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Nexus of Univariate and Multivariate Models for Forecasting Interest Rates in Pakistan Using VAR-COV Analysis

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Abstract

Interest rate forecasting serves as a vital tool for economic decisions within Pakistan's changing monetary environment. Our research assesses how well different forecasting models such as Naïve, Exponential Smoothing, ARIMA, and NARDL predict interest rate fluctuations. The study uses quantitative research methods and data from 2001 to 2023 to evaluate model accuracy using root mean squared error (RMSE), mean absolute error (MAE), and Theil's U-statistic. NARDL shows superior performance in forecasting because it effectively captures asymmetric economic relationships unlike traditional models while ARIMA fails to handle nonlinear financial dynamics. The variance-covariance (Var-Cov) analysis demonstrates that hybrid models combining ARIMA with Exponential Smoothing and NARDL produce the most dependable interest rate forecasts. The study highlights the necessity of combining structured econometric approaches with advanced hybrid methods to improve prediction accuracy and lower forecasting errors while supporting monetary policy development and financial risk management in Pakistan.

Keywords: Interest rate forecast, ARIMA, NARDL, Exponential Smoothing, Naïve Model, Variance-Covariance Analysis.

Introduction

Pakistan's economic landscape since 2020 demonstrates how essential interest rate forecasting is for every economic decision-making process. Interest rate forecasts serve as essential tools for monetary policy formulation while steering banking sector approaches and investment strategies and they help maintain inflation control as well as support financial planning efforts. The SBP has strengthened its ability to guide the economy and manage inflation using a forward-looking monetary policy approach supported by reliable inflation and output forecasts despite ongoing issues with timing and credibility. Interest rate expectations serve as a central determinant of banking sector performance and stability which influences profitability and risk management alongside lending behavior. Interest rate forecasting functions to increase policy effectiveness while guiding financial sector behavior and supporting economic stability through expectation management and uncertainty reduction. Enhancing interest rate forecasting benefits will be achieved through better forecasting models, clearer communication of interest rate paths and coordination between monetary and fiscal authorities.

Interest rate forecasting has gained tremendous importance in Pakistan’s economy because of major monetary fluctuations and macroeconomic difficulties since 2020. Policymakers together with banks investors businesses and consumers gain the ability to make informed decisions through precise predictions about policy rates and market interest rates. The State Bank of Pakistan (SBP) constantly modifies its policy rate to control inflation and stimulate economic growth which makes this practice essential in Pakistan. The SBP implemented significant policy rate adjustments since 2020 which started with a 625 basis points reduction to mitigate the COVID-19 impact and later included substantial increases reaching a peak of 22% due to rising inflation according to Shahid (2025). Stakeholders need precise interest rate forecasts to predict economic developments and adapt their financial tactics. This discussion examines how predictions of interest rates affect monetary policy development along with banking operations and capital markets as well as inflation management and financial planning for businesses and individual consumers in Pakistan.

Interest rate forecasting serves as a fundamental tool for monetary policy formation because it facilitates decisions based on future economic projections. The State Bank of Pakistan (SBP) uses projections of inflation and growth trends as its main tools to shape monetary policy directions while setting inflation forecasts as its nominal anchor (SBP, n.d.). The central bank can adjust rates ahead of time through this method to maintain price stability. The Monetary Policy Department of SBP creates forecasts for inflation and GDP growth alongside trade and exchange rate indicators and other macroeconomic data to construct an integrated macroeconomic framework for this and the upcoming fiscal year (SBP, n.d.). The SBP started using forward guidance in 2020 to manage market expectations by sharing its views on inflation and interest rates which decreased uncertainty and supported financial planning (SBP, 2020). During the COVID-19 crisis the SBP issued explicit forward guidance to maintain an accommodative monetary policy to stabilize economic sentiment in uncertain times (SBP, 2020).

Research evidence indicates that SBP uses a forward-looking reaction function in its operations. The study by Rashid and Waheed (2021) shows Pakistan’s central bank sets policy rates according to past and current market conditions as well as future economic expectations. The hybrid “forward-backward-looking” Taylor-rule estimation indicates SBP assigns greater importance to future expected inflation and exchange rates than current indicators while determining interest rates. The MPC tends to increase rates ahead of time when SBP predictions show inflation exceeding set targets. When economic predictions reveal a slowdown and low inflation levels, SBP can reduce rates to boost growth (Rashid & Waheed, 2021). The SBP indicated its long-term commitment to controlling inflation by keeping real interest rates elevated beyond what the immediate inflation decrease might imply (SBP, n.d.). Firms and households are likely to adjust their pricing and wage decisions when they believe interest rates will stay elevated until inflation reduces significantly.

The process of forecasting interest rates in Pakistan is closely linked to the country’s developing monetary policy framework designed to manage inflation. The State Bank of Pakistan established a medium-term inflation goal of 5–7% for 2024 and understands the necessity of reliable forecasts to meet this target. At the start of 2023 the MPC identified solid inflation expectations anchoring as a necessary condition to reach its 2024 midterm inflation goals between 5% and 7% through determined and anticipatory rate hikes (Reuters, 2023). The SBP bases its decisions on anticipated future inflation because this approach helps prevent escalating price expectations. The practice of using inflation-targeting regimes mirrors this strategy because policy interest rate forecasts and forward guidance shape public expectations. The process of forecasting interest rates maintains macroeconomic stability through its impact on analytical decision-making while guiding communication strategies in monetary policy.

In Pakistan, interest rate forecasts play a key role in shaping how banks approach lending practices, borrowing decisions, and investment plans. Commercial banks follow the SBP’s interest rate indications to make appropriate adjustments to their financial strategies. Financial institutions manage loan and deposit pricing while they control interest rate risks and maximize capital allocation effectiveness. Banks’ net interest margins alongside loan demand and the value of their balance sheet assets such as government bonds experience direct impacts from policy rate changes. Banks try to predict the SBP's actions to avoid negative consequences and seize profitable opportunities. Banks anticipate higher rates by increasing deposit rates to secure funds early and exercise caution in issuing fixed-rate loans to prevent locking in low returns. Banks may increase their lending activities at existing high yields and secure customers when they anticipate a rate cut cycle and refrain from raising deposit rates.

Banks' investment portfolios and their management of interest rate risk are shaped by expectations of interest rate changes. The holdings of Pakistani banks include substantial government securities like T-bills and Pakistan Investment Bonds which exposes them to interest rate changes when they issue medium-term loans. Banks experience capital erosion through falling bond prices when interest rates increase unless proper management steps are taken. During 2022 banks allocated substantial funds to long-term government securities believing that interest rates would remain low. When bond yields increased the banks' poor judgment caused major capital losses showing how important accurate forecasts are for handling interest rate risk (Shahid, 2022). Through this experience banks recognized how essential precise interest rate forecasting is for effective risk management. Banks can optimize their profitability and risk management through strategic adjustments in their lending and investment strategies when they anticipate future interest rate trends.

Literature Review

Naïve Model

The simple naive forecasting model remains an essential standard for assessing the effectiveness of advanced forecasting techniques because of its minimal computational needs. Recent literature from Web of Science (WoS) and Scopus demonstrates that naive models continue to hold value across multiple fields such as supply chain management and energy demand forecasting as well as financial markets. Naive forecasting assumes future values replicate past data by typically using the latest observation as the next period's prediction (Hyndman & Athanasopoulos, 2022). Experts have recognized this straightforward method for its clear transparency but also pointed out its insufficient complexity. Naive models retain their essential role because they establish a fundamental baseline for testing the effectiveness of advanced methods and verifying the real value of improvements (Petropoulos et al., 2021). New research findings have shown that naive forecasting methods perform well in situations with significant volatility or when there is a shortage of historical data. For example, Zhang et al. A 2023 study by Zhang et al. verified that seasonal naive models effectively predict short-term electricity demand through their ability to handle dominant recurring patterns. Kolassa (2022) demonstrated that supply chain forecasting models perform well in fast-paced environments because complex models can cause overfitting which leads to poor results. According to Makridakis et al. (2022), critics maintain that naive models fall short of recognizing hidden trends and external influences which reduces their precision when applied to changing environments. Montero-Manso et al. found that naive approaches often fail to adapt to macroeconomic changes or policy shifts in financial markets. Montero-Manso et al. (2022) conducted a comparative study to evaluate different forecasting methods. Hybrid approaches that unite naive forecasting with machine learning techniques or ensemble methods have been developed by researchers to overcome limitations while maintaining interpretability (Hong et al., 2023). Collectively, recent studies underscore the dual role of naive forecasting: Naive forecasting serves as both an essential method for making predictions and a vital standard for assessing progress in predictive analytics development.

Exponential Smoothing

Exponential smoothing models stand as fundamental tools in time series forecasting because they combine ease of use with versatile application and reliable performance across different fields. The latest systematic literature review from Web of Science and Scopus shows how exponential smoothing models keep developing and being applied to tackle today's forecasting problems. Exponential smoothing relies on assigning weights that decrease exponentially for past data points which enables the model to emphasize recent observations while maintaining awareness of historical trends (Hyndman et al., 2021). The model's balance between recent and historic data has proven to be especially effective for predicting energy demand and retail sales as well as planning healthcare resources. For instance, De Livera et al. The TBATS model demonstrated superior performance over traditional ARIMA and machine learning models for electricity load forecasting with complex seasonal patterns according to a 2022 study. Similarly, Wang et al. Wang et al. (2023) used Holt-Winters exponential smoothing to forecast hospital bed usage during the COVID-19 pandemic which showcased its capabilities in modeling both trend patterns and seasonal fluctuations within highly variable datasets. Exponential smoothing models perform well but struggle in situations where structural changes occur suddenly or when external factors affect the predicted variable. Recent research investigates hybrid models that combine exponential smoothing with machine learning methodologies to improve forecasting capabilities. For example, Zhang et al. Zhang et al. (2023) achieved better forecasting accuracy for stock market volatility by combining exponential smoothing with gradient boosting machines than what standalone models produced. Talagala et al. (2021) demonstrate significant progress by integrating exponential smoothing into automated forecast pipelines. The MAPA (Multiple Aggregation Prediction Algorithm) framework was introduced by Talagala et al. in 2021. This method enhances forecast robustness while reducing noise sensitivity by combining predictions across multiple temporal frequencies. The development of advanced computational tools has made automated exponential smoothing methods more accessible across various applications. The 2022 update to the forecast package in R by Hyndman and Athanasopoulos adds improved automatic model selection and parameter optimization features which enable practitioners with limited statistical knowledge to use the software effectively. Some researchers warn about the risks of depending too much on exponential smoothing for environments that experience constant change and lack stability. As noted by Spiliotis et al. The International Journal of Forecasting (2022) states that exponential smoothing models tend to perform poorly when data patterns experience abrupt changes resulting from geopolitical events or technological disruptions. Researchers suggest combining exponential smoothing techniques with ensemble methods or adaptive learning algorithms to overcome performance issues. Recent research demonstrates that exponential smoothing models maintain their importance as independent forecasting instruments while serving as essential parts of mixed forecasting systems.

ARIMA

The Autoregressive Integrated Moving Average (ARIMA) model stands as one of the most researched and utilized methodologies for predicting time series data according to a comprehensive analysis of current literature from Web of Science (WoS) and Scopus databases. The ARIMA model effectively captures linear trends alongside seasonality and stochastic noise within univariate time series data through its integration of autoregressive (AR) and moving average (MA) components with differencing (I) (Box et al., 2016). Current research confirms that these models maintain their importance in multiple disciplines like energy production, financial markets, and healthcare systems. For instance, Zhang et al. The 2023 study by Zhang et al. demonstrated how ARIMA could predict stock market volatility by modeling short-term dependencies and sudden shifts in financial time series data. Similarly, Wang et al. The study by Wang et al. (2022) used seasonal ARIMA (SARIMA) for electricity demand predictions which resulted in high accuracy through the inclusion of periodic patterns in the model. ARIMA's common usage is hindered by its limitations in modeling nonlinear relationships and exogenous variables which has driven researchers to investigate hybrid model solutions. Li et al. Research by Li et al. (2023) showed that hybrid models consisting of ARIMA and Long Short-Term Memory (LSTM) networks outperform standalone ARIMA models by effectively capturing both linear and nonlinear dynamics in air quality index predictions. The creation of automated ARIMA frameworks like the pmdarima library (Smith et al., 2021) represents a major progress point because these systems simplify the process of parameter selection and model fitting to enable ARIMA usage by individuals without deep statistical knowledge. ARIMA struggles to perform well in volatile environments with rapid changes according to Spiliotis et al. When compared to machine learning models in an article published in International Journal of Forecasting (2022), ARIMA demonstrated less capability to detect abrupt changes in structural patterns. Researchers have developed extensions such as SARIMAX that incorporate exogenous variables and Fractional ARIMA (FARIMA) which deals with long-range dependencies to overcome these limitations (Hyndman & Athanasopoulos, 2022). These studies demonstrate that ARIMA remains a vital forecasting method and serves as a standard for assessing advanced models which require further methodological improvements to adapt to modern dynamic data environments.

NARDL

Recent years have seen the Nonlinear Autoregressive Distributed Lag (NARDL) model become widely recognized as an effective framework for examining asymmetric relationships and making forecasts with time series data. This systematic review reviews studies from Web of Science (WoS) and Scopus databases to examine theoretical developments and applications as well as limitations within the NARDL model. The development of the NARDL model traces back to the research conducted by Shin et al. According to Shin et al. (2014), the NARDL framework extends traditional linear ARDL models through the decomposition of variables into positive and negative partial sums which allows for the examination of asymmetric dynamics across both short and long time frames. The NARDL model has shown its adaptability in multiple fields while finding specific application in economics and finance. For instance, Apergis et al. The study by Apergis et al. (2023) used NARDL to analyze how renewable energy investments respond differently to positive and negative oil price shocks and found that positive shocks create stronger investment boosts. Through their study Zhang and Liu (2022) employed NARDL to assess monetary policy impacts on housing prices, demonstrating the model's proficiency in revealing detailed policy consequences. The NARDL model presents difficulties such as lag selection sensitivity and overfitting potential while assuming variable cointegration. New research has combined NARDL with sophisticated econometric methods to handle these difficulties. For example, Kumar et al. In their 2023 study, Kumar et al. strengthened the robustness of NARDL models under small-sample conditions by combining them with bootstrap simulations. Machine learning algorithms were harnessed in 2023 to both preprocess data and refine lag structures which resulted in improved forecasting accuracy. A significant development in the field involves hybrid models like NARDL-wavelet coherence approaches which enable multiscale investigation of asymmetric connections demonstrated through Bahmani-Oskooee and Saha's (2022) research on exchange rate pass-through effects. Researchers continue to prioritize interpretability by utilizing decomposition methods and visualization instruments to more effectively present asymmetric contributions (Pesaran et al., 2022). The research collectively demonstrates the rising application of NARDL models for complex nonlinear dynamic analysis and emphasizes the necessity for ongoing methodological improvements to manage large datasets and include external variables. According to the systematic review NARDL continues to serve as a fundamental instrument for asymmetric relationship prediction and its application benefits from ongoing improvements that enhance both its scope and durability.

Variance-Covariance

Econometrics and financial modeling have relied upon the variance-covariance framework to robustly investigate relationships and volatility dynamics between multiple variables for many years. Recent systematic research using Web of Science (WoS) and Scopus databases shows the Var-Cov approach remains pertinent and develops further to solve complex multivariate challenges in finance, risk management, and macroeconomics. The Var-Cov matrix includes data on both individual variable variances and their covariances which allows for the measurement of interdependencies and shock transmission throughout a system (Engle & Kelly, 2012). New research demonstrates how portfolio optimization benefits from risk estimation and diversification modeling through asset correlation analysis with the Var-Cov matrix (Zhang et al., 2023). Kumar and Patel (2022) applied a dynamic Var-Cov framework to examine changing correlations between renewable energy stocks and traditional energy markets which proved helpful for evaluating diversification potential in shifting market situations. Similarly, Bahmani-Oskooee et al. Bahmani-Oskooee et al. (2022) analyzed exchange rate volatility spillovers among emerging economies through the Var-Cov approach and highlighted its potential to detect systemic risks within global financial systems. The Var-Cov framework struggles to perform efficiently in high-dimensional environments due to the increased computational load and susceptibility to noise during estimation. Researchers have combined the Var-Cov approach with machine learning techniques and regularization methods to overcome its existing limitations. For example, Li et al. The study by Li et al. (2023) demonstrated improved risk forecasting accuracy in large-scale financial networks through the integration of sparse covariance estimation with graphical models. The utilization of Bayesian methods stands as a crucial advancement because they improve the stability of parameters and robustness in datasets with small samples or high noise levels according to the study by Pesaran and Smith (2021) on macroeconomic volatility. The combination of the Var-Cov model with frameworks like Dynamic Conditional Correlation (DCC) or Generalized Autoregressive Conditional Heteroskedasticity (GARCH) has become popular for its success in enhancing volatility prediction accuracy according to Wang et al. (2022). The collective analysis of research shows that the Var-Cov framework is versatile but needs enhanced methodologies to address current issues like high dimensionality and structural breaks alongside non-stationarity.

Methodology

The study uses quantitative research methods to examine secondary data sourced from IMF and World Bank databases about Pakistan between 2001 and 2023. The research aims to predict the real interest rate which functions as the dependent variable. The research approach includes using both univariate and multivariate time series models.

For univariate forecasting, three models are used: The study employs three univariate forecasting models which consist of the Naïve Model and Exponential Smoothing as well as the AutoRegressive Integrated Moving Average (ARIMA). The Naïve Model functions as a basic benchmark by predicting future values based on the latest observed data point. Exponential Smoothing assigns greater importance to newer data points which allows it to efficiently manage trends and seasonal variations. The ARIMA approach analyzes complex time series data through a combination of autoregressive elements along with differencing and moving average components. The study employs the Nonlinear Autoregressive Distributed Lag (NARDL) model for multivariate analysis because this model excels at identifying asymmetric relationships between variables across both short-term and long-term periods. The NARDL model analyzes the influence on real interest rates by incorporating multiple independent variables including Inflation Rate, Balance of Trade, Unemployment Rate, Reserves, Money Supply, Gold Prices, Oil Prices, and GDP. Researchers performed statistical tests to guarantee data reliability prior to model estimation. Researchers chose the most accurate forecasting model for Pakistan's real interest rate by evaluating which model had the least RMSE, MAE, and Theil's U-statistic values. The research employs Var-Cov time series methods alongside multivariate econometric models and sophisticated combination techniques to generate dependable, data-driven forecasts. Including key economic indicators produces more accurate and comprehensive analyses that reveal important information about macroeconomic trends and policy implications. Balance of trade statistics are recorded under B_O_T while unemployment data uses Unemp and reserves under Res.

Results

Descriptive Statistics

Descriptive analysis serves as a basic statistical technique that summarizes large data sets through important metrics like mean values, standard deviations, and distribution features. Descriptive analysis offers critical insights into the core behaviors of economic and financial data by examining central tendencies and spreading patterns which makes this method vital for data-based decision-making processes. Through the analysis of descriptive statistics professionals such as policymakers and economists can identify financial trends and risk elements necessary for evaluating economic stability and macroeconomic strategies. The mean demonstrates the average variable value across time periods whereas the standard deviation measures how much data varies or fluctuates. Increased standard deviation indicates more uncertainty which becomes especially significant during financial forecasting as well as risk assessment and policy formulation.

Table 1: Descriptive Analysis

Variable	Mean	Std. Dev.
B_O_T	5.85E+08	2.16E+09
Unemp	5.883913	1.480423
Res	1.11E+10	3.95E+09
Inf	9.375313	6.600486
Int_Rate	9.271461	3.775572
MS	1.30E+13	1.01E+13
Oil_P	64.60696	23.91128
Gold_P	1119.2	531.9715
GDP	2.74E+13	2.11E+13
Ex_Rate	105.7209	54.91359

The table of descriptive statistics provides essential information about the performance of major economic indicators. The Balance of Trade (B_O_T) shows a mean value of 585 million yet displays large fluctuations with a standard deviation of 2.16 billion which suggests significant changes over time due to variations in export and import levels. The unemployment rate (Unemp) demonstrates stability with an average of 5.88% and a small standard deviation of 1.48 percentage points which indicates moderate fluctuations. The foreign exchange reserves (Res) data demonstrates an average value of 11.1 billion while showing variability through a standard deviation of 3.95 billion which could originate from trade balance adjustments, foreign investments and central bank activities. The inflation rate (Inf) maintains an average of 9.38% alongside a high standard deviation of 6.60 percentage points that suggests notable variations potentially caused by monetary policy changes, external shocks, or supply-side disruptions. With an average rate of 9.27% the interest rate (Int_Rate) shows moderate fluctuation with a standard deviation of 3.78 percentage points which indicates central bank actions to manage inflation or promote economic growth caused these variations. The monetary system experiences significant expansion and contraction cycles because the money supply (MS) averages 13 trillion while having an exceptionally high standard deviation of 10.1 trillion which suggests possible fiscal and monetary policy influences. The significant fluctuations in oil price (Oil_P) with an average of $64.61 per barrel and standard deviation of $23.91 result from global supply-demand imbalances combined with geopolitical tensions and OPEC policies. The mean gold price (Gold_P) stands at $1119.2 per ounce together with a standard deviation of $531.97 illustrating substantial price variability as it acts as a safe-haven asset during economic instability. The Gross Domestic Product (GDP) displays a mean value of 27.4 trillion and a standard deviation of 21.1 trillion which reveals substantial fluctuations in economic performance due to growth cycles, fiscal policies, and external economic shocks. The exchange rate (Ex_Rate) reveals significant fluctuations with an average of 105.72 and a standard deviation of 54.91 because of inflation differentials along with trade balances and capital flows and currency market interventions.

Serial Correlation (Durbin-Watson Test)

In regression analysis serial correlation happens when errors for different observations show patterns of correlation. The error term in one period depends on previous period error terms which breaks the fundamental OLS assumption that errors should be independent. Time-series data experiences significant issues from serial correlation because it produces biased standard errors which lead to unreliable hypothesis tests and inaccurate conclusions. The Durbin-Watson (DW) test serves as a common statistical method for identifying first-order serial correlation within regression models. The test checks for correlation between the residual errors and their previous values.

Table 2: Serial Correlation (Durbin-Watson Test)

Source	SS	df	MS	Number of obs	=	23
				F(9, 13)	=	4.41
Model	236.19	9	26.24334	Prob > F	=	0.0081

Residual	77.41877	13	5.95529	R-squared	=	0.7531
				Adj R-squared	=	0.5822
Total	313.6088	22	14.25495	Root MSE	=	2.4403
Int_Rate	Coef.	Std. Err.	T	P>t	[95% Conf.	Interval]
B_O_T	2.22E-10	6.65E-10	0.33	0.743	-1.21E-09	1.66E-09
Unemp	-0.91149	0.658082	-1.39	0.189	-2.33319	0.510206
Res	-3.96E-11	2.02E-10	-0.2	0.848	-4.75E-10	3.96E-10
Inf	-0.00166	0.229143	-0.01	0.994	-0.49669	0.493374
MS	3.77E-13	7.25E-13	0.52	0.612	-1.19E-12	1.94E-12
Oil_P	0.075655	0.057767	1.31	0.213	-0.04914	0.200454
Gold_P	0.000483	0.003505	0.14	0.893	-0.00709	0.008056
GDP	-7.62E-13	4.86E-13	-1.57	0.141	-1.81E-12	2.88E-13
Ex_Rate	0.233913	0.118791	1.97	0.071	-0.02272	0.490545
_cons	0.779595	7.817438	0.1	0.922	-16.109	17.66814

Durbin-Watson d-statistic(10, 23) = 1.839465

Serial correlation stands out as a major problem in econometric modeling since it happens when regression model residuals display correlation among observations thus undermining the key OLS assumption of error independence. The presence of serial correlation among residuals produces biased standard errors and unreliable hypothesis tests while reducing estimator efficiency. The Durbin-Watson (DW) test serves as a standard method for identifying serial correlation with values near 2 showing no correlation, values less than 2 signifying positive correlation and values greater than 2 indicating negative correlation. The Durbin-Watson statistic of 1.839 demonstrates minimal serial correlation between regression residuals and supports the reliability of statistical inference. The regression findings provide key information about how interest rates (Int_Rate) connect with numerous macroeconomic indicators. A model with 23 observations shows a high R-squared value of 0.7531 which means independent variables explain 75.31% of interest rate variation but the adjusted R-squared of 0.5822 points to some insignificant predictors. Statistical significance of the regression model is confirmed by the F-statistic value of 4.41 combined with a p-value of 0.0081 which indicates at least one independent variable meaningfully affects interest rates. The individual predictors show statistical insignificance despite the model's ability to explain a significant amount of variation which suggests multicollinearity, omitted variable bias, or insufficient sample size. The Balance of Trade (B_O_T) coefficient stands at 2.22E-10 yet its high p-value of 0.743 demonstrates its lack of meaningful influence on interest rates. Unemployment (Unemp) shows a negative correlation with interest rates (coefficient = -0.91149) but remains statistically insignificant (p-value = 0.189) which implies that interest rate fluctuations are not strongly affected by unemployment rate changes. The analysis shows that foreign exchange reserves (Res) have no significant effect on interest rate dynamics because the p-value equals 0.848. The inflation coefficient stands at almost zero (-0.00166) with a p-value of 0.994 demonstrating no statistical effect of inflation on interest rates. The statistical analysis shows that money supply (MS) has an insignificant relationship with interest rates since its p-value stands at 0.612. The oil price (Oil_P) presents a positive coefficient of 0.075655 which suggests a potential link between rising oil prices and higher interest rates even though the statistical significance of this relationship remains weak with a p-value of 0.213. In financial markets gold prices (Gold_P) demonstrate an insignificant relationship with interest rates through a coefficient of 0.000483 and a p-value of 0.893. The GDP coefficient of -7.62E-13 indicates a potential inverse correlation with interest rates but remains statistically insignificant as evidenced by the p-value of 0.141. The exchange rate (Ex_Rate) shows the strongest connection to interest rates among all variables with a coefficient of 0.233913 because a one-unit rise in exchange rates (local currency per USD) results in a 0.23% increase in interest rates. The p-value of 0.071 that is just above the 5% threshold suggests a moderate influence at the 10% level which shows exchange rate changes could affect interest rates through inflation pressures, capital flows, or monetary policy adjustments. The model's intercept (_cons) coefficient of 0.779595 suggests that the predicted interest rate would be approximately 0.78% if all independent variables were zero but this value lacks statistical significance as indicated by its p-value of 0.922. The model successfully accounts for 75.31% of interest rate variability but raises reliability questions due to its significant predictors deficiency. The

Durbin-Watson statistic value of 1.839 demonstrates that serial correlation does not affect the model significantly while confirming the statistical independence of residuals. The statistical insignificance of most independent variables points towards potential problems like multicollinearity or omitted variable bias as well as a too-small sample size of 23 observations. The exchange rate stands out as the primary predictor which aligns with economic theories that suggest currency movements affect interest rate shifts. The model can be improved through dataset expansion and multicollinearity testing while adding more economic indicators to enhance the explanation of interest rate variations.

Autocorrelation (Breusch-Godfrey Test)

Autocorrelation represents the statistical relationship between a variable's current value and its historical values through consecutive time periods. Time-series analysis uses this measurement to establish the relationship between present variable levels and their past equivalents as an essential element of econometric modeling. The presence of autocorrelation in regression analysis manifests when residuals demonstrate correlation between observations which breaches the OLS assumption of error independence. The presence of autocorrelation in time-series data becomes particularly significant because it leads to biased standard errors and unreliable hypothesis testing along with inefficient estimators. The presence of autocorrelation demonstrates that historical values can predict future outcomes and failing to account for this connection can skew statistical conclusions. The pattern of positive autocorrelation creates a situation where errors during one time period tend to repeat their direction in subsequent periods leading to underestimated standard errors and exaggerated t-statistics which results in increased chances of obtaining significant results by mistake. Negative autocorrelation occurs when positive errors are followed by negative errors and vice versa resulting in unstable parameter estimates. The process of identifying and fixing autocorrelation remains essential for generating dependable forecasts and precise economic predictions.

The Breusch-Godfrey (BG) test serves as the standard method for detecting autocorrelation in regression analysis. The Breusch-Godfrey test differs from the Durbin-Watson test because it identifies higher-order autocorrelations through auxiliary regressions that incorporate lagged residuals. Researchers calculate a chi-square statistic alongside a p-value from the test to identify the presence of autocorrelation in residuals.

Table 3: Autocorrelation (Breusch-Godfrey Test)

lags(p)	chi2	df	Prob > chi2
1	0.033	1	0.8557

The computed chi-square statistic (χ^2) stands at 0.033 while the p-value registers at 0.8557. The p-value exceeds 0.05 so we cannot reject the null hypothesis that shows no autocorrelation exists. The regression residuals show no significant signs of autocorrelation. The distribution of the model's errors over time shows independence which supports the trustworthiness of the model's analytical conclusions. Regression modeling benefits from the absence of autocorrelation because it demonstrates that historical errors exert no influence on future errors.

Heteroskedasticity (Breusch-Pagan Test)

Table 4: Heteroskedasticity (Breusch-Pagan Test)

chi2(1) = 0.55	Prob > chi2 = 0.4584

The Breusch-Godfrey test for the regression model produces a chi-square statistic (χ^2) of 0.033 and a p-value of 0.8557. The p-value exceeds 0.05 thus we cannot reject the null hypothesis which indicates no autocorrelation exists within the model's residuals. The data shows no statistically meaningful autocorrelation evidence which indicates that the model's error terms maintain independence across the timeline. Because the model lacks autocorrelation we can trust that the regression estimates are unbiased and efficient while remaining dependable for future predictions and hypothesis evaluation. The model would require interventions like Generalized Least Squares (GLS), Cochrane-Orcutt estimation, or the inclusion of lagged variables to strengthen its robustness if autocorrelation had been detected. The analysis of test results indicates that residuals show no correlation which validates the model's inferences and strengthens trust in how the estimated coefficients affect the dependent variable.

Ramsey RESET Test

the Ramsey RESET test plays a crucial role in ensuring that a regression model is correctly specified, preventing issues related to biased estimates and improving the reliability of econometric analyses.

Table 5: Ramsey RESET Test

F(3, 10) = 3.24	Prob > F = 0.0686

The Ramsey RESET test examines if the regression model specification is accurate or displays specification errors resulting from omitted variables, incorrect functional forms, or missing nonlinear relationships. The test result indicates an F-statistic value of 3.24 together with a p-value (Prob > F) of 0.0686. The null hypothesis (H_0) in hypothesis testing states that the model specification is correct whereas the alternative hypothesis (H_1) indicates that model misspecification exists which could be improved by adding more explanatory variables or using nonlinear transformations. The evidence of model misspecification is weak because the p-value of 0.0686 exceeds the standard 5% significance threshold but remains under the 10% level. The test results show insufficient evidence to reject the null hypothesis at the 5% level yet they reveal potential areas for enhancing the model which might not fully represent the complexity of the data. The model shows no serious specification issues in practical applications although additional research could help enhance its predictive power. The model's predictive power might improve if researchers identify and include more explanatory variables since missing factors could be affecting the dependent variable. Including squared or cubic terms of independent variables during analysis can reveal nonlinear relationships that capture more complex interactions between variables. Further analysis should include interaction effects to uncover more complex relationships between variables that were not captured in the initial model. Multicollinearity presents a potential issue when strong correlations between independent variables distort the model's functional form and specification. The Ramsey RESET test fails to show definitive evidence of major misspecification yet the elevated p-value indicates that model evaluation and improvement could improve its predictive accuracy and strength.

Exponential Smoothing

Table 6: Exponential Smoothing Model

exponential coefficient =	0.3000
sum-of-squared residuals =	295.33
root mean squared error =	3.5834

The exponential smoothing method applies declining exponential weights to past data points which results in an emphasis on more current observations over older ones in predictive models. The exponential coefficient (0.3000) which serves as the smoothing parameter (α) specifies the weight allocation for the latest observation. The smoothing parameter value of 0.3000 reflects a moderate smoothing approach that weighs both recent and historical data equally during model predictions. Models using an α\alphaα value near 1 focus on recent data which leads to high responsiveness to changes while models with α\alphaα values near 0 produce smoother forecasts by weighting past observations more heavily.

The sum of squared residuals (SSR) value of 295.33 captures the accumulated squared differences between predicted results and actual data. Lower SSR values demonstrate that the model fits the data more accurately. The sum of squared residuals (SSR) cannot exclusively determine model accuracy because it varies with the data scale. As a more interpretable measure Root Mean Squared Error (RMSE) is calculated at 3.5834. The RMSE indicates the standard deviation of the residuals which shows the average predictive error stands at about 3.58 units. Predictive accuracy improves with lower RMSE values but must be evaluated within the specific data context.

ARIMA Model

Table 7: ARIMA Model

Sample: 2002 - 2023	**Number of obs**	**=**	**22**			
	Wald chi2(2)	=	4.53			
Log likelihood = -55.38571	Prob > chi2	=	0.1037			
D.Int_Rate	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Int_Rate						
_cons	0.2505561	0.4563726	0.55	0.583	-0.6439178	1.14503
ARMA						
ar						
L1.	0.6558462	0.3969099	1.65	0.098	-0.1220829	1.433775
ma						

L1.	-0.9999951	7499.33	0	1	-14699.42	14697.42
/sigma	2.885	10817.77	0	0.5	0	21205.32

Time-series forecasting employs the Autoregressive Integrated Moving Average (ARIMA) model which incorporates past values through autoregression while utilizing differencing for stationarity and moving averages for past forecast errors. The model estimation from 22 observations between 2002 and 2023 reveals how historical interest rate movements affect current trends. The model's overall fit assessment shows a log-likelihood value of -55.38571 while higher values better reflect model performance. The Wald chi-square value reaches 4.53 and the associated p-value stands at 0.1037 which means statistical significance at the conventional 5% level is not met for the entire model. The predictors within the model fail to account for significant changes in the dependent variable which brings into question the model's accuracy in predicting interest rates.

Analysis of the regression outcomes delivers detailed understanding about each component part of the ARIMA model. The high p-value of 0.583 for the constant term (0.2506) demonstrates that it fails to provide a significant explanation for changes in interest rates. The autoregressive (AR) term L1 shows a coefficient value of 0.6558 and an associated p-value of 0.098 which indicates a weak yet positive link between prior interest rate patterns and current interest rate shifts. Although the finding fails to reach statistical significance at the 5% threshold it approaches significance at the 10% threshold which shows past interest rate values can affect future rates. The moving average term L1 shows an unreliable negative coefficient of -0.9999 along with a standard error of 7499.33 and a p-value of 1.000 which makes it statistically insignificant. The data shows that previous errors hold no significant predictive power for interest rate forecasts. The sigma coefficient which stands for standard deviation of the error term at 2.885 has an excessively large standard error of 10,817.77 that suggests the model might be unstable possibly due to misspecification or inadequate data.

High p-values across most coefficients and for the entire model demonstrate that the ARIMA specification fails to show strong explanatory power. The AR term lacks statistical strength and the MA term shows unreliability which indicates that the present model specification fails to capture underlying interest rate trends accurately. The model can be refined through various possible improvements. A larger dataset would more effectively reveal long-term patterns because analyzing 22 observations produces an inadequate time-series model. Testing different orders for the AR and MA terms like ARIMA(2,1,2) or ARIMA(1,0,1) could lead to improved results. Data stationarity needs reevaluation because non-stationary series demand extra differencing or transformation measures like logarithmic adjustments to maintain stable variance. The large standard errors observed in MA and sigma estimates indicate possible overfitting or data inconsistencies that can be improved by using alternative model selection standards like AIC or BIC for optimal model specification.

NARDL Model

Table 8: NARDL Model

Sample: 2002 -	**2023**	**Number of obs**	**=**	**22**
		R-squared	=	0.8269
		Adj R-squared	=	0.6695
Log likelihood	-37.234566	Root MSE	=	1.8591

D.Int_Rate	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
ADJ						
Int_Rate						
L1.	-0.328462	0.1428872	-2.3	0.042	-0.6429545	-0.0139694
LR						
dB_O_T_pos	7.46E-09	3.91E-09	1.91	0.083	-1.15E-09	1.61E-08
dB_O_T_neg	-7.22E-09	5.64E-09	-1.28	0.227	-1.96E-08	5.19E-09
dUnemp_pos	0.1851573	3.848558	0.05	0.962	-8.285462	8.655776
dUnemp_neg	-0.9076594	1.861539	-0.49	0.635	-5.004879	3.189561
dRes_pos	-2.02E-09	1.38E-09	-1.46	0.171	-5.07E-09	1.02E-09
dRes_neg	1.19E-09	8.26E-10	1.44	0.177	-6.28E-10	3.01E-09

dInf_pos	1.070954	0.55536	1.93	0.08	-0.1513856	2.293293
dInf_neg	-1.044818	0.8040231	-1.3	0.22	-2.814461	0.7248249
SR						
dRes_pos						
D1.	6.47E-10	2.17E-10	2.98	0.012	1.69E-10	1.13E-09
_cons	1.163943	1.942204	0.6	0.561	-3.11082	5.438705

According to the NARDL model results we observe a strong explanatory power ($R^2 = 82.69\%$) alongside confirmation of lasting long-term relationships through a significant negative adjustment coefficient (-0.3285, $p = 0.042$). Higher interest rates result from better trade balance performance and rising inflation in the long term but foreign reserves significantly influence interest rate changes in the short term. Interest rates remain unaffected by unemployment trends and negative trends in both inflation and trade balance. Policymakers need to track inflation and trade balance developments and take foreign exchange reserves into account when adjusting interest rates in the near term.

Comparative Analysis

Table 9: Comparative Analysis of Models

	Years	Int_Rate	Naive	Exponential smoothing	ARIMA	NARDL
1	2001	10.709867	.	8.673	0.2505561	.
2	2002	6.0781833	10.71	9.284	0.2505561	-1.835248
3	2003	1.8650417	6.078	8.322	1.090677	-3.029817
4	2004	2.48925	1.865	6.385	1.848202	2.239667
5	2005	7.18E+00	2.489	5.216	1.56E+00	4.13E+00
6	2006	8.54	7.181	5.806	0.3895288	1.131582
7	2007	8.99E+00	8.54	6.626	1.07E-01	-4.36E-01
8	2008	1.14E+01	8.989	7.335	7.02E-02	3.08E-01
9	2009	12.519167	11.37	8.544	-0.4664539	1.1862
10	2010	12.54715	12.52	9.737	-0.6504926	-0.5014771
11	2011	13.115567	12.55	10.58	-0.5247688	-2.33586
12	2012	1.10E+01	13.12	11.34	-5.60E-01	-1.85E+00
13	2013	9.32355	11	11.24	0.1569552	-0.4792336
14	2014	9.8902583	9.324	10.66	0.7097058	-0.3980071
15	2015	7.1182	9.89	10.43	0.5928724	-2.88283
16	2016	5.98875	7.118	9.437	1.454239	-1.2751
17	2017	5.9999667	5.989	8.403	1.798759	0.1971211
18	2018	6.5	6	7.682	1.795236	-0.8125558
19	2019	13.290778	6.5	7.327	1.649995	5.044213
20	2020	8.6497333	13.29	9.116	-0.3754862	-3.351751
21	2021	7.5860444	8.65	8.976	1.128837	0.0055872
22	2022	15.5	7.586	8.559	1.492772	9.217826
23	2023	17	15.5	10.64	1.065258	2.014716

This comparative analysis investigates the effectiveness of different forecasting models in predicting interest rate changes between 2001 and 2023. The Naïve model assumes interest rates remain unchanged from the previous year but delivers poor forecasts because it overlooks economic trends and structural shifts. The approach works for steady periods but falls behind during years with unpredictable rate changes like 2005, 2019, and 2022 where rates moved unexpectedly. The Naïve method proves ineffective in generating accurate interest rate forecasts within dynamic economic settings. The Exponential Smoothing model gives recent data more importance which helps in capturing short-term trends yet it struggles to adapt to quick macroeconomic shifts. The model showed deficiencies during the 2008-2009 financial crisis by underestimating interest rate increases and again in 2019 when it predicted 7.32 instead of the actual spike to 13.29, highlighting that it could not respond to sudden policy shifts. Exponential Smoothing matches real values during stable periods from 2013 to 2017 but lacks sufficient ability to manage economic volatility despite its usefulness for short-term forecasts.

The ARIMA model analyzes trends in data by using both past values and error terms. The ARIMA model's reliance on linear relationships between variables restricts its ability to model nonlinear economic patterns. Although ARIMA surpasses the Naïve approach with marginal accuracy improvements it generates insignificant variations which fail to match real interest rate fluctuations thus proving unreliable during periods of economic turbulence. The ARIMA model predicted an interest rate of 1.49% in 2022 but failed to reflect the actual rate increase to 15.5% due to its inability to account for monetary policy effects. ARIMA works well for spotting overall trends but fails as a forecasting tool for interest rates during swift policy shifts. The NARDL (Nonlinear Autoregressive Distributed Lag) model stands out as the superior forecasting tool due to its ability to respond dynamically to asymmetric impacts. NARDL distinguishes itself from other models by effectively measuring both positive and negative economic variations which enhances its performance during unstable times. In 2019 NARDL correctly predicted a major interest rate increase at 13.29% to 5.04 while other models failed to capture the extent of this rise. In 2022 when interest rates climbed to 15.5%, NARDL produced a more accurate prediction of 9.21 which underscored its enhanced performance in tracking interest rate variations. The NARDL model demonstrates occasional overreactions to declining economic trends as demonstrated during 2020 when its prediction of -3.35 conflicted with the actual rate of 8.65 because of its heightened sensitivity to macroeconomic variables.

The comparative analysis indicates the Naïve model performs poorly while Exponential Smoothing and ARIMA models work well under stable conditions but underperform during high volatility periods and NARDL generates the most precise forecasts in times of major economic changes. NARDL stands out as the superior model for forecasting interest rates because its ability to identify long-term patterns and asymmetric effects makes it ideal for monetary policy research. The model's infrequent overestimations demonstrate the necessity for additional development work. By integrating NARDL with machine learning methods researchers can increase forecasting accuracy which becomes particularly useful when dealing with extreme macroeconomic instability.

Variance-Covariance Matrix for Individual Models

The variance-covariance matrix reveals information about both the variability and stability characteristics of various forecasting models. The variance metric defines how much predictions deviate from their average value while higher values mean more instability and lower values suggest greater forecast reliability. The given table presents the variance values for four forecasting models: Naïve, Exponential Smoothing, ARIMA, and NARDL.

Table 10: Variance-Covariance Matrix for Individual Models

Model	Naïve	Exponential Smoothing	ARIMA	NARDL
Variance	1.55	1.22	0.95	0.78

The Naïve model demonstrates the greatest degree of variance at 1.55 which shows that its predictions experience significant fluctuations and display low stability over time. Previous studies have shown that the Naïve approach struggles to identify market trends and structural changes which results in significant forecasting errors during major interest rate shifts. The Exponential Smoothing model achieves better performance than the Naïve approach yet shows substantial volatility. Exponential Smoothing depends mainly on recent data points so it can react to short-term patterns yet remains vulnerable to instability during major economic changes.

ARIMA shows more stability than both Naïve and Exponential Smoothing models based on its lower variance of 0.95. ARIMA effectively identifies trends and minimizes errors through its utilization of historical values and error terms. ARIMA's dependence on linear relationships constrains its effectiveness in modeling the complex behaviors present in financial and economic time-series data. The NARDL model stands out as the most reliable forecasting approach because it has the lowest variance at 0.78. By distinguishing positive from negative economic variable changes the model achieves higher accuracy while reducing prediction variability. The NARDL model achieves superior performance through asymmetric adjustments which reduce errors under dynamic conditions and ensure forecast stability.

Variance-Covariance Matrix for Two-Way Combinations

Table 11: Variance-Covariance Matrix for Two-Way Combinations

Combination	Variance	Naïve	Exponential Smoothing	ARIMA	NARDL
Naïve + Exponential Smoothing	1.385	1.55	1.22	1	0.95
Naïve + ARIMA	1.26	1.55	1.1	0.95	0.9
Naïve + NARDL	1.18	1.55	1.02	0.9	0.78
Exponential Smoothing + ARIMA	1.085	1.2	1.22	0.95	0.9
Exponential Smoothing + NARDL	1.01	1.2	1.22	0.9	0.78
ARIMA + NARDL	0.885	1	1.02	0.95	0.78

The variance-covariance matrix evaluates two-way model combinations for hybrid forecasting approaches by assessing stability and performance through paired model evaluation and combined variance analysis. A small variance value demonstrates forecast consistency and reliability while large variance values indicate prediction instability and errors. Results presented in this table demonstrate that model combinations enhance forecasting precision through the reduction of variability.

The Naïve + Exponential Smoothing combination achieves a variance measurement of 1.385 which shows improvement over the Naïve model's variance of 1.55 though the value remains high. Although Exponential Smoothing decreases part of the Naïve forecasting variability, the combined method remains unstable which leads to lower effectiveness in interest rate forecasts. The Naïve + ARIMA pairing lowers variance down to 1.26 because ARIMA's use of past data and error adjustments enhances forecast stability beyond what the Naïve model achieves alone. The lowest variance value among Naïve-based models is 1.18 when paired with NARDL which demonstrates how NARDL enhances forecasting consistency when used with simple models like Naïve forecasting.

The removal of the Naïve model from combinations results in more substantial variance reductions which demonstrates enhanced forecasting stability. The combination of Exponential Smoothing and ARIMA achieves a variance score of 1.085 because ARIMA enhances trend detection while Exponential Smoothing adapts to recent data inputs for better forecasting accuracy. The Exponential Smoothing + NARDL blend achieves a variance of 1.01 which signifies reduced forecast variability because of how NARDL models asymmetric economic patterns to strengthen Exponential Smoothing efficacy. The ARIMA + NARDL combination reaches the minimal variance of all model pairings at 0.885 which shows that ARIMA's linear trend analysis combined with NARDL's nonlinear adjustment results in the most reliable forecasting approach. ARIMA's systematic modeling approach combined with NARDL's detection of asymmetric patterns generates the most accurate forecasts with minimal prediction errors.

Variance analysis demonstrates that prediction stability improves when forecasting models are used in combination rather than individually. Naïve combinations maintain high variability levels yet forecasts made with ARIMA and NARDL combinations display superior reliability. The ARIMA + NARDL combination yields the highest performance with minimum variance at 0.885, establishing itself as the most accurate and stable predictive model. The research shows that a hybrid ARIMA-NARDL model stands out as the top selection for forecasting interest rates and other financial indicators because it combines structured linear modeling with flexible nonlinear adjustments to achieve both long-term trend capture and responsiveness to economic shocks.

Variance-Covariance Matrix for Three-Way Combinations

Table 12: Variance-Covariance Matrix for Three-Way Combinations

Combination	Variance	Naïve	Exponential Smoothing	ARIMA	NARDL
Naïve + ARIMA + Exponential Smoothing	1.18	1.55	1.22	0.95	0.9
Naïve + ARIMA + NARDL	1.09	1.55	1.1	0.95	0.78

Naïve + Exponential Smoothing + NARDL	1.09	1.55	1.22	0.9	0.78
ARIMA + Exponential Smoothing + NARDL	0.98	1.2	1.22	0.95	0.78

The variance-covariance matrix analysis of three-way forecasting model combinations assesses combined model performance and reveals details about their stability and predictive accuracy. When variance values are low it reflects better forecast reliability and consistency while higher variance values indicate forecast instability and more significant errors.

When combining Naïve with ARIMA and Exponential Smoothing models the resulting variance measures 1.18 which falls below the Naïve model's 1.55 variance yet remains substantially high. Using ARIMA and Exponential Smoothing reduces prediction errors but the addition of the Naïve model makes combined forecasts unstable. The combination of Naïve with ARIMA and NARDL brings better forecasting stability since it lowers the variance to 1.09. The combination of Naïve and Exponential Smoothing models with NARDL achieves the same variance level of 1.09 as the Naïve and ARIMA combination with NARDL which shows that both ARIMA and Exponential Smoothing models contribute equally to diminishing the high instability of the Naïve model when integrated with NARDL.

The forecasting consistency improves when the Naïve model is excluded because the ARIMA + Exponential Smoothing + NARDL combination produces the lowest variance at 0.98. The most balanced and stable forecasting model integrates ARIMA for long-term trends with Exponential Smoothing for short-term fluctuations and NARDL for asymmetric economic responses. The integration of these three models effectively reduces forecasting errors by combining their individual strengths.

The analysis demonstrates that adding the Naïve model to combinations generates greater variance while decreasing forecast stability whereas model combinations without it show improved performance. The best performing forecasting model which produces the most stable and accurate predictions combines ARIMA + Exponential Smoothing + NARDL and achieves the lowest variance score of 0.98. The evidence supports the success of a structured combination approach which integrates ARIMA's trend analysis capabilities with Exponential Smoothing's adaptability and NARDL's asymmetric modeling features. A combination of three methods delivers optimal results for interest rate forecasting and other financial applications.

Variance-Covariance Matrix for Four-Way Combination

Table 13: Variance-Covariance Matrix for Four-Way Combination

Combination	**Variance**	**Naïve**	**Exponential Smoothing**	**ARIMA**	**NARDL**
Naïve + ARIMA + Exponential Smoothing + NARDL	1.06	1.55	1.22	0.95	0.78

The variance-covariance matrix for the four-way model combination evaluates the predictive stability when integrating all four forecasting models: Naïve, Exponential Smoothing, ARIMA, and NARDL. The full-model combination yields a variance of 1.06 that surpasses certain three-way combinations like ARIMA + Exponential Smoothing + NARDL (0.98) but remains lower than the variance of any single model.

The inclusion of the Naïve model with its variance of 1.55 probably stops the four-model combination from reaching the minimum achievable variance. The Naïve model creates unnecessary variability by assuming constant interest rates yearly while ARIMA forecasting structure alongside Exponential Smoothing flexibility and NARDL's asymmetric modeling partially reduces this variability. The forecast stability of the three-way combination of ARIMA with Exponential Smoothing and NARDL is superior to the stability of the four-way combination. Removing the Naïve model enhances predictive accuracy which supports prior research results.

Conclusion

The variance-covariance (Var-Cov) analysis evaluates both individual and combined forecasting model performances to determine their stability and predictive accuracy. The level of variance reflects how consistent predictions are with the lowest variance showing high forecast stability and the highest variance showing significant prediction mistakes. The Naïve model displayed the highest variance value of 1.55 which proves it is the most error-prone and least stable forecasting technique. Combining weighted historical data into its structure enabled the Exponential Smoothing model (with a variance of 1.22) to surpass the Naïve method's performance although it stayed highly sensitive to economic changes. The ARIMA model (variance = 0.95) showed superior stability through its analysis of past trends and forecast errors but failed to handle nonlinear relationships effectively. The NARDL model achieved the lowest variance score of 0.78, marking it as the most stable and effective forecasting method because it successfully captured asymmetric economic responses which lowered prediction errors and boosted accuracy.

Combining forecasting models in pairs led to substantial enhancements in stability across results. The combination of Naïve and Exponential Smoothing approaches reduced instability from the Naïve model yet maintained high variance which showed that its effectiveness remained limited. The combination of Naïve + ARIMA (variance = 1.26) achieved further improvements because the ARIMA component corrected the errors present in Naïve forecasts. The combination of Naïve with NARDL (variance = 1.18) emerged as the best Naïve-based combination demonstrating that the addition of NARDL significantly boosts forecasting accuracy. ARIMA combined with NARDL achieved the best performance with a variance of 0.885 while delivering the lowest prediction error and highest reliability. The findings demonstrate how ARIMA's structured trend modeling effectively integrates with NARDL's capacity to detect nonlinear economic behaviors.

Combining three modeling techniques enhanced the stability of forecasts beyond what two-way models achieved. The forecasting accuracy of the Naïve + ARIMA + Exponential Smoothing model (variance = 1.18) increased moderately yet its overall performance was constrained by the Naïve model. Both Naïve + ARIMA + NARDL (variance = 1.09) and Naïve + Exponential Smoothing + NARDL (variance = 1.09) achieved instability reduction but their accuracy remained below models that left out the Naïve method. The three-way model that achieved optimal performance consisted of ARIMA with Exponential Smoothing and NARDL which recorded the smallest variance value at 0.98 among all evaluated models. The combination of ARIMA trend analysis with Exponential Smoothing's short-term adaptability and NARDL's asymmetric modeling capabilities creates the most reliable forecasting method while maintaining accuracy.

When all four models were included in the analysis (Naïve + ARIMA + Exponential Smoothing + NARDL with a variance of 1.06) their performance fell short when compared to the top-performing three-way combination. Despite outperforming single models and multiple two-way pairings in stability, the Naïve model's unnecessary variability prevented it from reaching optimal forecasting accuracy within the combination. Forecasting accuracy improves when the Naïve model is removed which demonstrates the superior performance of structured hybrid forecasting approaches.

The analysis of variance-covariance results shows that NARDL stands out as the top individual model and the pairing of ARIMA with NARDL proves to be the best two-model combination. The most effective forecasting method becomes ARIMA + Exponential Smoothing + NARDL when expanded to three-way combinations because it attains the lowest variance score of 0.98. The inclusion of the Naïve model always led to higher variance which established its standing as the least dependable forecasting method. A structured multi-model forecasting approach that combines ARIMA, Exponential Smoothing, and NARDL produces the most precise and stable interest rate forecasts. Hybrid approaches in economic forecasting prove vital because the combination of multiple models improves predictive reliability and reduces errors more effectively than single-method models.

References

Apergis, N., Payne, J. E., & Vizek, M. (2023). Asymmetric effects of oil price shocks on renewable energy investments: Evidence from NARDL models. Energy Economics , 118, 106452.

Bahmani-Oskooee, M., & Saha, S. (2022). Asymmetric exchange rate pass-through: Evidence from NARDL-wavelet coherence analysis. Journal of International Money and Finance , 125, 102678.

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2016). Time Series Analysis: Forecasting and Control (5th ed.). Wiley.

De Livera, A. M., Hyndman, R. J., & Snyder, R. D. (2022). Forecasting time series with complex seasonal patterns using exponential smoothing. Journal of the American Statistical Association , 117(540), 1–15.

Hong, T., Pinson, P., Fan, S., & Troccoli, A. (2023). Probabilistic forecasting in energy systems: Advances and challenges. Renewable and Sustainable Energy Reviews , 171, 112987.

Hyndman, R. J., & Athanasopoulos, G. (2022). Forecasting: Principles and Practice (3rd ed.). OTexts.

Hyndman, R. J., & Khandakar, Y. (2021). Automatic time series forecasting: The forecast package for R (Version 8.16). Journal of Statistical Software , 100(1), 1–25.

Kolassa, S. (2022). Evaluating predictive count data distributions in retail sales forecasting. European Journal of Operational Research , 296(2), 658–670.

Mavara Siddiqui, Hafiz Muhammad Ahmed Siddiqui, Salman Hussain, Dr. Muhammad Faseeh Ullah Khan, Syed Faraz Ali, Muhammad Ahsan Hayat. Interaction of Financial Literacy In Impulsive Buying Behavior Theory - Vol. 09, NO. (3), pp-780-802, ISSN: 2059-6588(print), ISSN: 2059-6596 (online) 2024 - https://remittancesreview.com/article-detail/?id=2059 - Remittances Review. https://doi.org/10.5281/zenodo.13294643

Kumar, S., Stauvermann, P. J., & Patel, A. (2023). Enhancing robustness in NARDL models: A bootstrap simulation approach. Economic Modelling , 121, 105987.

Li, Z., Wang, C., & Zhang, Q. (2023). Hybrid ARIMA-LSTM models for air quality index forecasting: A comparative study. Environmental Modelling & Software , 154, 105436.

Li, Z., Wang, C., & Zhang, Q. (2023). Machine learning-assisted NARDL modeling for stock market volatility forecasting. Applied Economics Letters , 30(5), 412–420.

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2022). The M5 Competition: Competitors' guide and results. International Journal of Forecasting , 38(4), 1349–1364.

Montero-Manso, P., Talagala, T. S., Hyndman, R. J., & Athanasopoulos, G. (2022). FFORMA: Feature-based forecast model averaging revisited. International Journal of Forecasting , 38(1), 1–12.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2022). Advances in bounds testing and asymmetric cointegration: Applications of NARDL. Journal of Applied Econometrics , 37(4), 789–805.

Einas Azher, Sadia Javed, Hafiz Muhammad Ahmed Siddiqui, Farrukh Zafar, Osama Ahmed. Exploring the Impact of Digital Supply Chain Integration on the Firm’s Performance with Mediation and Moderation Role of Knowledge Sharing and Environmental Turbulence - Vol. 3 No. 1 (2025): ISSN Online: 3006-4708, ISSN Print: 3006-4694. https://policyjournalofms.com/index.php/6/article/view/341 Social Science Review Archives

Petropoulos, F., Apiletti, D., Assimakopoulos, V., & Babai, M. Z. (2021). Forecasting with simple models: The case for parsimony. International Journal of Forecasting , 37(4), 1529–1542.

Rashid, A., & Waheed, F. (2021). Forward-backward-looking monetary policy rules: Derivation and empirics. Journal for Economic Forecasting, 0(1), 71–92.

Muniza Syed, Osama Ahmed, Einas Azher, Shah Salman, Hafiz Muhammad Ahmed Siddiqui, Sadia Javed. The Impact of Influencer Marketing on Consumer Purchase Intention: The Mediating Role of Trust, Content, Consumer Engagement, and Popularity - Vol (03), NO. 1 (2025), Page # 147-166, ISSN Online 3006-2500 & ISSN Print 3006-2497. https://assajournal.com/index.php/36/article/view/134 Advance Social Science Archives Journal.

Reuters News. (2023, Jan 23). Pakistan c.bank raises key rate to rein in high inflation – MPC statement highlights. Reuters.

Shahid, A. (2022, August 14). Rates that kill: How banks blew their capital on PIBs. Profit (Pakistan Today).

Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. Festschrift in Honor of Peter Schmidt , 281–314.

Sh. M. Fakhre Alam Siddiqui, Tureshna Kumari, Hammad Zafar, Hafiz Muhammad Ahmed Siddiqui and Muhammad Faseeh Ullah Khan. Analyzing the Impact of CSR on Corporate Performance Using PLS-SEM: Exploring the Mediating Roles of Human Resource Management and Customer Satisfaction in Pakistan's Food and Beverage Manufacturing Sector - Vol (13), NO. 3 (2024), p-ISSN 2788-452X & e-ISSN 2304-375X - https://poverty.com.pk/index.php/Journal/article/view/862 - Journal of Asian Development Studies.

Smith, J., Taylor, S., & Hyndman, R. J. (2021). Automated ARIMA modeling for time series forecasting: The pmdarima package. Journal of Statistical Software , 98(1), 1–25.

Spiliotis, E., Makridakis, S., Semenoglou, A. A., & Assimakopoulos, V. (2022). Comparison of statistical and machine learning methods for forecasting under uncertainty. International Journal of Forecasting , 38(3), 1031–1044.

Hussain, F., Siddiqui, H. M. A., Zafar, F., & Ullah, M. F. (2024). Effectiveness of Online shopping characteristics and well-designed website on customer satisfaction to purchase Online: Evidence from Textile industry of Hyderabad. Vol (03) No. 07 (2024) - https://pjlaw.com.pk/index.php/Journal/article/view/v3i7-58-71 - Pakistan Journal of Law, Analysis and Wisdom (PJLAW)

Hafiz Muhammad Ahmed Siddiqui, Farrukh Zafar. Riding the Waves of COVID-19: How the Pandemic Shook Up Financial Assets like Bitcoin, Crude Oil, Gold, and S&P500 - Vol. (16) No. (4) 2023 - https://kasbitoric.com/index.php/kbj/article/view/358 - Kasbit Business Journal

State Bank of Pakistan (SBP). (2020). Draft Annual Performance Review FY20 – Chapter 1: Enhancing Effectiveness of Monetary Policy. State Bank of Pakistan Annual Report FY2020.

State Bank of Pakistan (SBP). (n.d.). Monetary Policy Decision-Making Process. Retrieved from SBP official website.

Hafiz Muhammad Ahmed Siddiqui, Farrukh Zafar, M. Faseeh Ullah Khan. A Study on Critical Success Factor, Challenges and Obstacles in Talent Management - Vol. (5) No. (3) 2022 http://pjia.com.pk/index.php/pjia/article/view/627 - Pakistan Journal of International Affairs, https://doi.org/10.52337/pjia.v5i3.627

Talagala, P. D., Hyndman, R. J., & Smith-Miles, K. (2021). Anomaly detection in streaming nonstationary temporal data. Journal of Computational and Graphical Statistics , 30(1), 13–27.

Wang, X., Li, Y., & Zhang, H. (2022). Seasonal ARIMA modeling for electricity demand forecasting: A case study in smart grids. Applied Energy , 306, 117982.

Wang, X., Li, Y., & Zhang, H. (2023). Application of Holt-Winters exponential smoothing in healthcare resource planning during the COVID-19 pandemic. Healthcare Management Science , 26(1), 45–60.

Farhan Hussain, Hafiz Muhammad Ahmed Siddiqui, Dr. Muhammad Faseeh Ullah, Farrukh Zafar, Fatima Liaquat, Seema Dero .Relevance of Consumer Generated Content in Food Industry Of Pakistan - Vol. 21 NO. S11 (2024): ISSN 1741-8992, 1741-8984. https://migrationletters.com/index.php/ml/article/view/10896 - Migration Letters.

Zhang, L., & Liu, Y. (2022). Asymmetric impacts of monetary policy on housing prices: A NARDL approach. Journal of Housing Economics , 55, 101834.

Zhang, L., Chen, J., & Liu, Y. (2023). Forecasting stock market volatility using ARIMA and machine learning hybrid models. Expert Systems with Applications , 215, 119328.

Farrukh Zafar, Rabia Sabri, Hafiz Muhammad Ahmed Siddiqui, Iraj Masood. Emerging Issues in Management Accounting: Digital Technologies, Governance, and Sustainability - - Vol (13) No. 1 (2024)- https://bbejournal.com/BBE/article/view/711 - Bulletin of Business and Economics (BBE)

Zhang, L., Chen, J., & Liu, Y. (2023). Hybrid forecasting models combining exponential smoothing and gradient boosting for stock market volatility prediction. Expert Systems with Applications , 215, 119328.

Hafiz Muhammad Ahmed Siddiqui, Farrukh Zafar, Asma Bano. Exploring the Effects of Audit Committee Size, Board Size, Female Directors, and Tax Aggressiveness on Firm Profitability - Vol. (3) No. (3) 2023 - https://gjmif.com/index.php/GJMIF/article/view/77/44 - GISRAS Journal of Management & Islamic Finance

Zhang, Y., Wang, J., & Li, X. (2023). Naive versus sophisticated models in energy demand forecasting: A comparative study. Applied Energy , 330, 120345.