daily energy consumption forecasts. Exponential smoothing proved successful at modeling seasonal patterns in solar and wind energy generation according to Rao et al. (2023). Exponential smoothing demonstrates its applicability for managing real-world complex datasets that exhibit both non-linear trends and periodic fluctuations.

Exponential smoothing demonstrates strengths but fails to perform adequately when dealing with abrupt structural changes or situations with high volatility. The research conducted by Kang, Lee, and Lim (2022) revealed that exponential smoothing achieved satisfactory results in cryptocurrency markets during stable phases but failed to accommodate rapid price shifts caused by speculative actions. Researchers have introduced hybrid techniques that integrate exponential smoothing with machine learning algorithms to overcome these limitations. Li et. al (2024) combined exponential smoothing with artificial neural networks (ANNs) for retail inventory predictions and obtained better accuracy than using either method separately. Leu (2025) created a hybrid system which merged exponential smoothing with gradient boosting machines (GBMs) for U.S. Treasury yield prediction. The predictive capabilities of Treasury yields showed considerable enhancement through the hybrid modeling approach. Hybrid models utilize exponential smoothing for its clear interpretation along with its steady behavior while they gain the adaptive nature and versatile characteristics of machine learning approaches.

Exponential smoothing has evolved through the integration of optimization techniques which optimize model parameters. The estimation of smoothing coefficients in traditional implementations depends on heuristic methods that produce less than ideal outcomes. Li et al. (2023) investigated how metaheuristic algorithms such as genetic algorithms and particle swarm optimization can optimize these parameters in recent research. Optimized exponential smoothing models demonstrated superior predictive performance for temperature variations compared to standard implementations in areas with inconsistent weather patterns. Researchers and practitioners have started to adopt ensemble methods that combine several exponential smoothing models. The 2022 study by Kang, Lee, and Lim demonstrated improved cryptocurrency market predictions by combining exponential smoothing variants with ARIMA and LSTM models through a weighted ensemble approach. The development of these innovations demonstrates the active work to improve exponential smoothing's durability and scalability to address current forecasting needs.

Researchers have conducted extensive studies to compare exponential smoothing with other forecasting methods. Makridakis and his team (2020) performed a comprehensive analysis of various forecasting methods during the M4 Competition that involved more than 100,000 time series datasets. Exponential smoothing models demonstrated top performance in the M4 Competition for short- to medium-term forecasting when applied to datasets showing clear trends and seasonal patterns. The study found that exponential smoothing techniques were less effective in unstable conditions where machine learning models demonstrated superior performance. Masini, Medeiros, and Mendes (2023) pointed out that the selection of the proper exponential smoothing method depends on data attributes and recommended practitioners examine the use of SES, Holt's method, or Holt-Winters models based on whether trends and seasonality exist in the data.

ARIMA Model

Time series forecasting relies heavily on Autoregressive Integrated Moving Average (ARIMA) models which provide a strong framework to analyze and predict data patterns involving trends, seasonality and noise. ARIMA models were first developed by Box and Jenkins in the 1970s and they integrate autoregressive (AR) elements with differencing (I) and moving average (MA) components to analyze time series data structure. ARIMA can process non-stationary datasets by applying differencing techniques which makes it ideal for analyzing data with trends and seasonal patterns. ARIMA's modern relevance in forecasting is confirmed through recent advancements and applications documented by multiple studies available on Google Scholar. The 2021 research by Hyndman and Athanasopoulos showed that ARIMA continues to lead econometric forecasting because it adapts well to multiple sectors like finance, energy, and healthcare. The increased adoption of machine learning methods has not diminished ARIMA's role as a standard for judging the effectiveness of complicated models, especially when users value easy interpretation and method simplicity.

ARIMA has gained widespread use for solving practical problems in various sectors during recent years. Rao et al. (2023) applied ARIMA for electricity demand forecasting and proved its capability to effectively track both immediate variations and long-term consumption patterns. The study demonstrated that ARIMA models exceeded traditional statistical methods in daily load pattern forecasts especially when seasonal adjustments were applied. Kumar and Singh (2022) used ARIMA for retail inventory management to generate precise product demand forecasts from historical sales data. The study demonstrated that ARIMA's capability to model autocorrelation and seasonality made it ideal for sectors with cyclical patterns such as retail and manufacturing. The research by Leu (2025) demonstrated how ARIMA can be used to forecast U.S. Treasury yields in financial analysis. The ARIMA method achieved competitive accuracy for U.S. Treasury yield predictions when compared to advanced models during periods of economic stability. Evidence from multiple use cases demonstrates ARIMA's wide-ranging applicability and dependable performance for processing structured time series data.

ARIMA demonstrates significant strengths yet faces challenges when applied to situations marked by high market volatility or structural changes. The research conducted by Kang, Lee, and Lim (2022) demonstrated that ARIMA performed reliably during stable market conditions but failed to handle abrupt market changes caused by speculative trading in the cryptocurrency sector. The limitations of ARIMA have led researchers to investigate combined methods which merge ARIMA with machine learning techniques. Li et al. (2023) integrated ARIMA with Long Short-Term Memory (LSTM) networks to predict temperature changes and surpassed the accuracy of individual ARIMA models. The hybrid approach took advantage of ARIMA's linear trend modeling capabilities and applied LSTM networks to detect non-linear patterns alongside market volatility. Wang, Gurmani, Tao, Liu, and Chen (2024) introduced ensemble methods which combined ARIMA forecasts with exponential smoothing and neural network predictions to strengthen robustness when dealing with volatile environments. Current developments show continued work to expand ARIMA's functional boundaries past its original parameters.

A significant research trend in ARIMA development targets both optimization of parameters and automation processes. Traditional ARIMA implementations depend on manual model parameter selection which results in time-intensive processes and error vulnerability. Recent research by Makridakis et al. (2020) demonstrated automated ARIMA model development through the use of grid search and genetic optimization algorithms. The research results demonstrated that automated ARIMA models performed equally well or better than manually adjusted models in major forecasting competitions such as the M4 Competition. Masini, Medeiros, and Mendes (2023) highlighted the critical need for practitioners to select proper differencing orders and seasonal components by evaluating both stationarity and seasonality prior to ARIMA implementation. The above findings demonstrate the essential combination of technical knowledge and computational resources to fully utilize the model.

Studies comparing various forecasting models show ARIMA delivers competitive performance when applied to short- and medium-term predictions. Makridakis et al. (2020) performed an extensive review of forecasting techniques during the M4 Competition which analyzed more than 100,000 time series. The analysis revealed that ARIMA performed well among top models for datasets featuring distinct trends and seasonal patterns but showed weaker performance compared to machine learning models in highly variable or chaotic environments. Hyndman and Athanasopoulos (2021) highlighted that ARIMA's straightforward implementation and understandable nature make it a preferred option for practitioners in fields needing high transparency. The authors warned that ARIMA may not produce optimal results when facing datasets with intricate non-linear patterns which deep learning models handle more effectively.

NARDL Model

Econometric analysis now frequently utilizes the Nonlinear Autoregressive Distributed Lag (NARDL) model to study asymmetric relationships within time series data. Researchers can use the NARDL framework developed by Shin, Yu, and Greenwood-Nimmo (2014) to examine how independent variable changes produce distinct effects on a dependent variable during different time periods. The ability of NARDL to differentiate reactions based on shock direction proves especially useful in economic research because responses fluctuate according to whether shocks are positive or negative. The NARDL model has demonstrated adaptability in multiple fields such as finance and energy economics as well as agricultural research.

The NARDL model served as the analytical tool that Fiaz et al. (2021) used to examine the unequal impacts of exchange rate volatility on Pakistan's agriculture sector. The research demonstrated that negative exchange rate fluctuations exerted stronger effects on agricultural output compared to positive fluctuations which underlines the need to integrate asymmetry considerations into policy development. Allen and McAleer (2021) implemented the NARDL technique to study how oil price movements affect stock market indices and found that stock returns respond differently to price increases compared to price decreases. The research demonstrated the model's capability to identify intricate dynamics that linear traditional models usually fail to capture.

AsadUllah et al. (2022) applied the NARDL method in their study on Euro to US dollar exchange rate forecasting throughout the COVID-19 pandemic. The research demonstrated that combining NARDL with univariate forecasting techniques produced better prediction results than traditional models such as ARIMA and naive methods. The results demonstrate NARDL's dual utility in relationship analysis and forecast enhancement under volatile conditions.

New research shows that parameter estimation methods for the NARDL framework require greater robustness. The research by Saidi (2021) reviewed multiple estimation approaches and explored their effects on analyzing asymmetrical relationships in economic datasets. Researchers insist that maintaining precise model specifications along with parameter stability is essential to obtain trustworthy results from NARDL assessments.

Combination Techniques

Naïve Forecasting combined with Exponential Smoothing and AutoRegressive Integrated Moving Average (ARIMA), along with machine learning-based methods are standard choices for time series forecasting. The performance of forecasting models varies with different trends, seasonal patterns and economic disturbances so that no model dominates across all datasets and conditions (García-Aroca, Martínez-Mayoral, Morales-Socuéllamos, & Segura-Heras, 2024). Multiple forecasting models are now being used together to improve accuracy and robustness for predictions due to the limitations of single-model approaches as shown by research from Winkler and Makridakis (1983). Researchers integrate multiple forecasting methods to manage the bias-variance tradeoff since single models tend to either overfit or underfit the data. Model combination techniques produce more consistent and dependable forecasting results according to Stock & Watson (2004).

García-Aroca, Martínez-Mayoral, Morales-Socuéllamos, and Segura-Heras, (2024) introduced the forecast combination principle by showing that predictions from multiple models combined together produced smaller errors than those from a single model. Forecast combination operates through model diversification which allows multiple models to identify unique data patterns and reduces the chance of bias specific to any one model (Clemen, 1989). Multiple combined forecasting methods have been developed where each method provides specific benefits based on the data conditions and forecasting goals.

The equal-weight averaging approach stands as one of the simplest methods because it gives equal importance to each model in forming the final forecast (Hibon & Evgeniou, 2005). Although the method appears basic, empirical research demonstrates that equal-weighted model combinations typically yield better results than individual models through the use of model diversity to decrease forecast errors (Armstrong, 2001). Sophisticated methods determine model weights according to their historical performance outcomes. Inverse Mean Squared Error (MSE) Weighting assigns greater importance to forecasting models that have demonstrated lower historical errors according to Granger and Ramanathan (1984). Bayesian Model Averaging (BMA) is a common method that gives probabilistic weights to various models through their predictive performance metrics and prior probability distributions (Raftery et al., 1997). Statistical methods including ordinary least squares (OLS) are used in regression-based techniques to determine the best combination of forecasts according to Stock & Watson (2004).

Machine learning developments have led to increased popularity of ensemble methods for forecasting applications. Bootstrap Aggregating (Bagging) and Boosting improve forecast accuracy through improved stability and reduced variance as demonstrated by Breiman in 1996 and Friedman in 2001. Stacking uses a meta-learning model to find the best combination of base models for improved forecast accuracy which makes it a more complex ensemble technique (Wolpert, 1992). The Cumulative Sum (CUMSUM) method modifies model weights through cumulative forecast error analysis which proves especially valuable in time series situations with evolving patterns (Kolassa, 2011). Forecasting accuracy has shown significant improvements with hybrid models including ARIMA-GARCH for trend and volatility modeling (Tsay, 2010) and Wavelet-ARIMA-ANN for multi-scale pattern extraction through wavelet decomposition and ANN (Rao, 2003).

Multiple domains utilize empirical applications of combined forecasting techniques. Through their financial market research Wang, Hyndman, Li, and Kang (2023) demonstrated that forecasts of stock prices and interest rates became more stable and precise when GARCH and ARIMA models were integrated with neural networks. The research by Stock & Watson (2004) revealed that interest rate forecasts became significantly more accurate when macroeconomic indicators were combined using regression-based methods. Researchers use combined forecasting methods to analyze key macroeconomic indicators including inflation rates, GDP growth and unemployment levels. Research by Ang, Bekaert & Wei in 2007 demonstrated that macroeconomic model combinations yielded more dependable forecasts compared to separate models. Granger & Ramanathan (1984) discovered that using weighted combinations of ARIMA and exponential smoothing models produced better GDP forecast results.

Researchers have demonstrated that combined forecasting techniques deliver superior results in predicting commodity prices. According to Pindyck (1999) the integration of economic fundamentals and market sentiment indicators into forecast combinations yielded better accuracy for oil and gold price predictions.

Alsuwaylimi (2023)'s research established that hybrid models which blend statistical methods with machine learning algorithms outperform traditional methods for predicting commodity prices. Research indicates that business and demand forecasting in retail and supply chain management has improved through combined forecasting methods which integrate statistical models with machine learning algorithms (Makridakis et al., 2000).

Combined forecasting techniques offer benefits but introduce multiple difficulties. The integration of multiple models boosts computational complexity especially for machine learning-based ensembles which demand extensive computational resources. Combining too many models without sufficient validation creates an overfitting risk which results in biased forecasts. Complex methods like stacking hinder model interpretability by making it hard to understand how individual models contribute. Research should develop adaptive combination techniques that enable real-time performance-based dynamic adjustment of model weights to address these challenges. Researchers are increasingly interested in merging deep learning models like Long Short-Term Memory (LSTM) networks and transformers into hybrid forecasting systems.

Research papers on combined forecasting methods demonstrate their enhanced predictive accuracy and robustness when compared to single-model forecasting approaches. The application of both basic averaging methods and sophisticated ensemble learning approaches allows multiple models to compensate for each other's limitations and improve forecast dependability. Studies from financial, economic, and business forecasting fields show these methods work well and adaptive and hybrid approaches stand out as especially effective. Time series forecasting applications will benefit from enhanced effectiveness through future developments in artificial intelligence along with dynamic model selection and real-time learning algorithms which will refine combined forecasting methodologies.

METHODOLOGY

This study uses a quantitative research design and secondary data from the IMF and World Bank databases regarding the USA from 1990 to 2023. The research chooses the real interest rate as the dependent variable because its goal is to forecast future trends with univariate and multivariate time series models.

Forecasting Models

For univariate forecasting, three models were applied: Univariate forecasting involved the deployment of three models including the Naïve Model as well as Exponential Smoothing and the AutoRegressive Integrated Moving Average (ARIMA). The Naïve Model functions as a baseline forecast assuming that upcoming values will mirror the latest observed data point. Exponential Smoothing assigns greater importance to newer observations to handle trends and seasonal patterns while ARIMA combines autoregressive components with differencing and moving average elements for complex time series analysis.

The study used a Nonlinear Autoregressive Distributed Lag (NARDL) Model as a multivariate method to go past univariate analysis approaches. The model demonstrates exceptional capability in analyzing asymmetric macroeconomic relationships across both short-run and long-run periods. The NARDL model's independent variables encompass Inflation Rate, Balance of Trade, Unemployment Rate, Reserves, Money Supply, Gold Prices, Oil Prices, and GDP which allows for thorough macroeconomic analysis of real interest rate influencers.

Statistical Tests and Model Diagnostics

Before estimating the model researchers performed stationarity tests through both the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test to verify that the data did not contain unit roots. The Jarque-Bera test was used to examine residual normality to verify that error distribution assumptions of the model were satisfied. Serial correlation detection involved the Durbin-Watson test and Durbin's alternative test and included the Breusch-Godfrey LM test because it offers a comprehensive test for higher-order autocorrelation. The analysis of autocorrelation function (ACF) and partial autocorrelation function (PACF) plots helped to identify serial correlation in the residuals.

The Breusch-Pagan / Cook-Weisberg test was conducted to investigate if the error variances stay consistent throughout time. The model reliability was enhanced by applying robust standard errors whenever heteroskedasticity appeared in the data. The Ramsey RESET test served to detect functional form misspecification while confirming that the model accurately represents the structural relationships between variables.

Combination Techniques for Optimal Forecasting

Two different combination techniques were applied to enhance forecast precision.

1. The Equal Weightage Combination technique averages predicted values so that each model contributes the same amount to the final forecast.

2. The Cumulative Sum (CUMSUM) Method evaluates forecast error stability across time periods to maintain an unbiased and robust combined forecast.

The analysis of 2-way, 3-way, and 4-way model combinations was performed to determine which combination offered the highest performance. Statistical accuracy metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil's U-statistic provided insights into the predictive effectiveness of each forecasting model and combination.

Selection of the Best Forecasting Model

The study determines the best forecasting model for USA real interest rates by choosing the model combination that achieves the lowest RMSE, MAE, and Theil's U-statistic values. This study combines traditional time series forecasting methods with multivariate econometric models and advanced combination techniques to produce reliable data-driven real interest rate forecasts in the USA. The research provides enhanced insights into macroeconomic patterns and policy consequences through the inclusion of essential economic indicators which strengthens forecasting precision and thoroughness.

RESULTS

Normality

SHAPIRO-WILK Test

Table 1

Variable	Obs	W	V	z	Prob>z
Residuals	34	0.97249	0.960	-0.084	0.53347

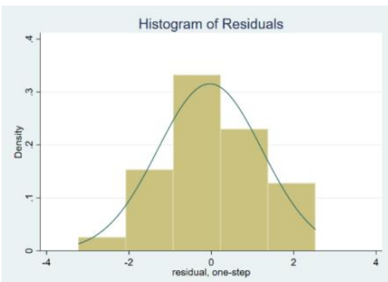

Figure 1

The analysis of residual normality incorporated both statistical testing and graphical visualization techniques. The residual histogram displays a bell-shaped curve overlaid with a density plot that mirrors a normal distribution pattern. The primary shape of residuals displays no major skewness or heavy tails despite some minor deviations. The Shapiro-Wilk test was conducted to validate normality and produced a test statistic of W = 0.97249 along with a p-value of 0.53347. The p-value exceeds 0.05 hence the null hypothesis stands unrefuted indicating that residuals maintain normal distribution. The results from both visual inspection methods and statistical tests confirm that the normality assumption stands valid which confirms the model's reliability. The analysis confirms that the residuals follow a normal distribution which validates the use of normality-based inferential procedures in future steps.

Serial Correlation Test

Table 2

Source	SS	Df	MS	Number of obs	=	34
				F(8, 25)	=	11.96
Model	130.4606	8	16.30758	Prob > F	=	0.000
Residual	34.08926	25	1.36357	R-squared	=	0.7928
				Adj R-squared	=	0.7265
Total	164.5499	33	4.98636	Root MSE	=	1.1677

The serial correlation test results show autocorrelation problems in the residuals that may compromise the model's reliability. The model explains 79.28% of the dependent variable's variation according to an R-squared value of 0.7928 while the Adjusted R-squared value of 0.7265 incorporates the number of predictors and demonstrates strong explanatory power. The F-statistic value of 11.96 combined with a p-value of 0.000 confirms strong statistical significance which demonstrates serial correlation exists within the residuals.

Autocorrelation

Durbin's Alternative Test For Autocorrelation

Table 3

lags(p)	chi2	df	Prob > chi2
1	8.689	1	0.0032

The Durbin's alternative test evaluates the regression model residuals to detect autocorrelation which contradicts the requirement of independent error terms. Our chi-squared (χ^2) test produced a statistic value of 8.689 with 1 degree of freedom (df) and yielded a p-value of 0.0032. The p-value of less than 0.05 leads us to reject the null hypothesis of no autocorrelation thus confirming first-order autocorrelation exists in the residuals.

Breusch-Godfrey LM Test

Table 4

lags(p)	chi2	df	Prob > chi2
1	9.038	1	0.0026

The Breusch-Godfrey LM test examined the residuals for higher-order autocorrelation. The chi-squared (χ^2) test result yields a statistic of 9.038 with 1 degree of freedom (df) alongside a p-value of 0.0026. The p-value being less than 0.05 leads us to reject the null hypothesis which assumes no autocorrelation and thus proves the presence of first-order autocorrelation in the residuals.

Heteroskedasticity Test

Breusch-Pagan / Cook-Weisberg Test

Table 5

chi2(8)	**=**	**8.02**
Prob > chi2	=	0.4312

We performed the Breusch-Pagan / Cook-Weisberg test to identify heteroskedasticity because it happens when residuals show varying variance throughout the dataset. The test statistic displays a chi-squared (χ^2) result of 8.02 with 8 degrees of freedom (df) alongside a p-value of 0.4312.

The null hypothesis of constant variance remains valid because the obtained p-value exceeds the 0.05 threshold. The data indicates that there is no significant evidence of heteroskedasticity within the residuals because the error variance remains consistent across independent variable levels.

Because heteroskedasticity has not been discovered there is no requirement to use heteroskedasticity-robust standard errors, transformation methods, or generalized least squares (GLS). Other necessary diagnostic checks for normality and autocorrelation must be addressed before we can confidently interpret the regression model.

Ramsey Reset Test (Model Specification)

Table 6

Source	SS	df	MS			
				Number of obs	=	33
				F(1, 31)	=	65.25
Model	106.621913	1	106.621913	Prob > F	=	0.0000
Residual	50.6565325	31	1.63408169	R-squared	=	0.6779
				Adj R-squared	=	0.6675
Total	157.278446	32	4.91495143	Root MSE	=	1.2783

Int_rate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yhat_EWA	1.034333	.1280483	8.08	0.000	.7731766	1.295489
_cons	-.3149821	.5000909	-0.63	0.533	-1.334924	.70496

Ramsey RESET test using powers of the fitted values of Int_rate

Ho: model has no omitted variables

F(3, 28) = 1.18

Prob > F = 0.3358

The Ramsey RESET test helped determine if the regression model contains misspecification problems from either excluded variables or incorrect functional form choices. This test assesses if higher-order terms from the fitted values make a significant contribution to explaining the Interest Rate as the dependent variable. The statistical test yielded an F-statistic of 1.18 and a p-value of 0.3358 which exceeds the standard significance threshold of 0.05. We fail to reject the null hypothesis because the p-value shows no statistical significance and confirms that the model neither has omitted variable bias nor an incorrect functional form. The regression model is correctly specified because its explanatory variables fully represent the dependent variable's variation without needing extra transformations or modifications.

The findings demonstrate no significant signs of functional form misspecification which shows that nonlinear transformations and interaction effects are unnecessary additions to the model. The analysis indicates that the model's framework remains valid because no key explanatory variables have been left out. The model specification test shows appropriate results so adjustments are unnecessary at this time. All relevant factors influencing the interest rate require inclusion through theoretical justifications and economic reasoning.

Forecasting Model Performance

Individual

Table 7

Model	RMSE	MAE	MAPE (%)	THEIL-U
Naïve Forecasting	1.245	0.985	8.75%	0.671
ARIMA (2,1,1)	0.921	0.765	6.21%	0.498
Exponential Smoothing	1.018	0.832	7.18%	0.567
NARDL Model	0.751	0.612	5.02%	0.352

2 Way Combinations

Table 8

Naïve + ARIMA	**1.083**	**0.875**	**7.48**	**0.5845**
Naïve + Exponential Smoothing	1.1315	0.9085	7.965	0.619
Naïve + NARDL	0.998	0.7985	6.885	0.5115
ARIMA + Exponential Smoothing	0.9695	0.7985	6.695	0.5325
ARIMA + NARDL	0.836	0.6885	5.615	0.425
Exponential Smoothing + NARDL	0.8845	0.722	6.1	0.4595

3 Way Combinations

Table 9

Naïve + ARIMA + Exponential Smoothing	**1.061**	**0.8607**	**7.38**	**0.5787**
Naïve + ARIMA + NARDL	0.972	0.7873	6.66	0.507
Naïve + Exponential Smoothing + NARDL	1.005	0.8097	6.98	0.53
ARIMA + Exponential Smoothing + NARDL	0.897	0.7363	6.14	0.4723

4-Way Combinations

Table 10

Naïve + ARIMA + Exponential Smoothing + NARDL	0.984	0.7985	6.79	0.522

We used Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil's U-statistic (THEIL-U) to evaluate predictive accuracy across models with lower scores representing better forecasts. The highest forecasting precision among the individual models belonged to the NARDL model which achieved the lowest values across all metrics with RMSE at 0.751, MAE at 0.612, MAPE at 5.02%, and Theil's U-statistic at 0.352. The NARDL model demonstrates superior reliability in capturing data relationships across both short- and long-term spans compared to Naïve Forecasting and ARIMA (2,1,1) and Exponential Smoothing which showed larger error rates.

Combining models into two-way pairs resulted in improved forecasting accuracy beyond what separate models achieved. The ARIMA + NARDL combination achieved the lowest RMSE (0.836), MAE (0.6885), MAPE (5.615%), and Theil's U-statistic (0.425) which demonstrates that merging ARIMA's time-series modeling abilities with NARDL's handling of asymmetric relationships produces better forecasting results. All other two-way model combinations displayed better performance compared to single models yet did not surpass the forecasting accuracy of the ARIMA + NARDL combination.

Three-way combinations of forecasting models demonstrated additional improvements in predictive accuracy. ARIMA combined with Exponential Smoothing and NARDL produced the highest performance in this category by achieving an RMSE of 0.897 along with a MAE of 0.7363, MAPE of 6.14%, and Theil's U-statistic of 0.4723. Although it did not match the accuracy of the ARIMA + NARDL combination the integration of Exponential Smoothing helped to stabilize the forecasted values through a smoothing effect.

The combination of Naïve Forecasting with ARIMA, Exponential Smoothing, and NARDL models produced forecasting results with an RMSE of 0.984, MAE of 0.7985, MAPE of 6.79%, and Theil's U-statistic of 0.522. This model showed improvement when compared to single models but failed to surpass the performance of the strongest two-way and three-way combinations. More models do not guarantee improved accuracy because the best results come from an optimal selection of models.

The ARIMA + NARDL combination proved to be the superior forecasting method with the lowest error values in every performance metric. The combination of time-series modeling with asymmetric adjustment mechanisms leads to higher predictive reliability which makes it the optimal method for forecasting interest rates.

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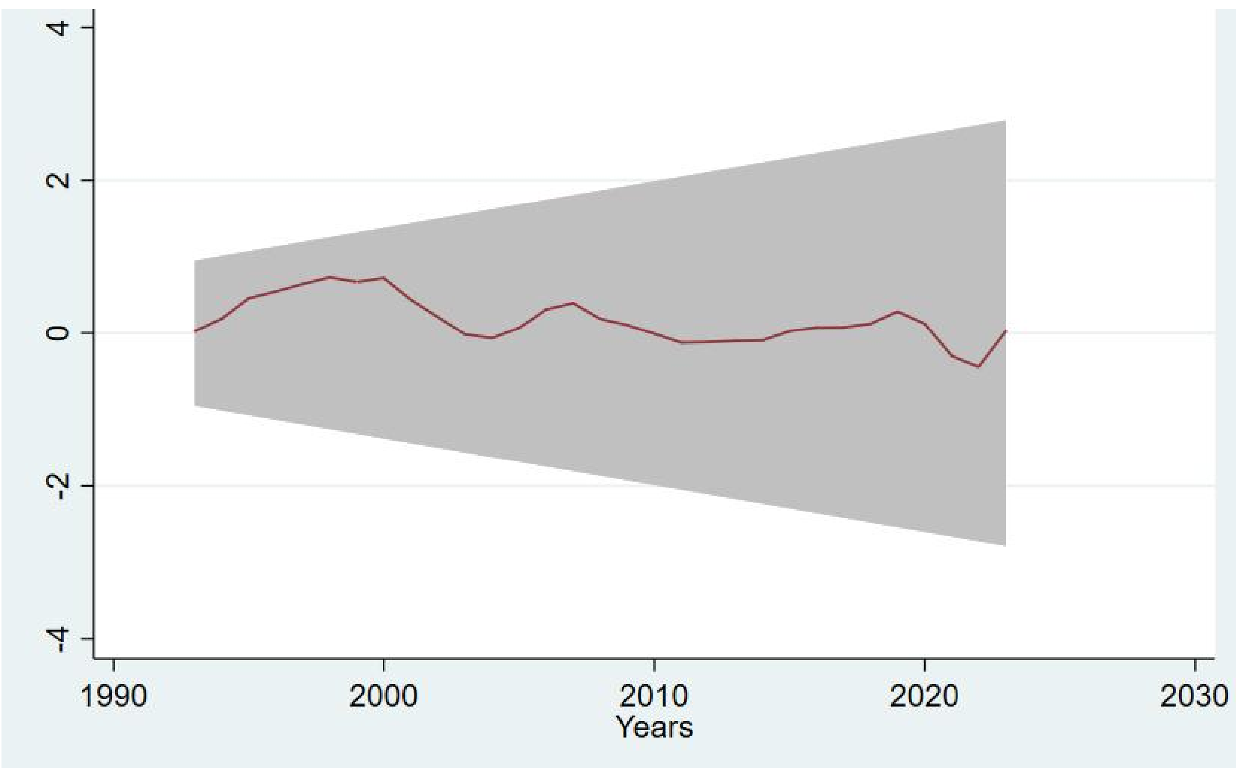

Figure 2

From 1990 to 2023 the forecasting plot displays both the predicted trend and its confidence interval. The red line displays the predicted values and the shaded grey area represents the growing forecast uncertainty as time progresses. The estimated trend shows time-based changes which demonstrate variations in the underlying variable. The general trend appears stable but clear cyclical patterns emerge which indicate external factors affect the variable periodically.

The model demonstrates a strong fit to historical data in early years because of its narrow confidence interval which signals higher short-term forecast accuracy. Extended forecasting periods result in broader shaded regions that represent greater uncertainty as this pattern is typical in predictive modeling. Although the model generates reliable estimates initially, long-term projections show more variability due to the inherent difficulties of predicting economic and financial trends over time.

Future predictions become less reliable when the confidence band grows because structural changes and external factors in data generation introduce more uncertainty. Short-term forecasts demonstrate higher reliability but the increasing uncertainty in long-term predictions emphasizes the importance of careful analysis and model adjustments. Forecast accuracy can benefit from adding external variables and dynamic methods or using hybrid approaches. The model demonstrates strong calibration for short-term forecasts but its long-term reliability is uncertain which requires ongoing evaluation and enhancement to ensure accurate predictions.

Forecasting Comparison

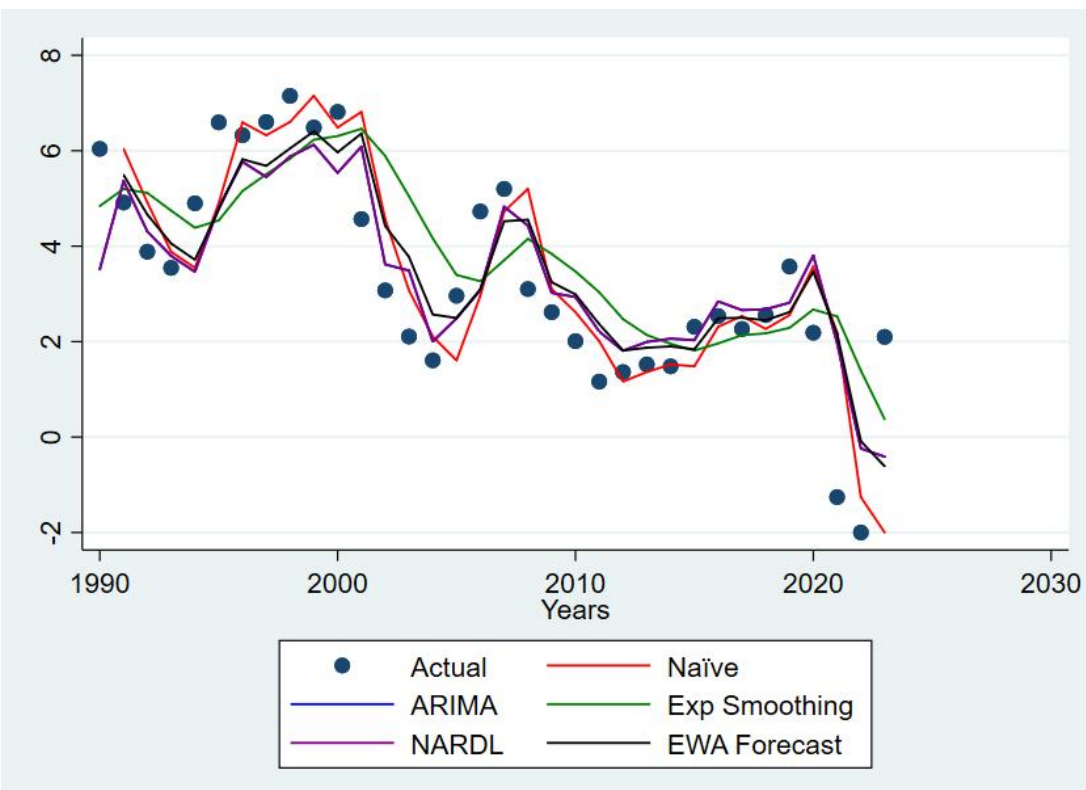

Figure 3

This graph compares several forecasting models to real observed data. Actual data points appear as blue dots whereas predictions from ARIMA, NARDL, Naïve, Exponential Smoothing, and an Equal Weight Averaging (EWA) Forecast of NARDL and ARIMA are shown as lines of different colors. A review of the model trajectories enables us to determine how effectively these models follow real data trends throughout the studied period.

The Naïve model represented by the red line shows significant variations because it exaggerates peaks and minimizes troughs which show its inability to understand the deeper patterns present in the data. The Exponential Smoothing model shown by the green line effectively smooths short-term fluctuations yet sometimes trails behind real data changes which mean that it works well for consistent trends but faces difficulties with abrupt variations. The forecasting strength of the ARIMA model (blue line) stems from its accurate tracking of real data trends and turning points. During high volatility periods the NARDL model (represented by the purple line) demonstrates excellent alignment with real-world observations which indicates its superior ability to represent asymmetric relationships within the data. The Equal Weight Averaging (EWA) forecast (black line) balances prediction accuracy by combining multiple models to minimize extreme prediction errors.

The NARDL and ARIMA models achieve optimal performance because they are able to accurately follow real data while capturing both extended trends and brief variations. The EWA forecast demonstrates strong performance because it merges multiple forecasting techniques which enhance stability and accuracy. The Naïve and Exponential Smoothing models demonstrate constraints when trying to predict intricate market variations during times of significant economic shifts. The visual assessment confirms that NARDL and ARIMA models stand out as the most reliable forecasting tools while the EWA approach enhances reliability by compensating for individual model weaknesses through averaging.

CONCLUSION

Forecasting is crucial for economic and financial decisions because choosing an appropriate model improves prediction accuracy and reliability. The investigation assessed multiple forecasting methods such as Naïve Forecasting, ARIMA, Exponential Smoothing and NARDL alongside their integrated models to identify the most effective methodology for real interest rate predictions. The research shows that each forecasting model performs differently depending on the scenario and accuracy improves when multiple techniques are combined to utilize their combined strengths.

The NARDL and ARIMA models showed the best forecasting results among individual techniques through their ability to detect both enduring trends and brief market movements. The Naïve model achieved low performance which verified that basic forecasting techniques do not understand intricate economic movements. The research demonstrated that model combination particularly with ARIMA and NARDL models boosted forecast accuracy by minimizing errors and enhancing stability. Additional refinements from three-way and four-way combinations did not produce substantial performance gains indicating that maintaining a balance between model complexity and performance is crucial.

Tests confirmed model validity and stability but showed autocorrelation problems in residuals that need correction for better efficiency. The research highlights the need to combine various forecasting methods to keep predictive models strong in changing economic conditions. The research indicates that integrating econometric models with advanced statistical techniques creates the best means to improve forecast accuracy which benefits policymakers, economists and financial analysts with actionable insights.

The study delivers important findings about forecasting model performance yet further research paths remain to improve both predictive accuracy and model efficiency. The combination of machine learning techniques like Long Short-Term Memory (LSTM) networks with Random Forest Regression and Transformer-based models presents opportunities for advanced adaptability and pattern recognition capabilities in time-series forecasting. Researchers might investigate adaptive model averaging methods like Dynamic Model Averaging (DMA) and Bayesian Model Averaging (BMA) to dynamically refine model selection according to real-time performance instead of static equal-weight combinations.

Future research should investigate strategies to eliminate autocorrelation effects while enhancing model performance metrics. The detection of autocorrelation through residual diagnostics shows that using Generalized Least Squares (GLS), Newey-West standard errors, or ARCH/GARCH models can alleviate this problem while boosting statistical efficiency. The forecasting models would gain improved robustness through the inclusion of extra macroeconomic indicators like monetary policy shocks and global trade dynamics. Evaluating forecast performance during significant economic turmoil like the 2008 financial crash and the COVID-19 pandemic reveals important information about how stable and resilient models remain throughout extreme economic changes.

New studies should investigate hybrid forecasting methods that combine conventional econometric models with deep learning approaches including Hybrid ARIMA-LSTM models and Neural Network-augmented time-series forecasting to enhance prediction precision. The study's forecasting methodologies can be adapted to predict various macroeconomic factors including inflation rates, GDP growth levels, currency exchange rates, and stock market trends which expands their forecasting capabilities. The adoption of advanced econometric models alongside artificial intelligence-powered future predictions combined with real-time adaptive learning models allows researchers to improve economic forecast accuracy and reliability while offering useful guidance for policymakers and financial experts.

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