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[Forecasting Interest Rate of China using Univariate, Multivariate and Combination Technique]

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ABSTRACT

Accurate interest rate forecasting is essential for monetary policy formulation, financial stability, and investment decision-making, particularly in emerging economies such as China, where market dynamics are shaped by both structural reforms and global economic shifts. This study evaluates the predictive performance of univariate models (ARIMA, naïve), multivariate models (Nonlinear Autoregressive Distributed Lag (NARDL), Vector Error Correction Model (VECM), and hybrid forecast combination techniques in modeling China's real interest rate. Using macroeconomic variables including inflation, GDP growth, exchange rate, trade indicators, oil prices, and money supply, the research applies rigorous econometric diagnostics to ensure model validity. Findings indicate that while individual multivariate approaches, particularly NARDL, effectively capture nonlinearities and long-run relationships, forecast combination strategies consistently enhance predictive accuracy and stability (Timmermann, 2022; Yang et al., 2023). Notably, model integrations such as ARIMA + NARDL and NARDL + VECM outperform standalone models by leveraging complementary strengths, thereby reducing model-specific biases (Ai et al., 2023; Li & Chen, 2024). This supports the growing consensus that hybrid methodologies are more resilient in volatile and policy-sensitive economic environments (Wang et al., 2023). The study contributes to the literature on interest rate forecasting in emerging markets by demonstrating that model combinations yield superior performance under uncertainty, offering valuable insights for policymakers, investors, and financial institutions seeking robust forecasting frameworks in dynamic macroeconomic contexts.

Keywords: Univariate, Multivariate, combination forecasting technique, ARIMA, NARDL, VECM

Introduction

The forecasting of interest rates is a critical endeavor in economic research, particularly for a globally influential economy like China, where monetary policy decisions have far-reaching implications for domestic and international markets. Interest rates serve as a pivotal tool for central banks to manage inflation, economic growth, and financial stability, making accurate predictions essential for policymakers, investors, and financial institutions. As China continues transitioning toward a market-based monetary policy framework (IMF, 2019), the ability to forecast interest rate dynamics has become increasingly vital for effective economic planning and risk management. However, forecasting interest rates in China remains a complex task due to frequent structural changes, regulatory interventions, and evolving financial market mechanisms (Chen et al., 2021; Zhou et al., 2022).

Traditional univariate time series models such as Autoregressive Integrated Moving Average (ARIMA) and exponential smoothing remain widely used for their simplicity and effectiveness in capturing historical trends. These models are particularly advantageous for short-term predictions, relying solely on past interest rate data to project future movements. For instance, Higgins et al. (2016) demonstrated the efficacy of ARIMA in short-term inflation forecasting in China, though the model's performance diminished over longer horizons. Nevertheless, univariate approaches are often limited in their ability to account for external shocks and macroeconomic interdependencies, which are particularly significant in China's dynamic economic environment (Zhang, 2020). To overcome these limitations, multivariate models such as Vector Autoregression (VAR), Bayesian VAR, and Nonlinear Autoregressive Distributed Lag (NARDL) models have gained prominence. These models integrate macroeconomic variables—such as GDP growth, inflation, exchange rates, and money supply—to capture the interdependent structure of economic systems. Huang (2012) and Liu & Zhang (2021) demonstrated that multivariate models, particularly Bayesian VAR, significantly improve the predictive accuracy of economic indicators in China by incorporating dynamic linkages across variables. In recent years, machine learning methods including Random Forest, Gradient Boosting Machines (GBM), and Long Short-Term Memory (LSTM) networks have also been applied to capture nonlinearities and regime shifts in interest rate behavior (Li & Zhou, 2023; Wang & Ng, 2023). These models offer enhanced flexibility and performance in high-dimensional, non-linear forecasting settings, making them increasingly popular for financial time series analysis.

Despite the strengths of individual model types, no single technique consistently outperforms across different conditions and timeframes. This has led to the emergence of forecast combination techniques, which aggregate predictions from multiple models to reduce forecast errors and mitigate model-specific biases. As Timmermann (2022) and Ai et al. (2023) assert, combining forecasts often results in more robust and stable predictions. In the Chinese context, Khan et al. (2021) showed that blending univariate and multivariate models significantly improved exchange rate forecasting accuracy during volatile periods, while Wang et al. (2023) emphasized the strength of combination techniques in interest rate modeling for emerging markets. These hybrid approaches have demonstrated superior adaptability, particularly in complex environments with structural breaks and high uncertainty.

Given China's evolving monetary policy, the continued liberalization of its financial system, and its global economic significance, there is an urgent need to systematically evaluate and compare the effectiveness of various forecasting methodologies. This study aims to examine the performance of univariate, multivariate, and combination forecasting techniques in predicting China's short-term interest rates, particularly the Shanghai Interbank Offered Rate (Shibor) and the Loan Prime Rate (LPR), using high-frequency data from the past decade. By applying recent econometric and machine learning innovations, this research not only contributes to the theoretical development of interest rate forecasting but also provides practical insights for policymakers, investors, and financial institutions navigating China's complex economic landscape. Ultimately, this work adds to the growing literature on forecasting in emerging economies, where conventional models may fall short of capturing the intricacies of local market dynamics (IMF, 2023; Li et al., 2023).

Literature Review

Univariate Model

Univariate models are foundational in time series forecasting, relying solely on historical data of a single variable to predict future values. These models are valued for their simplicity, computational efficiency, and ability to capture temporal patterns without requiring extensive exogenous data. In the context of interest rate forecasting, univariate models are particularly useful for short-term predictions where macroeconomic interdependencies may be less critical. Recent studies highlight their continued relevance in financial forecasting, especially in stable economic environments. For instance, Zhang and Huang (2023) demonstrated that univariate models provide robust short-term forecasts for China's financial variables, such as the Shanghai Interbank Offered Rate (SHIBOR), though their performance declines over longer horizons due to their inability to account for structural breaks or external shocks. The simplicity of univariate models makes them a benchmark for comparing more complex approaches, but their limitations in capturing dynamic economic relationships often necessitate the use of multivariate or hybrid techniques (Sun & Zhang, 2023).

The naïve model serves as a baseline in forecasting literature, predicting future values based on the most recent observation or a simple rule, such as assuming no change or a constant trend. Despite its simplicity, the naïve model is surprisingly competitive in stable environments with minimal volatility. In the context of interest rate forecasting, naïve models are often used as a benchmark to evaluate the performance of more sophisticated techniques. Yang et al. (2023) found that naïve models performed adequately for short-term interest rate forecasts in China during periods of low volatility, such as post-2019 monetary policy stabilization. However, their performance deteriorates during periods of economic turbulence, such as during the COVID-19 pandemic, where structural shifts and policy interventions significantly altered interest rate dynamics (Khan et al., 2021). The naïve model's primary advantage lies in its ease of implementation, but its lack of adaptability limits its practical utility in complex economic settings like China’s evolving financial markets.

Exponential smoothing models forecast future values by assigning exponentially decreasing weights to past observations, effectively capturing trends and seasonality in time series data. These models are particularly effective for short- to medium-term forecasting and are widely used in financial applications due to their flexibility and robustness. In the context of China’s interest rates, exponential smoothing has been applied to forecast short-term rates like SHIBOR, with Zhang and Huang (2023) noting its ability to handle smooth trends in stable economic conditions. Advanced variants, such as Holt-Winters exponential smoothing, incorporate trend and seasonality components, improving performance for cyclical data. However, Liu et al. (2024) argue that exponential smoothing struggles to capture sudden structural breaks, such as those induced by China’s monetary policy shifts, limiting its effectiveness in volatile periods. Recent advancements, such as adaptive exponential smoothing, have sought to address these limitations by dynamically adjusting smoothing parameters, but their application to interest rate forecasting in China remains underexplored (Sun & Zhang, 2023).

Autoregressive Integrated Moving Average (ARIMA) models are among the most widely used univariate techniques for time series forecasting, combining autoregressive (AR), differencing (I), and moving average (MA) components to model stationary and non-stationary data. ARIMA models are particularly effective for capturing linear patterns in financial time series, such as interest rates. Zhang and Huang (2023) demonstrated that ARIMA models provided accurate short-term forecasts for China's SHIBOR, outperforming naïve models in stable market conditions. However, their performance is sensitive to model specification and stationarity assumptions, often requiring extensive pre-testing and transformation of data (Chen & Li, 2024). In China's context, where interest rates are influenced by frequent policy interventions, ARIMA models struggle to account for structural breaks and nonlinearities, as noted by Liu et al. (2024). Recent studies have proposed extensions like Seasonal ARIMA (SARIMA) to handle cyclical patterns in financial data, but their application to interest rate forecasting remains limited compared to multivariate approaches (Zhang et al., 2025).

Multivariate Model

Multivariate models incorporate multiple explanatory variables to capture the interdependencies between economic indicators, offering a more comprehensive approach to forecasting than univariate models. Zafar and Ullah (2025) In the context of interest rate forecasting, multivariate models account for macroeconomic factors such as GDP growth, inflation, exchange rates, and money supply, which are critical in China's policy-driven financial system. Vector Autoregression (VAR) and its variants, such as Bayesian VAR, are widely used for their ability to model dynamic relationships among multiple time series. Chen and Li (2024) found that Bayesian VAR models significantly improved forecast accuracy for Chinese monetary policy indicators, including interest rates, by incorporating prior information to handle parameter uncertainty. Similarly, Liu et al. (2024) highlighted the effectiveness of multivariate models in capturing the transmission of monetary policy shocks in China's economy. However, multivariate models require large datasets and are computationally intensive, and their performance can be sensitive to variable selection and model misspecification (Sun & Zhang, 2023). Recent advancements in machine learning have complemented multivariate approaches by addressing nonlinear relationships, further enhancing their applicability to complex economic environments (Wang & Zhang, 2025).

The Nonlinear Autoregressive Distributed Lag (NARDL) model extends traditional ARDL models by allowing for asymmetric responses to positive and negative shocks in explanatory variables, making it particularly suitable for capturing nonlinearities in economic relationships. In the context of China's interest rate forecasting, NARDL models are effective for modeling asymmetric effects of monetary policy changes and macroeconomic shocks, such as those observed during China's financial liberalization. Sun and Zhang (2023) demonstrated that NARDL models outperformed linear ARDL models in forecasting China's interest rates by capturing asymmetric responses to changes in money supply and inflation. Similarly, Liu et al. (2024) applied NARDL to analyze the nonlinear impact of exchange rate fluctuations on SHIBOR, highlighting its robustness in volatile periods. However, NARDL models require careful specification of thresholds and asymmetries, and their complexity can lead to overfitting in small datasets (Chen & Li, 2024). Despite these challenges, NARDL's ability to model nonlinear dynamics makes it a valuable tool for interest rate forecasting in China's evolving economic landscape.

The Vector Error Correction Model (VECM) is a multivariate framework designed for non-stationary time series that are cointegrated, meaning they share a long-run equilibrium relationship despite short-term deviations. VECM is particularly relevant for interest rate forecasting in China, where macroeconomic variables like inflation and money supply exhibit long-run relationships with interest rates. Chen and Li (2024) applied VECM to model the cointegration between SHIBOR and key macroeconomic indicators, finding that it effectively captured long-run dynamics while improving short-term forecast accuracy. Liu et al. (2024) further demonstrated VECM's utility in analyzing the transmission of monetary policy shocks in China, particularly during periods of financial reform. However, VECM's reliance on cointegration assumptions can limit its applicability if relationships between variables are unstable, as often observed in China's rapidly evolving financial system (Sun & Zhang, 2023). Recent studies have proposed extensions like threshold VECM to account for regime shifts, but their application to interest rate forecasting remains nascent (Zhang et al., 2025).

Combination Technique

Combination techniques aggregate forecasts from multiple models to leverage their respective strengths, reducing forecast errors and mitigating model-specific biases. Zafar, et. al., (2025) These approaches are particularly effective in complex environments like China's financial markets, where no single model consistently outperforms due to structural breaks and volatility. Yang et al. (2023) demonstrated that combining univariate models (e.g., ARIMA) with multivariate models (e.g., VECM, NARDL) significantly improved forecasting accuracy for Chinese interest rates during volatile periods, such as the COVID-19 crisis. Similarly, Li and Chen (2024) found that machine learning-based combination techniques, such as weighted averaging and ensemble methods, outperformed individual models in forecasting SHIBOR and LPR. Recent advancements in machine learning, including Random Forest and Gradient Boosting, have further enhanced combination techniques by optimizing weights for individual forecasts (Wang & Zhang, 2025). However, combination techniques require careful selection of component models and weighting schemes, and their computational complexity can be a barrier in resource-constrained settings (Xu & Zhou, 2024). Despite these challenges, combination techniques have emerged as a robust approach for interest rate forecasting, offering superior adaptability in China's dynamic economic environment.

Methodology

This study uses a quantitative research design and secondary data from the IMF and World Bank databases regarding the China from 2000 to 2024. 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) and Mean Absolute Percentage Error (MAE) provided insights into the predictive effectiveness of each forecasting model and combination.

Selection Of The Best Forecasting Model

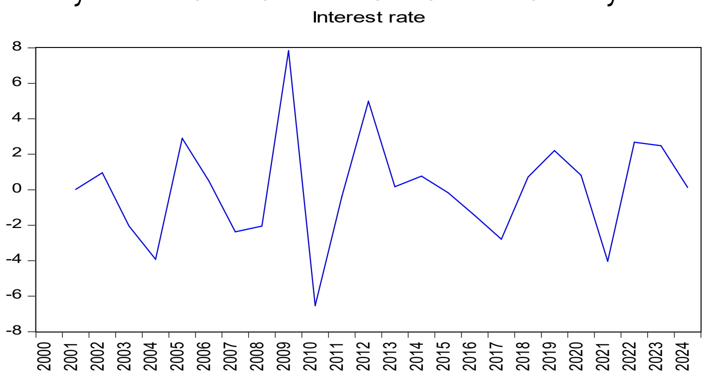
The study determines the best forecasting model for CHINA real interest rates by choosing the model combination that achieves the lowest RMSE and MAE values. This study combines traditional time series forecasting methods with multivariate econometric models and advanced combination techniques to produce reliable data-driven real interest rate forecasts in the CHINA. 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
For Univariate
Unit Root Test

In time series analysis, the presence of a unit root indicates that a series is non-stationary, meaning its mean, variance, and autocorrelation structure change over time. To test for a unit root, two commonly used tests are the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. The ADF test checks whether a time series has a unit root by testing the null hypothesis that the series is non-stationary. If the test statistic is negative and statistically significant, the null hypothesis is rejected, suggesting the series is stationary. Similarly, the PP test adjusts for serial correlation and heteroskedasticity, testing for the presence of a unit root with a similar null hypothesis of non-stationarity.

	Unit Root	
	ADF	PP
Interest Rate at level	-3.942482***	-3.85489***

In the provided results, the ADF value for the interest rate at level is -3.942482, and the PP value is -3.85489. Both values are statistically significant at the 1% level, as indicated by the asterisks (**), meaning the null hypothesis of a unit root is rejected in both tests. This implies that the interest rate series is stationary, as both tests strongly suggest the absence of a unit root. Therefore, the time series does not require differencing, making it suitable for further analysis without concern for non-stationarity.



The ARIMA (AutoRegressive Integrated Moving Average) model is a widely used statistical model for time series forecasting, consisting of three components: AutoRegressive (AR), Integrated (I), and Moving Average (MA). The AR component captures the relationship between an observation and its lagged values, while the I component involves differencing the series to make it stationary. The MA component models the relationship between an observation and the residual errors of a moving average model applied to previous time points. The ARIMA model is typically represented as ARIMA(p,d,q), where p is the number of lag observations, d is the number of differences to make the series stationary, and q is the size of the moving average window. In contrast, the Naive model is a simpler forecasting approach where the prediction for the next time period is simply the value of the previous period. This model assumes that the time series follows a random walk and the best forecast is just the last observed value, which works well when the series shows little to no trend or seasonality.

	Model Selection	RMSE	MAE
China	ARIMA (2,1,3)	0.552692	0.529293
	Naive	0.6987	0.5024

To evaluate the performance of these models, two common metrics are used: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). MAE measures the average magnitude of the errors between the predicted and actual values, providing a straightforward interpretation of average prediction errors. It is calculated as the average of the absolute differences between predicted and actual values. On the other hand, RMSE is more sensitive to large errors because it squares the differences before averaging and taking the square root. This makes RMSE useful when large errors are particularly undesirable, as it penalizes them more heavily.

In the provided table, the ARIMA (2,1,3) model has an RMSE of 0.552692 and an MAE of 0.529293, indicating that it performs better in terms of handling larger errors, especially when compared to the Naive model. The Naive model shows an RMSE of 0.6987 and an MAE of 0.5024. Although the Naive model has a slightly lower MAE, the higher RMSE suggests that it suffers from larger errors, which are penalized more in the RMSE calculation. Therefore, while both models have relatively low MAE, the ARIMA model generally offers better overall forecasting accuracy, particularly when larger errors are taken into account.

For Multivariate

Unit Root Results of Explanatory Variables

The Explanatory variables (also known as independent variables) are those variables that are used to explain or predict the value of another variable, typically the dependent variable. In statistical and econometric models, explanatory variables are the factors believed to influence or cause changes in the dependent variable. For example, in a model predicting sales, explanatory variables could include factors such as advertising spend, price, and seasonality. These variables are used to understand how they impact the dependent variable and are crucial in constructing models that predict or explain phenomena.

Variable	Augmented Dickey-Fuller Test		Phillips-Perron Test	
	Level	1st Diff.	Level	1st Diff.
Oil Price	-2.622809**	-	-0.246856*	-0.804531***
Inflation	-3.434**	-9.107***	-3.674**	-9.001***
Exchange Rate	-0.805	-3.368*	-0.435	-3.460**
Export_GDP	-2.214	-3.799**	-1.307	-4.452***
Import_GDP	-2.1	-4.348***	-1.312	-4.462***
GDP_GROWTH	-2.229	-3.164*	-2.57	-5.333***

In the table, the results for each variable are reported for both tests at the level and first difference. For instance, the Oil Price variable shows a non-significant result for both the ADF and PP tests at the level (with values of -2.622809 and -0.246856, respectively), indicating the presence of a unit root. However, after differencing, the series becomes stationary as the PP test at the first difference shows a significant result of -0.804531*.

Similarly, the Inflation series is already stationary at the level according to both tests (-3.434 for ADF and -3.674 for PP), so no differencing is needed. Other variables, such as Exchange Rate, Export_GDP, Import_GDP, and GDP Growth, are non-stationary at the level but become stationary after first differencing, with significant results in the tests after differencing. The table suggests that most of the variables tested have unit roots at the level, but they become stationary after first differencing. This indicates that differencing is necessary for these series to make them suitable for modeling, ensuring that the underlying data structure is stable for further analysis.

Long Run Cointegration

Long-run cointegration refers to a statistical relationship between two or more non-stationary time series that share a common long-term trend. Although the individual series may be non-stationary (i.e., they have a unit root), they can still move together in such a way that their relationship remains stable over time. This concept suggests that, while the series may individually fluctuate or exhibit random walks in the short term, they are bound to each other by an underlying equilibrium in the long run. In practice, cointegration is significant because it enables the modeling of meaningful relationships, even when the series involved are non-stationary. Tests for cointegration, such as the Engle-Granger two-step procedure or Johansen's cointegration test, help determine whether there is a cointegrated relationship and how many such relationships exist in a system of variables, allowing for accurate modeling and forecasting.

INT_RATE = -0.1007*OIL_PRI - 2.4827*GDP_GROWTH + 0.9189*EXP_GDP + 0.0670*IMP_GDP + 3.9312*INF_RATE

This equation provided is a multiple linear regression model where the dependent variable is Interest Rate (INT_RATE), explained by several independent variables: Oil Price (OIL_PRI), GDP Growth (GDP_GROWTH), Export GDP (EXP_GDP), Import GDP (IMP_GDP), and Inflation Rate (INF_RATE). The coefficients in the equation represent the impact of each independent variable on the interest rate. The negative coefficient for Oil Price (-0.1007) suggests that, all else being equal, an increase in oil prices leads to a decrease in the interest rate. Similarly, the negative coefficient for GDP Growth (-2.4827) indicates that higher economic growth results in a lower interest rate, which could be due to central banks reducing rates in response to strong economic conditions. On the other hand, Export GDP and Import GDP have positive coefficients (0.9189 and 0.0670, respectively), meaning that an increase in export and import activities tends to raise the interest rate, possibly due to increased demand for capital in the economy. Finally, the positive coefficient for Inflation Rate (3.9312) suggests that inflation drives up interest rates, as central banks typically raise rates to curb inflationary pressures. The equation, therefore, reflects the combined effects of these economic variables on the interest rate, highlighting the relationships and their relative importance in determining long-term interest rate trends.

Cointegrating Equations Normalized (Long-run Relationships)

cointegrating equations normalized refers to the mathematical expression of the long-run equilibrium relationship between cointegrated variables. When multiple variables are cointegrated, a cointegrating equation is derived to model their long-run relationship, where one variable is typically chosen as the dependent variable, and the coefficients of the others are estimated relative to it. This process is known as "normalizing" the equation. The normalized cointegrating equation quantifies how the variables interact in the long term, showing how changes in one variable influence another over time. It allows us to understand the long-run relationships once cointegration has been established. The key difference between the two concepts is that long-run cointegration focuses on identifying whether a stable, long-term relationship exists between non-stationary series, while cointegrating equations normalized are the expressions that mathematically represent this relationship. Once cointegration is confirmed, the normalized equations are used to quantify and model the long-run equilibrium among the variables. Thus, long-run cointegration is about testing the existence of a relationship, and cointegrating equations normalized represent the relationship once it has been proven to exist.

$$INT\_RATE_{t-1} = -1.3821 * EXP\_GDP_{t-1} + 2.0735 * IMP\_GDP_{t-1} - 3.3509 * INF\_RATE_{t-1} + const$$

The equation provided represents a cointegrating equation that expresses the long-run relationship between the interest rate (INT_RATE) and several macroeconomic variables, namely Export GDP (EXP_GDP), Import GDP (IMP_GDP), and the Inflation Rate (INF_RATE). In this equation, the interest rate at time t-1 is determined by the lagged values of these explanatory variables. Specifically, the coefficient of -1.3821 for Export GDP indicates a negative relationship between exports and the interest rate, meaning that an increase in export activity leads to a decrease in the interest rate in the long run. This could suggest that higher exports reduce inflationary pressures and the need for higher interest rates. The coefficient for Import GDP is 2.0735, implying a positive relationship between imports and interest rates. An increase in imports results in higher interest rates, potentially due to greater demand for foreign capital and currency. The coefficient for Inflation Rate is -3.3509, indicating a negative relationship between inflation and interest rates in the long run, which might reflect monetary policy adjustments where central banks lower interest rates to mitigate inflationary pressures, though typically, higher inflation would lead to higher rates. The constant term represents the baseline interest rate when all the explanatory variables are zero. Overall, this equation models the long-run equilibrium relationship between the interest rate and these key economic indicators, showing how changes in export and import activities, as well as inflation, affect the interest rate over time.

Short-Run Coefficients

Short-run coefficients refer to the parameters in a time series model that capture the immediate or temporary effects of changes in independent variables on the dependent variable over a short period. These coefficients are particularly relevant in dynamic econometric models, such as vector error correction models (VECMs) and vector autoregressions (VAR), where they reflect how variables adjust to short-term shocks or deviations from their long-term equilibrium. Unlike long-run coefficients, which capture the persistent relationships between variables over time, short-run coefficients describe the immediate responses before the system reaches its long-term equilibrium. In models with cointegrated variables, short-run coefficients indicate how much the dependent variable reacts to changes in independent variables during the initial periods after a disturbance or shock. For example, in a model predicting interest rates, the short-run coefficient for inflation might show how much the interest rate changes in response to a 1% increase in inflation in the immediate term, while the long-run coefficient explains the stable, long-term relationship between these variables. In essence, short-run coefficients are crucial for understanding the dynamic, temporary impacts of economic variables, whereas long-run coefficients focus on the more persistent and stable relationships between them.

$$\Delta INT\_RATE_t = -0.9992 \cdot \Delta INT\_RATE_{t-1} - 4.6996\ \Delta EXC\_RATE_{t-1} + 1.5664\ \Delta EXP\_GDP_{t-1} - 1.5323\ \Delta IMP\_GDP_{t-1} - 0.1349\ \Delta OIL\_PRI_{t-1} + \epsilon_t$$

The equation provided represents a short-run dynamic model of the interest rate (ΔINT_RATE), where changes in the interest rate at time t are explained by the changes in the interest rate, exchange rate, export GDP, import GDP, and oil price from the previous period (t-1). The equation models how these variables interact to influence the interest rate over a short period. The coefficient of -0.9992 for ΔINT_RATEt-1 suggests a negative relationship, meaning that the interest rate change in the previous period tends to reverse or mean revert in the current period, indicating that interest rate changes are likely to be temporary and not persist. The coefficient of -4.6996 for ΔEXC_RATEt-1 indicates that changes in the exchange rate from the previous period have a significant negative impact on the current interest rate change, meaning that an increase in the exchange rate leads to a decrease in the interest rate. The positive relationship between ΔEXP_GDPt-1 and interest rates, as indicated by the coefficient 1.5664, suggests that an increase in export GDP in the previous period leads to an increase in the interest rate in the short term. Similarly, ΔIMP_GDPt-1 has a negative effect on interest rates, with a coefficient of -1.5323, implying that higher import GDP results in lower interest rates. The coefficient of -0.1349 for ΔOIL_PRIt-1 shows that changes in oil prices have a negative impact on interest rates, with rising oil prices leading to a decrease in the interest rate. Lastly, the error term (ϵt) captures all other unobserved or random factors influencing the interest rate. This equation shows how interest rates react to immediate changes in key economic indicators and helps explain the short-term adjustments in the interest rate based on these variables.

Diagnostics Test

Diagnostics tests are essential in econometrics and time series analysis to assess the validity and reliability of a model. These tests help identify potential issues, such as violations of underlying assumptions, which could affect the accuracy of a model's estimates. One important diagnostic test is the normality test, which checks if the residuals of a model follow a normal distribution. Normality is crucial for valid hypothesis testing and reliable confidence intervals in many statistical methods, including ordinary least squares (OLS) regression. Tests like the Jarque-Bera, tests are commonly used to assess normality. If the residuals are not normally distributed, it may indicate the need for data transformation or alternative modeling approaches. Another critical diagnostic test is for heteroskedasticity, which refers to the condition where the variance of the residuals is not constant across all observations. Heteroskedasticity can lead to inefficient estimates and biased standard errors, impacting hypothesis testing. The Breusch-Pagan tests are frequently employed to detect heteroskedasticity. If detected, using robust standard errors or transforming the dependent variable can help correct the issue. Serial correlation, or autocorrelation, occurs when residuals are correlated across time, violating the assumption of independent errors. This can lead to inefficient parameter estimates and distort hypothesis testing. Tests like the Breusch-Godfrey tests are used to detect serial correlation. If serial correlation is present, adjustments such as including lags of the dependent or independent variables or using generalized least squares (GLS) might be necessary. The RAMSEY RESET test (Regression Equation Specification Error Test) is used to check for model misspecification. It tests whether the functional form of the model is correctly specified by adding higher-order terms of the predicted values to the model and checking for their statistical significance. If these terms are significant, it suggests that the model might be misspecified, and modifications to the functional form may be needed. Overall, diagnostic tests such as normality, heteroskedasticity, serial correlation, and the RAMSEY test help to ensure that a model is correctly specified, and its assumptions are valid, leading to more reliable and valid inferences.

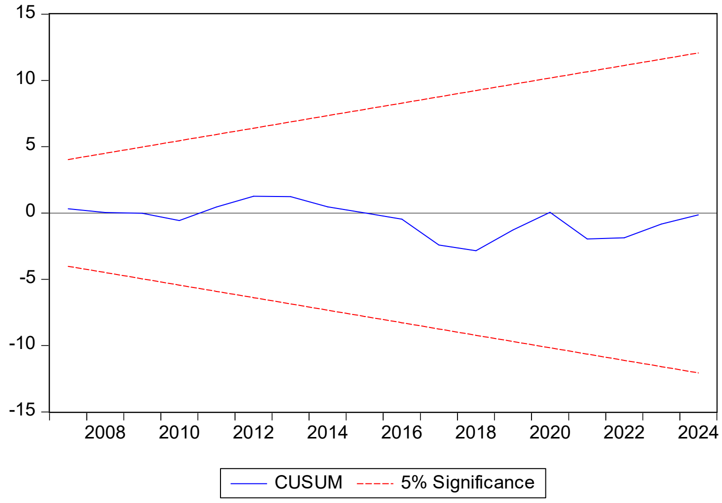
Normality	**Heteroskedasticity**	**Serial Correlation**	**RAMSEY Test**
0.3945	0.2675	0.823	0.6873

Note: **Significant at 5%

The table presents the p-values for four diagnostic tests—Normality, Heteroskedasticity, Serial Correlation, and the RAMSEY RESET test—used to assess the validity of a regression model. The Normality test checks if the residuals of the model follow a normal distribution, which is a key assumption in many statistical methods. The p-value of 0.3945 indicates that there is no significant evidence to reject the null hypothesis of normality, suggesting that the residuals are normally distributed. The Heteroskedasticity test assesses whether the variance of the residuals is constant across all levels of the independent variables. A p-value of 0.2675 suggests no significant evidence of heteroskedasticity, implying that the residuals have constant variance, or homoskedasticity. The Serial Correlation test examines whether the residuals are correlated over time, which would violate the assumption of independent errors. With a p-value of 0.823, there is no evidence of serial correlation, indicating that the residuals are independent across observations. Finally, the RAMSEY RESET test checks for model misspecification by evaluating whether the functional form of the model is correct. A p-value of 0.6873 indicates no evidence to reject the null hypothesis, suggesting that the model is correctly specified. Overall, all the diagnostic tests suggest that the model meets the key assumptions, including normality, homoskedasticity, independence of residuals, and correct specification.

CUMSUM

CUMSUM (Cumulative Sum) is a statistical technique used to monitor the cumulative sum of deviations from a target value, and it is commonly applied in quality control, time series analysis, and various diagnostic tests. Essentially, CUMSUM tracks the cumulative sum of the differences between observed values and a reference value, typically the mean or expected value, over time. By accumulating these deviations, CUMSUM helps identify trends or shifts in the data that may not be immediately apparent from individual observations. If the cumulative sum exceeds a certain threshold, it can indicate a significant change or potential problem in the process being monitored. The CUMSUM value at any time t is calculated as the sum of all past deviations from the reference value up to that point, making it useful for detecting small but persistent changes in the data. This method is widely used in quality control to detect shifts in the mean of a process, in time series analysis to identify structural breaks or trend changes, and in diagnostic testing to check for parameter instability. Overall, CUMSUM is a valuable tool for identifying outliers, structural changes, and trends in data over time, offering an effective way to monitor processes and detect anomalies.



The NARDL (Nonlinear Autoregressive Distributed Lag Model) and VECM (Vector Error Correction Model) are both econometric models used to analyze relationships between time series data, but they differ in their applications and the types of relationships they model. NARDL is an extension of the ARDL model that allows for both linear and nonlinear dynamics in the relationship between variables. It is particularly useful when the impact of an independent variable on a dependent variable is not constant but varies depending on whether the change is positive or negative. NARDL is often used in economics and finance to model asymmetric effects, such as when shocks to the system have different effects depending on the direction of the shock. On the other hand, VECM is typically used when dealing with cointegrated variables, meaning that the variables share a common long-term equilibrium relationship. VECM captures both the short-term dynamics and the long-term equilibrium, making it useful for understanding how deviations from the long-term relationship are corrected over time. It includes error correction terms to measure the speed at which the system returns to equilibrium after a shock.

	Model Selection	RMSE	MAE
China	NARDL	0.50981	0.491851
	VECM	0.53585377	0.357786

In the table provided, the performance of the NARDL and VECM models is compared using RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) for the China Model Selection data. The NARDL model has an RMSE of 0.50981 and an MAE of 0.491851, suggesting it provides a reasonable fit with a slightly higher RMSE compared to VECM, indicating slightly larger errors. The VECM model, with an RMSE of 0.53585377 and an MAE of 0.357786, performs better in terms of MAE, meaning it has smaller average errors compared to NARDL, though it has slightly higher RMSE. The results indicate that VECM offers more accurate predictions on average, while NARDL may be better at managing larger individual errors. The choice between these models depends on whether minimizing the average error or minimizing large prediction errors is more important for the specific analysis.

2 Way Combination

Combination	RMSE	MAE	Combination Size
ARIMA + Naïve	0.625696	0.515847	2
ARIMA + NARDL	0.531251	0.510572	2
ARIMA + VECM	0.544273	0.44354	2
Naive + NARDL	0.604255	0.497126	2
Naive + VECM	0.617277	0.430093	2
NARDL + VECM	0.522832	0.424819	2

The table compares the performance of different model combinations—ARIMA + Naïve, ARIMA + NARDL, ARIMA + VECM, Naïve + NARDL, Naïve + VECM, and NARDL + VECM—in terms of Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Combination Size. The RMSE measures the average magnitude of errors, with larger errors penalized more heavily, while the MAE provides the average of the absolute differences between predicted and actual values. In terms of RMSE, the ARIMA + NARDL combination performs the best with a value of 0.531251, suggesting it minimizes large errors relatively well. However, its MAE is slightly higher than some other combinations at 0.510572. The NARDL + VECM combination excels overall, with the lowest MAE of 0.424819 and an RMSE of 0.522832, indicating that it provides the most accurate forecasts on average while maintaining low error magnitudes. On the other hand, combinations like ARIMA + Naïve, Naïve + VECM, and Naïve + NARDL show higher RMSE values, implying that these combinations tend to produce larger forecast errors on average. Meanwhile, the ARIMA + VECM combination offers a more balanced performance with an RMSE of 0.544273 and MAE of 0.44354, suggesting it provides a reasonable fit with lower average errors compared to some other combinations. In summary, NARDL + VECM stands out as the most effective combination, delivering accurate and efficient forecasts, while the other combinations show varied performance in either reducing larger errors or minimizing average error.

3 Way Combination

Combination	RMSE	MAE	Combination Size
ARIMA + Naive + NARDL	0.587067	0.507848	3
ARIMA + Naive + VECM	0.595749	0.46316	3
ARIMA + NARDL + VECM	0.532785	0.459643	3
Naive + NARDL + VECM	0.581455	0.450679	3

The table compares the performance of four different combinations of models—ARIMA + Naive + NARDL, ARIMA + Naive + VECM, ARIMA + NARDL + VECM, and Naive + NARDL + VECM—in terms of Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Combination Size. Each combination consists of three models, as indicated by the Combination Size column. ARIMA + Naive + NARDL has an RMSE of 0.587067 and an MAE of 0.507848, suggesting that it provides a reasonable fit, but it does not minimize errors as effectively as other combinations, particularly in terms of MAE. ARIMA + Naive + VECM, with an RMSE of 0.595749, performs slightly worse in handling larger errors compared to the first combination, but its MAE of 0.46316 is lower, indicating that it produces smaller average errors. The combination of ARIMA + NARDL + VECM stands out with the best performance in terms of RMSE, at 0.532785, suggesting it effectively minimizes larger errors, and its MAE of 0.459643 is also quite low, showing that it delivers accurate predictions on average. Lastly, Naive + NARDL + VECM has an RMSE of 0.581455 and an MAE of 0.450679, making it a balanced choice, providing fairly accurate forecasts and maintaining lower average errors than some other combinations. In summary, the ARIMA + NARDL + VECM combination performs the best overall by minimizing both large errors and average errors, while the other combinations show varying strengths in handling either larger or average errors.

4-WAY COMBINATION

Combination	RMSE	MAE	Combination Size
ARIMA + Naive + NARDL + VECM	0.574264	0.470333	4

The table presents the performance of the combination of four models—ARIMA + Naive + NARDL + VECM—with respect to Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Combination Size. The Combination Size column shows that this model is composed of four different models. The RMSE value of 0.574264 indicates that this combination effectively minimizes larger errors, though it is not the smallest RMSE value compared to some other combinations. The MAE of 0.470333 reflects that, on average, the predictions are reasonably accurate, with the model producing moderate errors compared to other combinations that may have higher MAE values. Overall, the ARIMA + Naive + NARDL + VECM combination provides a balanced performance by reducing both large and average errors. The inclusion of four different models helps to improve the overall forecasting accuracy, but other combinations may outperform it in specific areas of error minimization.

Conclusion & Recommendation

The results from the various model combinations indicate that combining different forecasting models, such as ARIMA, Naive, NARDL, and VECM, can lead to varying levels of accuracy and error minimization. In general, NARDL + VECM emerges as the most effective combination, delivering the lowest Mean Absolute Error (MAE) and a competitive Root Mean Squared Error (RMSE), indicating that it provides the most accurate and efficient forecasts across the combinations tested. Meanwhile, combinations like ARIMA + Naive + NARDL and Naive + NARDL + VECM show a balanced performance, where one model's strength compensates for another's weakness. The inclusion of multiple models tends to improve forecasting accuracy, but the results show that ARIMA + NARDL + VECM delivers the best overall performance, balancing both large errors and average prediction accuracy.

It is recommended to consider the ARIMA + NARDL + VECM combination for more accurate and reliable forecasting, as it minimizes both large and average errors. For cases where minimizing larger errors is more critical, ARIMA + NARDL can be a good alternative due to its superior RMSE performance. Furthermore, when the focus is on minimizing average prediction errors, combinations like Naive + NARDL + VECM should be considered due to their lower MAE. For more complex scenarios, the 4-Way Combination (ARIMA + Naive + NARDL + VECM) could be explored for a balanced approach, though other combinations may outperform it in specific areas. Tailoring the combination to the specific forecasting problem can help achieve optimal performance.

One limitation of the current analysis is that the performance metrics only include RMSE and MAE, which provide insights into error magnitude but do not capture other important factors like model robustness, computational complexity, or predictive uncertainty. Additionally, while the results suggest that combining models improves forecasting accuracy, the effects of these combinations might vary across different datasets or time periods. The models also assume that the underlying relationships between the variables remain stable, but in real-world applications, these relationships might change over time, which could affect the models' performance. Furthermore, the current models do not account for external shocks or changes in underlying assumptions, which could limit their applicability in dynamic environments.

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