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Exchange Rate Dynamics in Ukraine's War Time: A Combined Forecasting Framework

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ABSTRACT

This study investigates the dynamics and forecasting performance of the Ukrainian exchange rate against the US Dollar using a range of time-series and econometric models. Monthly data covering the period from 2010 to 2024 are employed for model estimation, while 2025 observations are forecasted to evaluate out-of-sample predictive accuracy. Prior to empirical analysis, unit root tests based on bothAugmented Dickey–Fuller and Phillips–Perron approaches are applied to ensure stationarity of the variables. Linear time-series dynamics are examined using ARIMA modeling, whereas nonlinear and asymmetric long-run and short-run relationships with key macroeconomic fundamentals are explored through the Nonlinear Autoregressive Distributed Lag (NARDL) framework. In addition, exponential smoothing techniques are used to capture trend behavior under uncertainty. Forecast accuracy is assessed using the Mean Absolute Percentage Error (MAPE), and further improvements are examined through forecast combination methods based on equal weighting and variance–covariance schemes. The results confirm the presence of a long-run equilibrium relationship between the exchange rate and selected macroeconomic variables, with asymmetric effects playing a significant role. Among individual models, NARDL demonstrates the highest forecasting accuracy, followed by ARIMA. Combined forecasts, particularly those integrating ARIMA and NARDL under variance–covariance weighting, yield the lowest forecasting errors. Overall, the findings highlight the importance of combining structural economic relationships with time-series dynamics to improve exchange rate forecasting in periods of economic and geopolitical uncertainty.

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1.0 Introduction

Exchange rate simply refers to the rate of the currency that can exchange with another. For instance, the Ukrainian hryvnia (UAH)/U.S. dollar (USD) exchange rate can be used to determine how much of local currency is required to purchase a single U.S. dollar. The exchange rates serve as determining factors of the economic health of the country, its trade activities, investments, inflation and policies. Various Foundational theories including Purchasing Power Parity theory (Cassel, 1918), Interest Rate Parity (Keynes, 1923) and Dornbusch's Overshooting Model (Dornbusch, 1976) have explained how the exchange rate is determined. Resultantly, the modern forecasting approaches have been provided with the theoretical basis for how inflation, interest rates, and expectations drive the exchange rate fluctuations. One of the most significant parameters in the economy is the volatility of the currency exchange rates especially in countries that are not well geopolitically secured. Since Ukraine is a state that encountered a large number of political and economic risks over the last several years, there has been a sophisticated valuation tradeoff in its currency Hryvnia (UAH) and the US Dollar (USD) (Mykytyn, 2023; Shevchuk & Kopych, 2018). This volatility of the Ukraine's exchange rate does affect the economic stability, inflation, foreign trades and foreign investments to a greater extent (Shevchuk & Kopych, 2018)).

To capture the exchange rate trends that are both stable and predictable, Linear models are used. However, Non-linear models are used to record regime shifts, structural breaks volatility that are often caused by high-shock situations such as War. In this context, the main aim of this research is to design and analyze a robust forecasting model for the UAH/USD currency exchange rate under conditions of increased economic and geopolitical instability. The paper analyzes the forecasting ability of both linear and nonlinear time series models as well as tests whether the integration of both models will provide better forecasting results when there is a structural break and high volatility in the market. The current study concentrates on the economy of Ukraine under war conditions.

In spite of the wide variety of research devoted to exchange rate prediction, predicting the value of UAH/USD currency rate proves to be quite a challenging task because of the unique economic and geopolitical circumstances caused by the current war situation in Ukraine. Most of the available forecast models were built for stable economic conditions or using only one model which cannot provide enough tools for forecasting exchange rate under the condition of high uncertainty and nonlinearity of its behavior. As a result, the research gap in developing an appropriate forecast framework for taking into account both linear and nonlinear factors under the wartime remains unfulfilled.

Figure 1 shows the data from January 2011 through December 2024. The data was extracted from National Bank of Ukraine (NBU). The figure shows that the exchange rate has witnessed many ups and downs throughout these 14-years, which is due to the influence of economic shocks, geopolitical crises and changes in monetary policy. Initially, from 2011 t0 2013, the UAH remained comparatively stable at approx. 8 UAH/USD when there was a fixed exchange rate regime under the guidance of the National Bank

of Ukraine (NBU) trying to control inflation thus making it predictable (National Bank of Ukraine 2013). This stability was, however, not favorable as the economy of Ukraine was inefficient and had slow growth (The World Bank, 2013).

A complete turnaround was witnessed in the 2014-15 period when the UAH/USD lost more than 60 percent of its value after the Russian NARDLexation of Crimea, eruption of war in Donbas, and economic shrinkage. Consequently, by the end of 2015, the exchange rate closed to 22-24 UAH/USD, with hyperinflation (reaching 43 percent) (NBU 2015). This crisis compelled Ukraine to request a $17.5 billion IMF bailout, which contained stern reforms among them, including switching to a flexible exchange rate regime (IMF 2015). In 2016, the NBU decided to abandon the fixed rate to increase market confidence, eliminate speculations, and replenish foreign reserves, preparing the ground to stabilize the currency at 26–28 UAH/USD during 2017–2019 (Elia Yathie Matsumoto, Del-Moral-Hernandez, Yoshinaga, & de Campos Pinto, 2025)

More structural reforms especially the introduction of inflation targeting in 2016 aided in stabilizing expectations and the volatility. During COVID-19 pandemic, the measures of the NBU aimed to curb a rapid decline in the exchange rate and provide its stability within the range of 28-29 UAH /1 USD even though the world economy was disrupted (NBU 2020). The currency strengthened to 27-28 UAH/USD in 2021 due to remittance inflows and export recovery, indicating cautious stability (The Wolrd Bank 2022). When Russia launched its full-scale invasion in February 2022, the NBU first set a fixed peg rate of 29.25 hryvnia to the dollar to calm the expectations and reject panic. Nevertheless, on 21 July 2022, increasing pressure front the outside world caused a devaluation of about 25 percent, putting the value of the peg at 36.57 UAH/USD (Olena Harmash 2023). The NBU stepped in to stabilize the reserves, which fell to the low of USD 30.9 billion by the mid-2022, only to be rising back to record levels USD 41.7 billion by July 2023 (European Parliament, 2024).

In October 2023, the NBU switched to a managed floating regime compared with the peg, capital controls were eased, and more FX interventions were introduced. The official rate stood close to 36.6 UAH/USD, whereas cash rates were briefly above 40.5 to the dollar at the beginning of 2023 (NBU 2023).

By the beginning of 2024, the exchange rate stood at approximately 38 UAH/USD. The exchange rate plummeted beyond 42 UAH/USD resulting in the 9.5% depreciation of the hryvnia by the end of the year due to the influence of war and the budget deficit.

Such Indigenous and exogenous factors that besiege Ukraine, predicting the Hryvnia exchange rate is not only difficult but complex. Further, the war in the east of Ukraine and occupation of Crimea by Russia since 2014 have had an important influence on the instability of the UAH/USD exchange rate (Plastun, Makarenko, Khomutenko, Shcherbak, & Tryfonova, 2019). Besides, the exchange rate dynamics are also influenced by economic reforms, changes in the monetary policy of the Central Bank of Ukraine, and volatility of foreign capital flows. The geopolitical shocks, economic risks and structural



Figure 1: Figure 1: NBU's data for the UAH/USD Exchange rates

changes, all these factors create a distinct and difficult trend of exchange rates movements to model (AsadUllah, Hassan, & Siddiqui, 2021). These above-mentioned factors rule out the possibility of a single forecasting model to integrate all the effects. Therefore, the primary objective of this study is that it will employ a blend of models in forecasting of the UAH/USD exchange rate against past facts. Approach employing a combination of linear and non-linear forecasting models can supplement stability and precision in unstable circumstances, a lack that this research can fill in a new forecasting design specific to the war-time Ukraine.

The paper is structured in seven sections after abstract, namely introduction, literature review, methodology, empirical results and discussions, conclusions, policy implications and future recommendations. The structured way is showing clarity and precision in the paper.

2.0. Literature Review

Exchange rate dynamics is defined by theories explaining exchange rates' fluctuations depending on various factors including fundamentals, expectations, and policy changes. According to PPP, exchange rates tend to adjust to ensure equality between price levels in different countries (Cassel, 1918). IRP theory suggests that interest rate differential is the determinant of exchange rates. Therefore, it states that changes in interest rates result in changes in exchange rates due to arbitrage opportunities (Keynes, 1923).

Contemporary theories of exchange rate dynamics pay much attention to expectations and market responses to them. For example, monetary theory claims that exchange rates depend on such variables as money supply, interest rates, inflation rates, and income levels (Frenkel, 1976). Besides, according toDornbusch (1976) overshooting theory, exchange rates will temporarily overshot their long-term equilibrium as goods' prices are sticky in the short run, while financial markets react instantly to changes (**??**).

Furthermore, behavioral theory suggests that exchange rate dynamics is determined by psychological factors, while portfolio balance theory claims that expectations regarding interest rates also affect exchange rates. Thus, expectations about economic conditions and risk play an important role in exchange rate dynamics besides other determinants mentioned above. The long-term equilibrium is determined by PPP and IRP also known as foundational theories; whereas, the short-term volatility is explained by overshooting and behavioural theories. Therefore, the use of ARIMA is the justification for linear dynamics, and the use of NARDL is the justification of non-linear shocks. However, for instability caused by global conflicts such as Russia-Ukraine war it is better to use hybrid models combining both to improve the accuracy.

The issue of exchange rate prediction has been a complex issue in many years. To this effect, an extensive body of research has reported the importance of historical performance of exchange rates to the econometric analysis and the performance of the economy. Those studies primarily use statistical models, which forecast the future values on the basis of the past observations (Epaphra, 2017). Several models have therefore been invented to predict the exchange rate. These include the following as some of the most frequently used models.

The Autoregressive Integrated Moving Average (ARIMA) model has been used to predict the INR/USD exchange rate with which the ARIMA (5,1,0) specification has been used to identify the linear tendencies and time-related shifts of the data. The model was able to forecast and identify short-term trends using the historical exchange rates (MADHULATHA and ATHEEQ SULTAN GHORI 2025). Another study by (Hakkar, 2025) used ARIMA model to predict the GBP/USD exchange rate based on the daily data of May 2023- May 2025. The model tried to explain the linear dynamics and history of the exchange rates in the series. Furthermore, an analysis of the Nigerian foreign exchange market has resorted to the use of the Box-Jenkins approach in order to model the Naira exchange rate against leading currencies of the world during the forecast of the study period between 2024 and 2028. The study used ARIMA model to identify the underlying trends and short-term relationship in the exchange rate data. The results indicated that once the stationarity was attained at the first difference, the ARIMA model was found to be an acceptable fit to the Naira value against the USD, NZD, CAD, and AUD (Ayoade I. 2024). One more study, conducted recently, predicted the trend of dwindling Indian rupee by using the ARIMA model. The authors of the study used historical data since 1991 regarding the exchange rate which showed how the currency reserves, external debt and trade imbalances make the Rupee vulnerable. Their ARIMA forecasting showed that even

with the build-up of a foreign exchange reserve rated as one of the largest in the world, the Rupee still has depreciation tendencies and is therefore more vulnerable than other currencies like Chinese Yuan and Russian Ruble. The results indicate that even though reserve management has a stabilizing effect, structural loopholes in the Indian economy still put pressure on the currency hence the need to have more serious policy measures that will counter the exchange rate volatility (Deepak, Subramanian, Lalitha, & Vidhya, 2024).

A recent study (Srichaikul, Chanaim, Saijai, & Yamaka, 2024) comparing exchange rates prediction (January 2018 to July 2023) indicated the usefulness of the ARIMA (p, d, q) model when predicting some of the largest currency pairs. The results showed that ARIMA worked exceptionally well with EUR/USD and USD/CHF as the forecasts were very close to the real exchange rate values.

Moreover, to predict the Chinese real interest rate, the Nonlinear Autoregressive Distributed Lag model, commonly known as (NARDL), came to be effective. It was also used to include both the short run dynamics and long run asymmetry of the major macroeconomic variables, including inflation, GDP growth, exchange rate, trade indicators, oil prices, and money supply. The results show that individual multivariate models, especially NARDL, are good at capturing nonlinearities and long-run relationships, but that strategies of forecast combinations invariably result in a significant improvement of predictive power and stability (AsadUllah et al., 2021; Zafar & AsadUllah, 2025). (Bhattacharyya & Deb, 2025; Deepak et al., 2024) also used NARDL to forecast and predict the India/US exchange rate. They examined the impact of positive and negative impacts of the exogenous variable on the short and long-runs exchange rate. Thepublished results of Zafar and AsadUllah (2025) demonstrated that while comparing the outputs, including RMSE, MAE and Theil's U statistic, NARDL model was agood way to forecasting than linear method of naïve. Since NARDL can identify the short run adjustments and see the long run equilibrium dynamics, itis a reliable model in bygone analysis of interest rate under changing monetary environment for Pakistan economy, which may provide valuable insights to policy makers and financial analysts. The data applied in the development of prediction model was collected over the period ranging from 2001 and 2023to predict interest rates in Pakistan. For the analysisof asymmetric reactions towards both positive and negative changes in the variables, we use the NARDL model. In addition, an analysis of the trade balance in Ethiopia from 1992 to 2022 with the Non-linear Autoregressive Distributed Lag (NARDL) model reveals that there is a minimalsignificant asymmetric effect caused by real exchange rate on trade balance. The finding also revealed that the effect ofexchange rate depreciations and appreciations are statistically significant but not the same at short- and long -run rejecting a linearity notion (Abegaz, 2024).

The Forecast was based on Exponential Smoothing approach, constructed in the research of MYR/USD Exchangerate applying daily data from July 2013 to June 2023. The conclusion the results showed that Holt's Linear Exponential Smoothing model had very accurate forecasts at both frequencies with error measureslower in MAPE and MAE. This method was good to explain the short-term fluctuations and underlying trend movements

of the exchange rate series (Tor Shin Y. 2025). An exchange rate study of the Kyrgyz som-US dollar (2010-2023) used the Holt Winters triple exponential smoothing in the modeling and forecasting of the daily exchange rate variations based on the official data provided by the National Bank of the Kyrgyz Republic. Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were used to determine the accuracy of the model. Findings proved that the trend and seasonality of exchange rate movements were captured well using the smoothing method, thus making it useful in short term forecasting (Doszhanov, 2025). Another study by (Putri, Afrimayani, Hasibuan, Ul Hasanah, & Jannah, 2024) that used the Double Exponential Smoothing (DES) technique on the Central Statistics Agency (BPS) data to predict the number of foreign tourists per month that will arrive in the country through land routes (2018-2023) was used. Because one of the factors that positively impact the economy of a country, particularly adding foreign exchange, is the access of the country by foreign tourists. Having a Mean Absolute Percentage Error (MAPE) = 0.108530 (10) when alpha =0.9, and beta =0.2, the DES model with its variable capability to adapt to changing data patterns and minimize random fluctuation was used. These findings point to the fact that the DES technique presents credible and true forecasts.

With two datasets, quarterly data, which could be utilized since 1974 through 2023, and monthly data, which could be utilized since 2000 through 2023, a study by compared the different forecasting models, such as ETS, ARIMA, BVAR, LSTM, and XGBoost to the simple naïve forecast. The findings indicated that all the complex models performed worse than the naïve prediction in the most volatile time series including exchange rates and prices of NASDAQ100. The research reached a conclusion that complex machine learning models are prone to overfitting when the data is similar to random walks, whereas more simple models such as the naïve forecast have more consistent results (Beck, Dovern, & Vogl, 2025). One of the studies by (Elia Yathie Matsumoto et al., 2025) that predicts the USD/BRL exchange rate between April 2006 and March 2022 analyzed how Behavioral Finance Theory can enhance machine learning ensemble models. The researchers realized the Best Model per TAG (BMT) ensemble framework by incorporating the calendar effects, which are predictable patterns that affect the behavior of investors. Interestingly, the naïve model emerged as the best amongst all other models including the BMT model. The naïve model was again useful as a part of the ensemble technique, boosting the performance of the BMT over VOTING models by 51.3 percent and averaging a gain of 108.3. The paper found that naive model is both an effective benchmark and useful element in the enhancement of ensemble-based forecasting models, which supports the necessity of simplicity in financial predicting. A nonlinear Ridge-RFF model versus a simple linear regression and the naive random walk benchmark were analyzed in a study of the virtue of complexity in exchange rate forecasting. The results on complex models revealed that only limited improvements and only temporary ones were obtained using datasets based on monetary and non-monetary fundamentals and different training windows of 12, 60, and 120 months. Although Ridge-RFF did sometimes do better than linear regression in small samples, it never overperformed the naive random walk model. The more complex models, especially the random walk became more stable and reliable as the sample sizes got larger. The results re-establish the idea that complexity has marginal benefits, and the

naive random walk is a very strong and practical standard of exchange rate forecasting under different conditions of data (Kilic, 2025).

Yet, in most of the exchange rate forecasting methods, the hybrid approach that combine both the linear and non-linear forecasting models was preferred. Contrary to single models, these hybrid models yielded better results as they mitigated the cons of using separate models and benefited from the advantages of both approaches (Khashei & Bijari, 2011; Zhang, 2003). In recent years, hybrid approaches started combining machine learning and deep learning models with traditional econometric forecasting models in order to increase the accuracy of forecasts during periods of high volatility and regime changes (Makridakis, Spiliotis, & Assimakopoulos, 2022). Despite these advancements in methodology, there are still not many works that analyze hybrid forecasting frameworks in relation to exchange rates influenced by geopolitical instability and wartime conditions. The works concerning the Ukrainian hryvnia usually analyze the factors that determine the behavior of the currency or the impact of the monetary policy on the exchange rate, but not hybrid forecasting frameworks that would be able to account for the regime changes caused by the current war. It is this gap in literature that forms the basis for the current research that evaluates a combination of forecasting frameworks in the conditions of persistent geopolitical and economic instability.

Another recent research that has investigated the predictability effectiveness of the naive random walk and exponential smoothing model on the daily exchange rate between USD and the Turkish Lira and Yen (TRY) examined the predictive ability within Turkey using the USD/TRY exchange rate series. The study noted that the relationship in financial time series, specifically the exchange rates, is essential in forecasting the market trends in case investors want to understand the upcoming market changes due to economic uncertainty. Although there is an increasing focus on the use of complex models, the research determined that simple methodology may give better predictive results. Particularly, Brown exponential smoothing model had the highest forecasting accuracy with a near value of the naïve random walk model, which was the benchmark. The results established that there was no ARCH or leverage effect despite the time series not being normally distributed with a skewed leptokurtic curve to the left. These findings corroborated the findings of earlier studies that simple forecasting models like exponential smoothing and the naive random walk are still very useful instruments especially in volatile markets like the Turkey exchange rate market where model parsimony and model stability are the most important in order to apply the models in practice (Sarkandiz & Ghayekhloo, 2024)

Many countries like Pakistan, India, Turkey and Nigeria use hybrid models such as NARDL, ARIMA etc to mark regime hifts and capture volatility in their economy. The same hybrid models can also be used for Ukrain's economy in the times of war. Recent literature suggests that forecasting has been carried out in most works through integration of various models to increase accuracy and reflect complicated relations. Nevertheless, having reviewed the recent and past studies, it is evident that the NARDL model has been yet to be integrated with the univariate models to make predictions. That is to say the prediction power of non-linear multivariate model combined with linear univariate models has not

been ventured in to date. Consequently, this research paper will address this research gap by proposing a combined method that will integrate these models to enhance prediction efficiency and give more comprehensive information on dynamic relationship.

3.0. Research Methodology

3.1 Research Design and sample

The current study depends upon monthly data of the Ukrainian Hryvnia (UAH) US Dollar (USD) exchange rate between January 01, 2011, and December 31, 2024, and anticipates 2025 values. The period reflects major geopolitical and economic changes, such as the conflict in eastern Ukraine in 2014 and the occupation of Crimea which contributed to the increase in the volatility of exchange rates (Plastun et al., 2019). The monetary policy changes, economic reforms, and foreign capital flows are additional factors that influence the exchange rate dynamics, and the explanatory variables such as oil prices, GDP, gold prices, foreign reserves, trade balance, inflation and interest rate, which are well known in literature to be major factors that contribute to the exchange rate fluctuations (Dornbusch, 1976; MacDonald & Taylor, 1994). The data has been extracted from the IFS IMF Statistics. Table 1 shows the variables name and their assessment.

Table 1: Variables and their Assessments

Variable	Variable Name	Assessment
MS	Money Supply	Money Base
IR	Interest Rate	Central Bank Policy Rate
INF	Inflation	Consumer Price Index
IPI	Industrial Production Index	Economic Activity
TB	Trade Balance	Exports – Imports
FR	Foreign Reserves	Official Foreign Reserve's excluding Gold reserves
OP	Oil Price	Crude Oil Price
GP	Gold Price	Gold Price

3.2 Methodological Approaches

The main classes of models used in time-series forecasting are linear and non-linear models, the former finding application in forecasting future values by using a linear combination of previous observations and the latter aimed at capturing more complex associations between explanatory and control variables than can be explained by a simple linear model(Alsuwaylimi, 2023) .

3.2.1 ARMA/ARIMA

The Box-Jenkins methodology (Box & Jenkins, 1994) is one of the most common frameworks that have been used to forecast and forms the basis of ARIMA family of models. The ARMA models are characterized as statistical methods of the analysis of time series where two polynomials one as autoregression and the other as the moving average are used (Kissell, 2021). ARIMA models are used to obtain future values by using past values and previous forecast errors. Once the series has been differenced, usually one or twice, to produce a series that is stationary, the model represents its dynamics in the form of autoregressive (AR) and moving-average (MA) terms. AARIMA (a, b, c) model assumes a to be the autoregressive order, b to be the degree of differencing and c to be the moving-average order. In cases where no differencing is needed (i.e. the series is already stationary) the model reduces to ARMA (a, c) specification.

3.2.2 Naïve

The naive forecasting model is based on the assumption that the best predictor of the upcoming observation is just the latest actual value, which is given as

$$y(t+1) = y(t).$$

Also, this principle is consistent with exponential smoothing when the smoothing constant 0.5 = The Naïve model is widely applied to establish a baseline against which other more advanced models like exponential smoothing and ARIMA models are compared, due to its simplicity and strength (Hyndman & Athanasopoulos, 2018). It can be used to evaluate whether the advanced models can offer any meaningful improvements compared to a minimal-assumption forecasting method.

3.2.3 Exponential Smoothing (ES)

Gardner (1985) was the one who first formalized Exponential Smoothing (ES), which can be described as one of the most popular forecasting models used in economics and finance because of its simplicity and good empirical results. In contrast to ARIMA models that use linear relationships between past observations and past errors (Brooks 2014), ES uses data of the past with exponentially decreasing weights, a more recent information being more significant.

3.2.4 The Non-Linear Autoregressive Distributed Lag (NARDL)

(Shin et al. 2014) presented NARDL. To both represent asymmetric long-run and short-run effects, the author uses positive and negative partial-sum decompositions. NARDL has a number of strengths compared to traditional cointegration methods: it works well on small samples already as well as it can be estimated despite the regressors being stationary either at the level or at the first difference (I(0) or I(1)). Nevertheless, just like the

standard ARDL, the model NARDL be used when one or more of the variables is an integrated of order two, I(2).

The best lag specification for the models was obtained by using the Akaike Information Criterion (AIC) due to its capability of finding a balance between model fitness and parsimony (Akaike, 1974; Pesaran, Shin, & Smith, 2001). Alternative lags were used to estimate the models, but the best model specification according to AIC values was chosen. In order not to overfit the model and maintain the degrees of freedom, a constraint was set for the highest lag length according to the monthly frequency of the data and sample size available. In addition, residual diagnostics were performed to ascertain that the best lag specification resulted in properly specified models.

Consequently, a rigorous study of the existing literature indicates that ARIMA, Naive, Exponential Smoothing and NARDL frameworks have been heavily applied in the prediction of both economic and financial time series. All these models have been empirically tested and have always been proved to be very good predictors in their respective contexts. Their overwhelming use highlights their efficacy and adequacy into coming up with solid forecasts in environments where both linear processes (ARIMA, ES, Naïve) and any possible nonlinear or asymmetric alterations (NARDL) are required to be measured. The use and advantages of these models have been widespread and thus the author has opted to extrapolate the exchange rate between Ukrainian Hryvnia (UAH) and US Dollar (USD) in the year 2025 using these techniques.

The variables which have been selected as independent variables are shown below in Table 2. All variables were selected with the support of previous literature and their findings.

Table 2: Summary of Non-Linear Relationship between Explanatory Variables and Exchange Rate

Authors	Findings
Chinn (1991)	The author concluded that most of the times the trade balances show a non-linear behavior in the relationship of exchange rate.
Arghyrou et al (2006)	The relationship between current account balance and exchange rate is mostly non-liner in case of EMU-States.
Aghion et. al. (2009), Ndambendia et al (2011), Vieira et. al. (2013) and Alagidede et al(2016)	Found the non-linear relationship between the exchange rate and GDP.
Alhayky (2011)	Found the non-linear relationship between exchange rate and economic growth for sixteen sub-Saharan countries.

Authors	Findings
Shahid et al (2013)	The devaluation of currency resulted into the appreciation of exports which simultaneously stable the trade balance in case of Pakistan and Bangladesh.
Aliyu et al (2015)	This study satisfies the negative relationship between the trade balance and exchange rate in case of Nigeria.
Qayyum et al (2016)	The negative sign of RER2 confirms the nonlinear relationship in case of bilateral trade between these two countries.
Ben Cheikh & Louhichi (2016)	There is a non-linear relationship between Inflation and exchange rate.
Jašová et al. (2016)	
Hussain & Bashir (2013)	Trade balance has a non-linear relationship with the exchange rate.

3.2.5 Combination Techniques

Armstrong (2001) states that in the event of a lack of signs as to which method of forecasting is the best, a combination of the forecasts with equal weights can be the surest course of action. (Granger & Ramanathan, 1984) also suggested a linear combination model where the weights have to be estimated by OLS using previous forecasts and actual values. Equal weighting is often used but later studies have examined the unequal and flexible weighting schemes. As an illustration, (Deutsch et al. 1994) proposed regime-switching and smooth transition autoregressive (STAR) models wherein time-varying weight changes are possible in a nonlinear and nonparametric way. According to this literature, the current study uses both variance covariance weighting as well as equal weights proportions to increase the accuracy of exchange rates forecasting.

(a)Variance-Covariance (Var-Cor Method):

The Var-Cor Method is more advanced than equal weights in the sense that it computes weights from forecast error variance and covariance. The goal is to minimize the variances of forecast errors by allocating larger weights to the better performing models. The weights for combining two models is calculated as:

$$a_1 = \frac{\sum_{t=1} t\ e^2_{MODEL\ 2(t)}}{\sum_{t=1} t\ e^2_{MODEL\ 2(t)} + \sum_{t=1} t\ \ e^2_{MODEL\ 1(t)}}$$

It can also be extended in case of combining more than two forecast models which shows

as below; For the three-way model, the weights are given by:

$$\begin{aligned} a_1 = & \frac{\sum_{t=1} t\, e^2_{\text{MODEL 2}(t)} \sum_{t=1} t\, e^2_{\text{MODEL 3}(t)}}{\sum_{t=1} t\, e^2_{\text{MODEL 1}(t)} \sum_{t=1} t\, e^2_{\text{MODEL 2}(t)}} \\ & + \sum_{t=1} t\, e^2_{\text{MODEL 1}(t)} \sum_{t=1} t\, e^2_{\text{MODEL 3}(t)} \\ & + \sum_{t=1} t\, e^2_{\text{MODEL 2}(t)} \sum_{t=1} t\, e^2_{\text{MODEL 3}(t)} \end{aligned} \tag{1}$$

$$\begin{aligned} a_2 = & \frac{\sum_{t=1} t\, e^2_{\text{MODEL 1}(t)} \sum_{t=1} t\, e^2_{\text{MODEL 3}(t)}}{\sum_{t=1} t\, e^2_{\text{MODEL 1}(t)} \sum_{t=1} t\, e^2_{\text{MODEL 2}(t)}} \\ & + \sum_{t=1} t\, e^2_{\text{MODEL 1}(t)} \sum_{t=1} t\, e^2_{\text{MODEL 3}(t)} \\ & + \sum_{t=1} t\, e^2_{\text{MODEL 2}(t)} \sum_{t=1} t\, e^2_{\text{MODEL 3}(t)} \end{aligned} \tag{2}$$

And $a_3 = 1 - a_1 - a_2$.
Similarly, four-way models' weights can be derived as follows;

$$\begin{aligned} a_1 = & \frac{\sum_{t=1} te^2_{\text{MODEL 2}(t)} \sum_{t=1} te^2_{\text{MODEL 3}(t)} \sum_{t=1} te^2_{\text{MODEL 4}(t)}}{\sum_{t=1} te^2_{\text{MODEL 2}(t)} \sum_{t=1} te^2_{\text{MODEL 3}(t)} \sum_{t=1} te^2_{\text{MODEL 4}(t)}} \\ & + \sum_{t=1} te^2_{\text{MODEL 3}(t)} \sum_{t=1} te^2_{\text{MODEL 1}(t)} \sum_{t=1} te^2_{\text{MODEL 2}(t)} \\ & + \sum_{t=1} te^2_{\text{MODEL 2}(t)} \sum_{t=1} te^2_{\text{MODEL 1}(t)} \sum_{t=1} te^2_{\text{MODEL 4}(t)} \\ & + \sum_{t=1} te^2_{\text{MODEL 4}(t)} \sum_{t=1} te^2_{\text{MODEL 1}(t)} \sum_{t=1} te^2_{\text{MODEL 3}(t)} \end{aligned} \tag{3}$$

$$\begin{aligned} a_2 = & \frac{\sum_{t=1} te^2_{\text{MODEL 1}(t)} \sum_{t=1} te^2_{\text{MODEL 3}(t)} \sum_{t=1} te^2_{\text{MODEL 4}(t)}}{\sum_{t=1} te^2_{\text{MODEL 2}(t)} \sum_{t=1} te^2_{\text{MODEL 3}(t)} \sum_{t=1} te^2_{\text{MODEL 4}(t)}} \\ & + \sum_{t=1} te^2_{\text{MODEL 3}(t)} \sum_{t=1} te^2_{\text{MODEL 1}(t)} \sum_{t=1} te^2_{\text{MODEL 2}(t)} \\ & + \sum_{t=1} te^2_{\text{MODEL 2}(t)} \sum_{t=1} te^2_{\text{MODEL 1}(t)} \sum_{t=1} te^2_{\text{MODEL 4}(t)} \\ & + \sum_{t=1} te^2_{\text{MODEL 4}(t)} \sum_{t=1} te^2_{\text{MODEL 1}(t)} \sum_{t=1} te^2_{\text{MODEL 3}(t)} \end{aligned} \tag{4}$$

beginequation

$$a_4 = 1 - a_1 - a_2 - a_3 \tag{5}$$

(b) Equal Weights Method

The Equal Weights Method is used to aggregate the forecasts for interest rates. In the case of merging two individual forecasts, the aggregate forecast is denoted as follows:
$Y_{Combined}$ (t) = a Y_{Model1} (t) + (1a) Y_{Model2} (t)
When applied in forecasting interest rates, the equal-weighted forecast would look like this:
$Y_{Combined}$ (t) = 0.5×Y_{Model1} (t) + 0.5×Y_{Model2} (t)
For three models, it would be:
$Y_{Combined}$ (t) = 0.33 × Y_{Model1} (t) + 0.33 × Y_{Model2} (t) + 0.33 × Y_{Model3} (t)
For four models, it would be:
$Y_{Combined}$ (t) = 0.25 × Y_{Model1} (t) + 0.25 × Y_{Model2} (t) + 0.25 × Y_{Model3} (t) + 0.25 × Y_{Model4} (t)
The algorithm has been widely adopted for interest rate forecasting in countless research endeavors, particularly due to its resilience to diverse economic conditions .

The Mean Absolute Percentage Error (MAPE) is the main measure of evaluation of forecasting accuracy. MAPE is one of the most popular criteria used in various forecasts due to the fact that this measure represents the forecast errors in percentages which helps to better understand the results of forecasting (Lewis, 1982). Moreover, MAPE is considered independent from the scale and gives a clear measure of accuracy which is especially important in economic and financial time-series forecasting. Nevertheless, other forecast performance criteria like Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) have also been taken into account because these criteria are often utilized when it comes to capturing the error magnitude (Hyndman & Koehler, 2006)

4.0 Empirical Results & Discussion:

4.1. Unit Root Analysis

It is mandatory to analyze the trend in selected time series before the further procedure that's why the unit root test of parametric and non-parametric classification has been applied in this study to avoid the biasedness and ensure the stationarity of the time series. For time series analysis, the variables must satisfies the unit root test either at level or at first difference. If the time series is stationary at second difference then such time series could not include in the further time series analysis.
The above table 2 results indicate that all of the variables include independent and dependent are stationary at level and first difference therefore they all satisfy the preliminary requirement of the time series analysis.

Table 2: table 3: Unit Root Test Results

Variable	ADF Test		PP Test	
	Level	1st Diff.	Level	1st Diff.
Gold Price	3.8280	2.5195**	5.3279	21.4410**
Exchange Rate	-0.6716	-15.2450**	-0.5759	-15.1370
Foreign Reserves	-0.8942	-10.8847**	-0.8469	-10.9217**
Money Base Growth	-2.0939	-10.8905**	-2.5529	-10.9427**
Inflation Rate	-2.3751	-5.2971**	-2.1170	-5.0484**
Interest Rate	-3.1527	-11.1574**	-3.2445	-11.2008**
Trade Balance	-2.6999	-18.7299**	-5.3537**	-
GDP	-2.0413	-3.7531**	-4.0928**	-

4.2 ARMA/ARIMA Results:

Table 3 depicts the results of ARMA / ARIMA model where the best fitted model is ARIMA(1,1,1). The foreign exchange time series was found stationary therefore the resulted model is ARIMA due to integration of 1st difference. The R-squared and F-statistics are 0.990 and 5915.617 respectively. The AIC, SC. And HC values are 3.154, 3.225, and 3.182 respectively. The MAPE value of forecasting the last year observations are 2.70 which is less than 3 % as shown in Table 3. It shows the highly robustness of the ARIMA model in terms of forecasting Ukrainian exchange rate against the US Dollar.

Table 4: ARIMA Model Estimation Results

Dependent Variable: FE
Method: ARMA Maximum Likelihood (OPG–BHHH)
Sample: January 2011 – December 2025
Observations: 180
Convergence: Achieved after 63 iterations

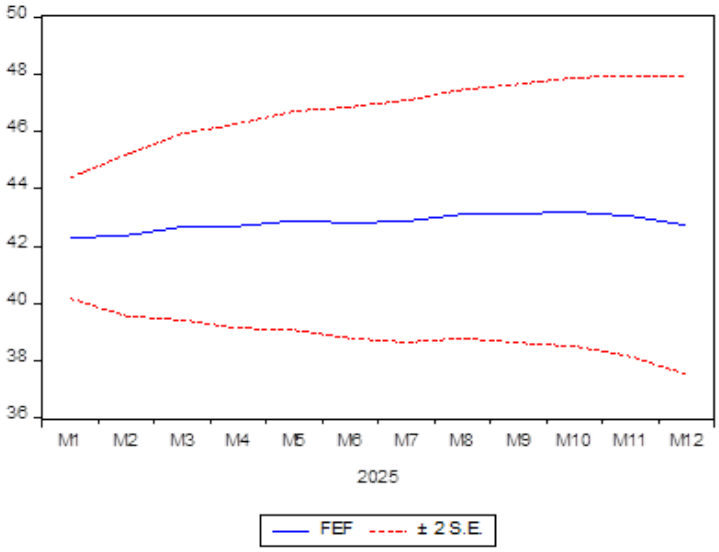
Estimated Coefficients

Variable	Coefficient	Std. Error	t-Statistic	p-value
C	25.0784	17.8231	1.4071	0.1612
AR(1)	0.9980	0.0175	57.0250	0.0000
MA(1)	−0.1092	0.0345	−3.1648	0.0018
SIGMASQ	1.2742	0.0418	30.4593	0.0000

Model Diagnostics

Statistic	Value	Statistic	Value
R^2	0.9902	Mean Dependent Variable	25.1476
Adjusted R^2	0.9900	S.D. Dependent Variable	11.4231
S.E. of Regression	1.1416	Akaike Info Criterion	3.1541
Sum Squared Residuals	229.3638	Schwarz Criterion	3.2250
Log Likelihood	−279.8653	Hannan–Quinn Criterion	3.1828
F-statistic	5915.617	Durbin–Watson Statistic	1.9930
Prob(F-statistic)	0.0000		

Figure: 1 ARIMA Forecasting



Forecast: FEF	
Actual: FE	
Forecast sample: 2025M01 2025M12	
Included observations: 12	
Root Mean Squared Error	1.213933
Mean Absolute Error	1.124201
Mean Abs. Percent Error	2.702906
Theil Inequality Coefficient	0.014365
Bias Proportion	0.857627
Variance Proportion	0.000101
Covariance Proportion	0.142272
Theil U2 Coefficient	4.698722
Symmetric MAPE	2.660926

4.3 NARDL Results

In NARDL analysis, the authors have selected independent variables from the previous literature (as shown in Table 1) to find out the long-run and short-run relationship with the exchange rate. Furthermore, the primary objective is to forecast the exchange rate via symmetric and asymmetric relationship between the dependent and independent variables.

The integrated equation was transformed into log-linear equation where the dependent variable due to satisfaction of the diagnostics of time series analysis i.e. Autocorrelation, Heteroscedasticity, Omission, etc.

table 5: Long-Run Coefficients

Ukraine	$\text{LOG(FE)} = 2.3156 + \underset{(2.287)}{\underset{[0.03]}{0.085}}\text{*INF_NEG} - \underset{(-3.510)}{\underset{[0.001]}{0.0071}}\text{*OP_POS} - \underset{(-2.406)}{\underset{[0.024]}{0.0072}}\text{*OP_NEG}$
	Bound Test, F Statistic: 4.819902
	I0 Bound: 2.54 , I1 Bound: 3.86 (1 % significance)

In long run, it is found that the F-Statistics of Bound Test is 4.819 which is higher than upper and lower bound and indicates the existence of co-integration among dependent and independent variables. It means that the dependent variable possess long-run relationship with the independent variables. Table 4 further illustrates that one unit decrease in lead to increase in 0.085 percent of exchange rate. The Ukrainian economy has been affected by the oil significantly due to Russia war because earlier, Russia was the major

importer of crude oil to the Ukraine. Results shows almost symmetric relationship of exchange rate against the oil price. If oil price increase by one unit the Ukrainian currency devalues by 0.0072 percent and vice versa. T-values and P-values are also shown in parenthesis and square brackets respectively.

Table 6: Short-Run Coefficients

Ukraine	$\Delta \text{FE}_t = -0.1190 - 0.222 \cdot \Delta \text{FR_POS}_t$
	(-4.666)
	$[0.000]$
	$F = 31.66\ [0.000]$

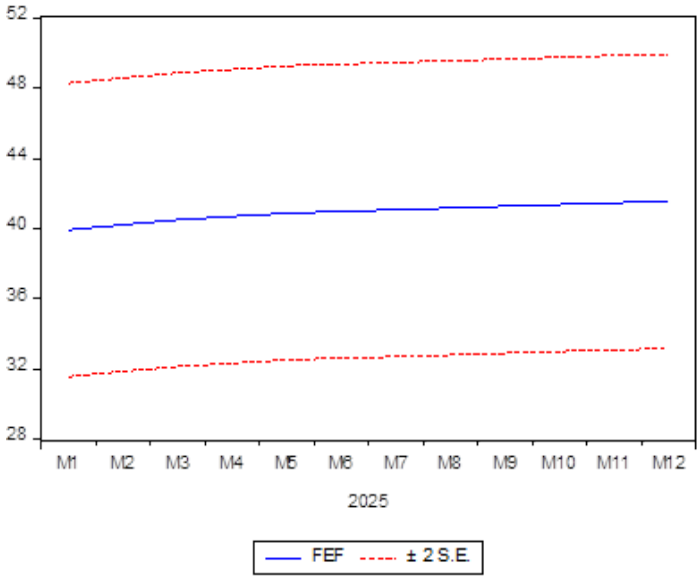
In short run, only foreign reserves play a significant role with the exchange rate. The current month increase in foreign reserves by one unit stabilizes the exchange rate by 0.222 percent. All remaining variables remains insignificant. Table 6 describes the results of diagnostic tests which are the requirement of time series analysis in order to validate the results. The Normality, Heteroscedasticity, serial correlation, and RAMSEY test shows insignificant values which satisfies the assumptions of time series analysis that the selected data is free from the problem of heteroskedasticity, autocorrelation, omission and the date is normally distributed.

Furthermore figure 3 shows the forecasting accuracy of NARDL model for the Ukrainian exchange rate against the US Dollar. The resulted MAPE values is 1.84 which is highly robust with less than two percent of error. It means that the symmetric and asymmetric long-run and short-run plays and important role in determining the exchange rate equilibrium in case of Ukraine during war break out.

One of the factors explaining the superior forecasting capability of the NARDL model lies in its capacity to model the nonlinear and asymmetric responses of the exchange rate to macroeconomic shocks. In particular, the fluctuations of the exchange rate in Ukraine during the research period are associated with the structural breaks related to the events in 2014 (Crimea crisis), transition to the managed exchange rate regime, coronavirus pandemic and the Russian invasion in 2022. In this context, positive and negative shifts in macroeconomic indicators (oil prices, inflation, foreign reserves, etc.) affected the UAH/USD exchange rate in an asymmetric manner. In contrast to the traditional models that postulate symmetric responses, the NARDL approach makes it possible to distinguish positive and negative macroeconomic shocks and measure their short-run and long-run impacts separately (Shin et al., 2014). Thus, NARDL model is more appropriate for capturing the nonlinear dynamics of the exchange rate due to the extended period of geopolitical and economic uncertainty in Ukraine.

Table 7: Diagnostic Tests

Normality	**Heteroskedasticity**	**Serial Correlation**	**RAMSEY Test**
0.0975	0.7834	0.0934	0.3166



Forecast: FEF	
Actual: FE	
Forecast sample: 2025M01 2025M12	
Included observations: 12	
Root Mean Squared Error	0.946146
Mean Absolute Error	0.771967
Mean Abs. Percent Error	1.847605
Theil Inequality Coefficient	0.011453
Bias Proportion	0.665704
Variance Proportion	0.044096
Covariance Proportion	0.290200
Theil U2 Coefficient	2.686367
Symmetric MAPE	1.873611

Figure 2: NARDL Forecasting

4.4 Exponential Smoothing Analysis:

Table 7 depicts that for Ukraine, the dampened trend exponential smoothing model emerges as the most suitable specification, supported by the lowest Akaike Information Criterion value (AIC = 547.51). The choice of this model indicates that the series follows a trend, but one that is expected to slow down over time rather than continue at a steady rate indefinitely. The estimated level smoothing parameter ($\alpha = 0.8438$) is relatively high, showing that recent observations play a major role in updating the level of the series. This suggests that the Ukrainian data responds quickly to new information, which may be linked to frequent economic disturbances, structural changes, or external shocks influencing the series.

In contrast, the trend smoothing parameter ($\beta = 0.1219$) is quite low, indicating that changes to the trend are introduced gradually. While a trend is present, the model updates it cautiously, helping to prevent exaggerated responses to short-term variations. The damping parameter (= 0.000) reflects a fully dampened trend, meaning that the influence of the trend diminishes almost entirely in longer-term projections. In practical terms, this implies that although short-run movements may display some direction, forecasts eventually stabilize rather than showing persistent growth or decline. Such a pattern is consistent with an environment marked by sustained uncertainty or binding economic and policy constraints. The absence of a seasonal smoothing parameter (γ) confirms that no seasonal structure is detected in the Ukrainian series. This indicates that the behavior of the variable is driven mainly by trend and irregular movements rather than recurring seasonal patterns.

Table 8: Exponential Smoothing Model Results

Country	Model/Trend	A	B	Φ	γ	A.I.C
Ukraine	Dampened	0.8438	0.1219	0.000	—	547.5051

Taken together, the findings suggest that Ukraine's time series is strongly influenced by recent developments, contains a weak and heavily dampened trend, and does not exhibit seasonality. The selected model therefore captures short-term movements effectively while generating cautious and stable long-term forecasts, which is appropriate for settings characterized by instability or ongoing structural change.

4.5 Accuracy of Individual Models:

Table 9: Forecasting Accuracy of Individual Models (MAPE Values)

ARIMA	Exponential Smoothing	Naïve	NARDL
2.70	4.74	3.21	1.847

The forecasting performance of the individual models is evaluated using the Mean Absolute Percentage Error (MAPE) in Table 8, where lower values indicate higher predictive accuracy. Among the competing approaches, the ARIMA model demonstrates the strongest performance with a MAPE of **2.70**, indicating a high level of forecast precision. This result suggests that ARIMA effectively captures the underlying time-series dynamics and short-term dependencies present in the data. The naïve model records a MAPE of 3.21, performing reasonably well despite its simplicity. This outcome implies that the series contains a strong persistence component, where recent observations serve as a useful benchmark for short-term forecasting. However, its higher error compared to ARIMA highlights the limitations of relying solely on past values without explicitly modeling the data structure. The exponential smoothing model yields a comparatively higher MAPE of 4.74, indicating weaker forecasting accuracy. This suggests that the smoothing framework may not adequately reflect the complexity of the series, particularly if abrupt changes or non-linear patterns are present.

In contrast, the NARDL model achieves the lowest MAPE value of 1.847, substantially outperforming all other approaches. This superior performance highlights the model's ability to capture asymmetric long-run and short-run relationships within the data. The results imply that allowing for non-linear adjustments and asymmetric responses significantly improves forecasting accuracy. Overall, the comparison reveals that while traditional time-series models such as ARIMA provide reliable forecasts, models that incorporate asymmetry and non-linearity, such as NARDL, offer a clear advantage in terms of predictive performance.

Among the two-model combinations, the pairing of ARIMA and NARDL performs best, producing the lowest MAPE as shown in Table 9. This result shows that combining a strong linear time-series model with a nonlinear framework leads to more accurate forecasts. Other two-model combinations that include NARDL also perform relatively well,

Table 10: Combined Models via Equal Weightage Method

Equal Weightage Method					
Two-Ways Combination					
AR-ES	AR-N	AR-NARDL	ES-N	ES-NARDL	N-NARDL
3.72	2.96	1.82	3.98	2.84	2.08
Three-Ways Combination				**Four-Ways Combination**	
AR-NARDL-N	AR-ES-N	AR-ES-NARDL	ES-NARDL-N	AR-ES-N-NARDL	
1.28	3.55	2.79	2.96	2.90	

Note: AR = ARIMA, N = NAÏVE, ES = Exponential Smoothing, NARDL = Non-Linear Auto Regressive Distributive Lag Model.

whereas combinations involving exponential smoothing tend to show higher errors, suggesting weaker contribution from that model. For the three-model combinations, forecasting accuracy generally declines compared to the best two-model combinations. While adding more models increases diversity, it also introduces less accurate forecasts into the combination, which reduces overall performance. Nevertheless, combinations that still include NARDL continue to outperform those that do not, confirming its importance in capturing key dynamics of the series.

The four-model equal-weight combination, which includes all individual models, does not outperform the best smaller combinations. Instead, its MAPE lies between the strong and weak models, indicating that equal weighting can dilute forecast accuracy when less reliable models are included. Overall, the results suggest that forecast combinations are most effective when they involve a small number of well-performing models rather than many models with equal importance.

Table 11: Combined Models via Variance-Co Variance Method

Variance Co-Variance Method (Var-Cor)					
Two-Ways Combination					
AR-ES	**AR-N**	**AR-NARDL**	**ES-N**	**ES-NARDL**	**N-NARDL**
3.44	2.94	1.40	3.83	1.89	1.43
Three-Ways Combination				**Four Ways Combination**	
AR-NARDL-N	**AR-ES-N**	**AR-ES-NARDL**	**ES-NARDL-N**	**AR-ES-N-NARDL**	
1.59	3.36	1.67	1.89	1.78	

Note: AR=ARIMA, N=NAÏVE, ES= Exponential Smoothing, NARDL= Non-Linear Auto Regressive Distributive Lag Model

Table 10 illustrates the results of combined model via variance and co-variance method. The least value is 1.40 with the combination of AR and NARDL under variance and co-variance method. It shows that the recent observations and long-run relationships with the macro-economic fundamentals play an important role in the forecasting of exchange rate and determining the exchange rate equilibrium. All in all, in most of the cases the

combined models outperform individual models in forecasting the Ukrainian Hryvnia against the US Dollar which supports the postulation of (Granger & Ramanathan, 1984).

The results are also in line with the literature on forecasting and model diversification. Forecasting combination studies have found that each model explains different features of a time series, and their combination can decrease both biases and variances of forecasts and hence improve prediction accuracy(Bates & Granger, 1969; Timmermann, 2006) (. ARIMA model is successful at identifying linear relationships, while NARDL can predict asymmetric effects of macroeconomic fundamentals on exchange rate in the short run and long run. Additionally, variance-covariance weighting can increase efficiency because higher weights are given to models with low forecast errors compared to equal weighting of models. Thus, the superiority of the combination of ARIMA and NARDL can be explained by the theoretical proposition that model diversification makes forecasts more robust due to incorporation of complementary features of linear and nonlinear models in case of structural break and economic uncertainty.

5.0 Conclusion

This study examined the behavior and forecasting performance of the Ukrainian exchange rate against the US Dollar using a comprehensive set of econometric, time-series, and forecasting techniques. The analysis began with unit root testing to ensure the suitability of the data for time-series modeling. Results from both parametric (ADF) and nonparametric (PP) tests confirmed that all variables were stationary at either level or first difference, satisfying the necessary preconditions for reliable empirical analysis.
The linear dynamicsof the exchange rate was first taken into account using the ARIMA model. ARIMA(1,1,1) model was the best-selected model with a good fit andexcellent forecast performance. The low MAPE demonstrates that, despite greater uncertainty, lineartime-series models are still effective in explaining short-term momentum and persistence of the exchange rate.

In studying the effects of macroeconomic fundamentals and asymmetries, we employed the NARDL model (Tabash et al., 2024). Through the bounds test, there was also a finding for the existence of long run equilibrium between the exchange rate and some regressors. It was also found that inflation and oil price changes would affect the exchange rate over the long haul, in line with the inherent vulnerabilities of the Ukrainian economy amid times of geopolitically instable environments. Foreign reserves provided stability in the short run, a clear reflection of the importance of possessing buffers in dealing with exchange rate volatility. NARDL's excellent predicting capability makes it superior over all the individual models. The model also supports the use of nonlinearity and asymmetry in forecasting exchange rates.

Exponential Smoothing has demonstrated once more that the exchange rate of Ukraine has a weak heavily damped trend without any seasonality. "The recent observations play the major role and the trend quickly fades away, that is, exchange rate variations result from short term shocks and not long term drifts."

Forecast comparisons showed that ARIMA models and naïve forecasts are performing good, while the best forecasts performance is seen in models having structural relations and asymmetry,especially NARDL. Based on this, forecast combination approaches were applied usingequal weight combination and variance-covariance forecast combination techniques. It is evident from the findings that forecast combination produces higher accuracies compared to individual models, and thus there is strong support for forecast combination approaches. ARIMA and NARDL combination forecasts produced minimum forecast error rates among all theforecast combinations used, and variance-covariance forecast combination performed better than others.

Overall, it can be concluded that a more accurate forecast of exchange rate inUkraine could be achieved using hybrid model which would have both short-run time series and long-run structural relations with asymmetry. For example, forecast combination using models having high forecasts performances instead of all models is highly effective in improving forecast accuracy. This will be useful in terms of exchange rate forecasting during times of uncertainty due to external factors because of structural relations in addition to current information.

To demonstrate the effectiveness of using hybrid forecasting models, which integrate both linear and non-linear models, and preferring them over individual models, especially in the era of geopolitical instability, is the main contribution this study makes to the literature.

6.0 Policy Implications

The results of this research have some significantimplications for policy makers and regulators in Ukraine. First, the high sensitivity of theExchange Rate to macro fundamentals such us inflation rate, oil price and foreign reserves problems points to responsible macroeconomic management. Decision makers should focus on accumulating appropriate levels of foreign reserves to stabilizethe currency in the short term, since foreign reserves are proved to produce immediate positive effect on exchange rate volatility. Furthermore, based on the empirical evidence obtained from the regression analysis, exchange rate policies that focus on minimizing the effects of short-run instability should be centered around addressing inflation, sustaining adequate foreign reserve balances, and curbing extreme market volatilities using monetary policy measures. Due to the fact that foreign reserves play an important role in mitigating exchange rate instability in the short run, it is recommended that policymakers formulate better reserve management strategies and improve inter-agency collaboration in fiscal and monetary policy decision-making processes to ensure effective responses to external risks.

Second, the large asymmetric effects we find in the NARDL framework impliesthat the exchange rate reactions to shocks are heterogeneous hence perhaps standard linear policy measures may not work. Hence, policy frameworks shouldbe flexible and take into account the asymmetric effects of positive and negative shocks to exchange rates. In terms of formulating policies for the long run, policymakers are encouraged to concen-

trate more on economic transformation strategies that increase economic diversification and institutional credibility while decreasing reliance on externalities like oil price fluctuations. Given that asymmetric responses have been revealed in the empirical analysis using NARDL models, policymakers are advised to adopt tailored policy measures when responding to positive and negative economic stimuli, respectively. Thus, adaptive and flexible policy strategies may contribute to exchange rate stability in the long run.

Third, the better forecasting performance of mixed models combined with both counterparts alsosuggests that hybrid forecasting systems can be helpful for decision-makers. Central banks and other financialinstitutions might take such methods in consideration for exchange rate forecast, risk management evolution, and intervention on foreign exchange markets.

Finally, in a situation of geopolitical instability, like for the ongoing conflict with Russia, based on these results it can be concluded that forward looking policies are needed combining short-term market dynamics and long-term structural relationships to preserve currency stability and economicresilience. As shocks become frequent and asymmetric in Ukrain's wartime economy, the findings of the study highlight the need to adopt flexible forecasting and policy responses to preserve the stability of exchange rate.

7.0 Recommendations for Future Researchers

Future research may consider the use of high frequency data, such us dailyor weekly observations, in exchange rate forecasting so as to improve short-term volatility and market dynamics.

Previewing: Beyond traditional determinants of exchange rates, representation in the set of 38 explanatory variables of fiscal aggregates, capital flows,commodity shocks and some measures of geopolitical risk could provide a better insight about those underlying drivers.

Also, the use of different nonlinear models, machine learning methods, and hybrid forecasting might enhance prediction accuracy by accounting for intricate dynamics beyond the classical or NARDLframework.

It is also suggested that future studies may consider the potential influence of policy interventions, structural breaks or crisis periods on exchangerate dynamics by testing for the power to escape from mean reversion under extreme situations.

Across-country analysis over developing or post-conflict countries may contribute in the evaluation of the external validity about nonlinear movements and forecast combination schemes. Similarly, the analysis of longer forecast horizons would give a sense of model stability and reliability over long run which are needed for policymakers, financial institutions and market participants to make decisions on hedging (currency) risk in turbulent times.

Moreover, possible research directions in the future will benefit from the consideration of methodological extensions that carry high impact, including the use of high-frequency financial information and the use of machine learning and hybrid approaches. The application of high-frequency data will enable the forecasting model to incorporate short-run fluctuations and abrupt responses in the foreign exchange market. Likewise, the incorporation of machine learning and hybrid forecasting models will increase the efficiency of predictions by allowing the identification of complicated and nonlinear structures, interdependencies, and shifts in the model.

Finally, the consideration of variables like geopolitical risk factors, capital inflows, and fiscal policies is likely to generate a better theoretical understanding of exchange rates in times of crises and economic instability. The examination of structural shifts, intervention strategies, and other unusual market conditions can test the stability of the forecasting model when there are abnormal economic circumstances. This will not only lead to improved forecasting results but also to enhanced theories of exchange rate movements in developing and post-conflict countries.

Future research should expand hybrid approaches to other post-conflict economies, testing their robustness under extreme volatility.

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