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Forecasting Exchange Rates: An Empirical Application to Pakistani Rupee

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Abstract

This study aims to forecast the exchange rate by a combination of different models as proposed by Poon and Granger (2003). For this purpose, we include three univariate time series models, i.e., ARIMA, Naïve, Exponential smoothing, and one multivariate model, i.e., NARDL. This is the first of its kind endeavor to combine univariate models along with NARDL to the best of our knowledge. Utilizing monthly data from January 2011 to December 2020, we predict the Pakistani Rupee against the US dollar by a combination of different forecasting techniques. The observations from M1 2020 to M12 2020 are held back for in-sample forecasting. The models are then assessed through equal weightage and var-cor methods. Our results suggest that NARDL outperforms all individual time series models in terms of forecasting the exchange rate. Similarly, the combination of NARDL and Naïve model again outperformed all of the individual as well as combined models with the lowest MAPE value of 0.612 suggesting that the Pakistani Rupee exchange rate against the US Dollar is dependent upon the macro-economic fundamentals and recent observations of the time series. Further evidence shows that the combination of models plays a vital role in forecasting, as stated by Poon and Granger (2003).

Keywords: Forecasting, Exchange Rate, Auto-Regressive, Naïve, Exponential Smoothing

JEL Classification Code: E37, E47, F47

1. Introduction

The adoption of a flexible exchange rate regime has drawn researchers' interest to explore its effects on the primary macroeconomic aggregates (Goh et al., 2020). The main reason for such high interest is the fact that the exchange rate plays a critical role in determining macroeconomic variables for any nation. The literature is replete with such evidence and analysts argue that growth rates and other important macroeconomic targets can only be reached and sustained with the assistance of a country's competitive exchange rate. The positive impact of competitive exchange rates on economic performance is widely substantiated by evidence from advanced and emerging economies (Hussain et al., 2019).

Pakistan is one of the developing economies in South Asia where the economy is struggling with a persistent trade deficit and insufficient foreign exchange reserves as a result. Pakistan's exports have remained stagnant at US$25 billion for almost a decade, while imports rose to US$50 billion, placing immense pressure on the external balance (Hussain et al., 2019). Such a low output in the country's export sector could be due to the small export basket of textiles, chemical and pharmaceutical products, and leather, rice, and sports products. Besides, the country lacks diversification of goods and value addition, which makes exporting products less competitive, and as a result, fluctuations in exchange rates tend to have little effect on export efficiency.

Like other developing countries, Pakistan has had an overvalued currency and significant changes have been observed in the exchange rate policy in recent years (Hamid & Mir, 2017). Bad exchange rate management is another issue in the country and is often driven by individuals who do not have a basic understanding of economics. Consequently, the exchange rate remains more or less transparent and sometimes subjected to arbitrary changes. Some studies (Hamid & Mir, 2017) claimed that the overvalued exchange

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rate and misalignment are the main causes of loss of competitiveness in the international market and declining growth in the tradable sector during the last decade. Intuitively, the strategy of making the currency undervalued to get competitiveness in the international market may not work in correcting the deficit in the external account in Pakistan. In certain situations, foreign exchange demand forms, and supply curves might be such that devaluation will intensify the trade deficit instead of correcting it (Hussain et al., 2019).

It is found that a single Non-linear model itself is not capable to capture all dynamics of time series (Khashei et al., 2009). There is no consensus today on which technique is superior in terms of precision in forecasting. Therefore, to predict, combinations of forecast techniques derived from individual models are used in this study. Academics and practitioners commonly apply many models to gauge the upcoming trend of the exchange rate forecast as it was suggested by Poon and Granger (2003) that combination forecasting in this area is a research priority. Therefore, it motivates authors to fill an important gap by considering combinations of forecasting methods for exchange rates by univariate forecasting techniques & Non-Linear Auto Regressive Distributive Lag (NARDL) model which has never been done before by any researcher.

This research also compares the efficiency of forecasting with univariate time series methods as these models provide different results when there is a change in time series as explained by Kauppi et al. (2020). In developing and frontier countries, they perform equally well, and this research also includes this report. The seldom implemented NARDL-co-integration technique focuses on exploring the linear and non-linear & long-and short-run relationships between exchange rates and fundamentals of macroeconomics.

Economists and policymakers have long been involved in predicting exchange rates. Forecasting is beneficial because it can decrease doubt and lead to better decision-making. Therefore, forecasting exchange rates and associated volatility is essential, as high volatility is a risk for any economy. Volatility poses significant barriers to every country's economic growth. Precise forecasting of exchange rate volatility is critical for the pricing of derivatives, asset pricing, allocation policies, and complex hedging. Accurate predictions can also serve as an input for models at value-at-risk. Financial and managerial decision-makers call forecasting an important tool (Majhi et al., 2009; Moosa, 2000).

Exchange rate forecasting is required for spot speculation, portfolio investment, exposure to hedging transactions, calculation and hedging of economic openness, exposure to translation hedging, short- and long-term funding, decisions on investment, pricing, strategic planning, deciding the foreign equilibrium of payments, and direct foreign investment. The powers of the economy set the exchange rates. The industry's supply and demand drive exchange rates to rise and fall every day, putting risks on overseas participants' markets in trade. Accurate forecasts of exchange rates will therefore allow companies, investors, and policymakers to decide efficiently when conducting foreign decisions policies in business and economics (Levich, 2001). A main financial element is exchange rates, which affect the decisions of foreign exchange holders, exporters, importers, and bankers; therefore, the fluctuation in exchange rate adversely affects the business cycle and capital flow of any economy.

2. Literature Review

In previous literature regarding combining models for the forecasting exchange rate, the researchers extensively emphasize combining time series models, machine learning, and ANN models. MacDonald and Marsh (1994) combined different time series forecast models to analyze the exchange rate of US Dollar/British Pound Sterling, Deutschemark/USD, and USD/Yen exchange rates. The authors demonstrated that combined models provide more accurate forecasts. Dunis et al. (2006) examined the forecasting characteristics of sixteen different models. None of the single models emerged as an optimum forecasting model, whereas the "mixed model" outperformed all other individual models. The mixed model includes volatility, Neural Network Regression & other time series models found best in different cases. Ince and Trafalis (2006) studied different exchange rates for the purpose of forecasting. The methodology employed by the author was parametric and non-parametric.

The parametric models include ARIMA, VAR models, etc., and incorporate non-parametric models, i.e. (SVR) and artificial neural network (ANN). It was concluded that all parametric models outperform non-parametric models. Khashei et al. (2020) forecasted the exchange rate by a combination of ARIMA and ANN models. The results concluded that the combined models performed better forecasting than individual models. Lam et al. (2008) and Altavila and Grauwe (2008) tested the different major global currencies. The outcomes recommended that combined models generally yield better forecasting than relying on individual models. The authors included Purchasing Power Parity (PPP), Sticky price monetary model, Bayesian models, combine averaging model, Uncovered Interest Parity, and Uncovered Interest Parity against the benchmark of random walk models. The results revealed that combined forecasts outperform random walk and all individual model estimations. Shahriari (2011) and Nouri et al. (2011) proposed that 20 groupings of Naïve and cubic regression models provide more accurate results than individual findings.

Matroushi (2011) proposed two combined models for forecasting exchange rates, i.e., ARIMA-ANN and ARIMA-MLP. The author concluded that ARIMA-MLP performed better forecasting than other combined and individual models. Wang et al. (2016) predicted the exchange rate by combining the ARIMA model with a three-layer ANN Model. The time-series data of the Euro against the US Dollar was collected from 2010-2013. The experimental findings concluded that the proposed combined models outperform the individual forecasting techniques.

Mucaj et al. (2017) forecasted the time series of USD/ALL by incorporating ARIMA, ANN, and the combined hybrid model of ARIMA-ANN. The findings concluded that the ARIMA-ANN combined hybrid model performs better forecasting than ARIMA and ANN models. Amat et al. (2018) found that combining typical exchange rate models with machine learning and Taylor Rule models performs better forecasting estimations than individual models. Zhang and Hamori (2020) speculated the exchange rate by combining the fundamental models with machine learning compared to random walk models. The analysis showed that combined modeling of fundamental models with machine learning outclasses the random walk models.

In the previous literature, it can be easily observed that previous researchers extensively emphasized the combination of models of the artificial neural network, time series, and machine learning related models for predicting exchange rate. This study will cover the gap to combine the univariate time series and NARDL model to provide a better estimate and check whether the combined econometric and time-series models are more efficient than individual models or not.

3. Data and Methodology

3.1. Data Set

The authors collect the monthly data of the Pakistani Rupee's Exchange rate against the United States Dollars from the first month of 2011 to the last month of 2019. The remaining observations from M1 2020 to M12 2020 were held back for forecasting. The reason for selecting data from 2011 is the base year of IMF IFS statistics, i.e., 2010, from where the authors collect all the data of explanatory variables in the case of the NARDL Co-Integration model. The explanatory variables include Money Stock, Trade Balance, Gross Domestic Product, Interest Rate, Inflation Rate, Oil Prices, and Gold Prices. Extensive literature provides evidence of a significant relationship between exchange rate and selected macro-economic fundamentals.

3.2. Methodological Approaches

In the literature of forecasting time series, we have mainly two types of models i.e. linear and non-linear. In linear models, the model estimates the future observations by considering different linear combinations of the sample whereas, in the case of non-linear models, the models were developed to challenge and hypothesized the concept of linearity among explanatory and control variables (Khashei & Bijari, 2010).

3.3. ARMA/ARIMA

One of the most commonly used models for potential forecasting values is Box and Jenkins (1976). To estimate the time series's future values, the ARIMA model used the past and current values. The ARIMA model is an integrated model when, after taking the first or second difference, the time series becomes stationary. It takes the historical data and decomposes it into the mechanism of Autoregression. ARIMA models are written as ARIMA (a, b, c, where, according to the Box-Jenkins technique, *a* defines the order of the autoregressive model, *b* establishes the order of the moving average, and *c* indicates the order of the stationary one. If the time series is stationary, it will be referred to as the model of ARMA (a, b). Joshe et al. (2020) predicted the Indian Rupee exchange rate time series against the US Dollars using the ARIMA model. The authors concluded that ARIMA (1, 1, 5) had given the most appropriate results. Al-Gounmein and Ismail (2020) forecasted the exchange rate of the Jordanian Dinar against the US Dollar. The results concluded that better forecasting was given by ARIMA (1, 0, 1). Deka et al. (2019) also applied ARIMA methodology for the forecasting of the Turkish Lira exchange rate against the US Dollar and found it suitable. AsadUllah et al. (2020) also found ARIMA suitable for the forecasting of the exchange rate of the Pakistani Rupee against the US Dollar. Alshammari (2020) applied ARMA/ARIMA approach with other combinations of models for the forecasting of stock return in the case of Saudi Arabia.

3.4. Naïve

This model implies that the time series forecast values would be equal to the real-time series values for the last available time period, i.e., $y(t + 1) = Y(t)$, which also applies to the exponential model smoothing where $\alpha = 1$. The Naïve 1 model is often used as a benchmark for comparison with other models with the same features, i.e., Smoothing Exponential & ARIMA (McKenzie et al., 2002). Dunis et al. (2008) used the Naïve model to model the US Dollar/Euro exchange rate as a measure. In forecasting the exchange rate of Saudi Riyal to Indian Rupee, Newaz (2008) ranked the Naïve model as seventh.

3.5. Exponential Smoothing

The ES model (Gardner, 1985) is widely used in economics and finance for forecasting purposes. It is distinct from the

ARIMA method, according to Brooks (2004), where the model used an earlier linear combination of the previous time series value for the prediction of future values. The new values will be more useful for predicting future time series than the old values for previous time series results. The ordinary model in the exponential smoothing model is the single parameter exponential smoothing model, i.e., Next forecast = Last forecast + the share of the last mistake. However, the single parameter model is only valid for the time series and has no trend and seasonal effects. It can be described as:

$$Y_t(k) = L\ (t)$$

Where $L(t) = \alpha\ Y(t) + (1 - \alpha)\ LL\ (t - 1)$

$Y_t(k)$ is the time series k speculated values, $y(t)$ is the time t observed values, and x an is the weighting parameter. Its scale ranges from 0 to 1. High alpha values suggest that the influence of historical knowledge will soon be wiped out and vice versa.

Borhan et al. (2011) tested various models, including the exponential smoothing forecasting model, to forecast the Bangladeshi Takka exchange rate with the US Dollar. The researchers concluded that the prediction of exponential smoothing is better than that of other predicted models. Maria et al. (2011) evaluated different forecasting models for the exchange rate speculation of significant currencies. The researchers found that the exponential smoothing model beats the researchers' integrated ARIMA and other forecasting models.

3.6. Non-Linear Autoregressive Distributed Lag (NARDL)

The Non-linear ARDL model recently developed by Shin et al. (2014) used positive and negative partial sum decompositions, allowing detecting the asymmetric effects in the long and the short-term. Compared to the classical co-integration models, the NARDL models present some advantages. First, they perform better for determining co-integration relations in small samples. Second, they can be applied irrespective of whether the regressors are stationary at a level or the first difference (i.e., $I(0)$ or $I(1)$). They cannot be applied, however, if the regressors are $I(2)$.

Le et al. (2019) tested the asymmetric effects of exchange rate volatility on trade balance by using the NARDL approach. Bahmani et al. (2015) had tested the exchange rate's impact using the NARDL approach. They found an asymmetric effect of the exchange rate on the variation of the trade balance. Moreover, Turan et al. (2018) employed the current account case and found that changes in the current account deficit significantly affect the budget deficit. Due to the extensive application and benefits of the above technique, the author has decided to include the NARDL technique in this study to analyze the non-linear relationship between the exchange change rate and different explanatory variables. Qamruzzaman et al. (2019) tested the non-linear relationship between the exchange rate and FDI in the context of Bangladesh by applying the NARDL model. The findings suggest that there is a non-linear relationship among these variables in the long-run.

3.7. Combination Techniques

The inference of Armstrong (2001) was drawn from his analysis of *"The combination of forecasts is that you should weigh forecasts equally when you are uncertain about which method is bes*t." Another fast technique suggested by Granger and Ramanathan (1984) is a linear mixture of individual forecasts, integrating weights from the matrix of past predictions and the vector of past observations as calculated by OLS (ordinary least square - assuming unbiasedness). For the combination reason, some researchers tend to use unequal weights instead of fixed equivalent weights. Using regimen switching models and smooth transition autoregressive (STAR) models, Deutsch et al. (1994) altered the fixed weights in their study, and a time-dependent weighting scheme was proposed in a non-linear way. Due to the above reasons, the authors include var-cor and equal weightage methods to combine forecasting the exchange rate.

The authors take the Industrial Production Index (IPI) as a proxy of GDP due to its extensive application in previous studies. Soybilgen (2019) identified the Turkish business cycle regime during real-time by applying the BBQ model & MS model. In this study, the author employed IPI as a proxy of GDP and stated that the IPI and GDP move together in most cases; the contrary behavior is infrequent. Modugno et al. (2016) forecasted the Turkish GDP through proposed econometric models. The authors stated that the IPI is positively correlated with the GDP; therefore, it has been used by numerous researchers when they require GDP data in high frequency, i.e., monthly. The author further argues that a significant portion of the service sector consumes by the production sector; therefore, the argument against the reliability of IPI due to the increase of service sector share in GDP is insignificant.

Table 1: Explanatory Variables Assessment

Variable	Variables Name	Assessment
MS	Money Supply	Money Stock
IR	Interest Rate	Central Bank Rate
INF	Inflation	Consumer Price Index
GDP	Real GDP	IPI
TB	Trade Balance	Exports – Imports
FR	Foreign Reserves	Official Foreign Reserves
OP	Oil Price	Crude Oil Price

4. Results and Discussion

The first step towards different univariate and multivariate series analyses is to ensure that the time series does not possess any upward or downward trend. There should not be any seasonality issue that eventually leads to non-stationary problems. To overcome this problem, the authors tested each time series' unit root by integrating the Augmented Dickey-Fuller and Phillip Peron tests.

Table 2 depicts that the time series of the exchange rate of USD versus Pakistan Rupee was not stationary at a level with a *t*-value of –1.1042. The authors took the first difference to adjust the trend, which indicates that the time series is now stationary with a *p*-value of 0.000 and *t*-value of –8.8503 in both Augmented Dickey-Fuller and Phillip Peron tests as shown in the results.

Table 2 also represents the unit root results of all explanatory variables. It concludes that only Gross Domestic Product, described by IPI, is stationary at a level whereas trends in other explanatory variables have been adjusted by taking 1st difference. ARDL Co-Integration technique requires that all variables be stationary at Level (0) or first difference (I); therefore, the results of Table 2 reveals that the pre-requisite has been fulfilled.

4.1. Forecasting Exchange Rate from Univariate Model

The author forecasts the exchange rate from the ARIMA model as it has been earlier mentioned that the time series of the exchange rate was found stationary at 1st difference. From the correlogram, the authors choose significant ACF and PACF lags to run the ARIMA model. From chosen lags, three models were selected as per rules i.e. ARIMA (1, 1, 1) ARIMA (1, 1, 7) & ARIMA (1, 1, 12). The *p*-value is significant in ARIMA (1, 1, 12); therefore, it has been excluded. The author chooses the best-fitted model by considering parsimony, i.e., high *R*-square, low Akaike & Schwarz criterion. The results are as below:

Table 3 represents the results of the *R*-square, Akaike-Info & Schwarz criterion for the selected models. The ARIMA (1, 1, 7) is the best-fitted model for forecasting by applying the parsimony rule. Table 4 interprets the result of the exponential smoothing model for forecasting. The Akaike Info Criterion was used to choose the best-fitted model; therefore, in this case, the additive trend has been spotted, and the best-fitted model A.I.C result is 658.98. The Winters' additive model is appropriate for a series with a linear trend and a seasonal effect that does not depend on the series' level. In the above model, the α value is maximum, concluding that the impact of historical values on future trends will die out quickly. The higher of β, i.e., 0.79125, implies that the weightage of the previous estimation on future values is significant. The null value of Φ and γ indicates that historical values & recent observations on future values are insignificant.

4.2. Forecasting Via Non-Linear Autoregressive Distributive Lag

Table 4 portrays the relationship between macro-economic fundamentals and exchange rates throughout the long run. It is found that an increase of one unit in foreign reserves leads to a rise in 0.0021 units of exchange, whereas, a decrease of one unit in foreign reserves leads to an increase in 0.0026 units of the exchange rate. Thus, there is a non-linear relationship between foreign reserves and the exchange rate. In the case of inflation, an increase of one unit leads to a decline in the exchange rate by 0.839 units. However, a decrease of one unit in inflation leads to a reduction in the exchange rate by 6.049 units. The result of inflation's positive and negative impact justifies the asymmetric relationship with the exchange rate.

Table 2: Unit Root Test of Explanatory Variables

Variables	Augmented Dickey-Fuller Test		Phillip Peron Test	
	Level	1st Diff.	Level	1st Diff.
ER	–1.1042	–8.8503***	–1.2119	–8.8503***
GDP	–4.8521**	–	–3.6011**	–
MS	–3.0633	–12.457**	–5.8793**	–
INF	0.82527	–9.7683**	0.6509	–9.8490**
IR	–2.4428	–4.0171**	–1.8666	–9.1857**
OP	–2.6640	–8.5447**	–2.2434	–8.3373**
TB	–1.6268	–11.2737**	–1.4723	–11.8537**
FR	–1.3598	–5.726**	–1.6088	–9.8595**

**Significant at 1%.

Table 3: Univariate Models Forecasting Results

Models	Selected Models	*R*-Squared		Akaike-Info		Schwarz Criterion
ARMA/ARIMA Model	ARIMA (1,1,7)	0.16959		4.45118		4.55109
	ARIMA (1,1,1)	0.11350		4.50828		4.60817
Exponential Smoothing Model	**Trend**	**α**	**β**	**Φ**	**γ**	**A.I.C.**
	Winters' Additive Trend	1.0000	0.79125	–	–	658.98

Table 4: NARD Long Run Coefficients

Variables	Estimates	Standard Error	*T*–Statistics
FR_POS	0.0021	0.0009	–2.1720**
FR_NEG	–0.0026	0.0011	–2.3478**
OP_POS	0.1980	0.1229	1.6111
OP_NEG	–0.2130	0.0858	–2.4934**
MS_POS	–0.0982	0.1689	–0.5816
MS_NEG	–0.1276	0.1617	–0.7891
INF_POS	–0.8396	0.4067	0.0436**
INF_NEG	6.0498	1.5428	3.91505*
IR_POS	4.6238	0.7114	6.4999*
IR_NEG	0.6877	1.1342	0.606328
TB_POS	0.0012	0.0014	0.815953
TB_NEG	–0.0017	0.0007	–2.3214**
GDP_POS	–0.1331	0.0812	–1.6397
GDP_NEG	0.0421	0.061375	0.686894
F-Statistics	443.7320	*R*–Squared	0.9945
Bound Test	4.230227	I0 Bound: 3.77	I1 Bound 3.23
Diagnostic Tests		*P*-Value	
Breusch-Godfrey Serial Correlation LM Test		0.1471	
Heteroskedasticity Test: Harvey		0.2297	
RESET Test		0.0730	

*Significant at 1%.
**Significant at 5%.

In case of a decrease in a unit of oil price and trade balance, there is an increase in exchange rate by 0.213 and 0.0017 units, respectively; however, the exchange rate changes against the rise in these units remains insignificant. The exchange rate increases by 4.623 units with an increase in one unit of interest rate, whereas the impact due to a decrease in interest rate is insignificant. The GDP is the only variable that does not show any effect on the exchange rate. The reason behind it is Pakistan's economic system, which is still under developing stage; therefore, it does not provide the actual impact as a macro-economic fundamental (Asadullah, 2017). The *F*-statistics show the value of 443.732, which indicates that the model is fit, and this model has explained 99% of the variation according to *R*-squared estimation. The value of the bound test also shows the existence of co-integration and long-term relationships. It also shows the values of diagnostic results that all three tests' insignificant values indicate that there is no issue of serial correlation & heteroskedasticity in the data set. Furthermore, the RESET test also shows the fitness of the model for the analysis.

4.3. Performance of Individual and Combined Models in Forecasting Exchange Rate

The authors compare all individual models' forecasting by calculating the Mean Absolute Percentage Error of each model separately. The criteria behind calculating MAPE is lower the value, the better the forecasting. The results of MAPE are as below;

Table 5 illustrates the accuracy of forecasting from individual univariate and multivariate time series models. It is found that the NARDL model has outperformed all the univariate time series in the context of forecasting the exchange rate of the US Dollar against the Pakistani Rupee on an individual basis. The NARDL has scored the lowest MAPE value, i.e., 0.292 whereas, the exponential smoothing model has the highest value of MAPE, i.e., 4.02, although it is not bad but highest in this case. The CUSM and CUSUMSQ graph shows that the model has been stable at a 5% confidence interval as shown below under figure 1.

As mentioned earlier, the authors aimed to forecast the exchange rate via combination techniques, i.e., the var-cor method and equal weightage method. Each technique utilizes the permutation of a two-way, three-way, and four-way combinations. By combining different individual models, the results of Table 8 show that the optimal model for forecasting exchange rate under an equal weightage model is the combination of NARDL and Naïve models via a two-way combination. The MAPE value of the combination of the Naïve and NARDL model is 0.612, which is the lowest among all the models. It shows that macro-economic fundamentals and the last period's estimation play a significant role in estimating the future exchange rate time series' future values.

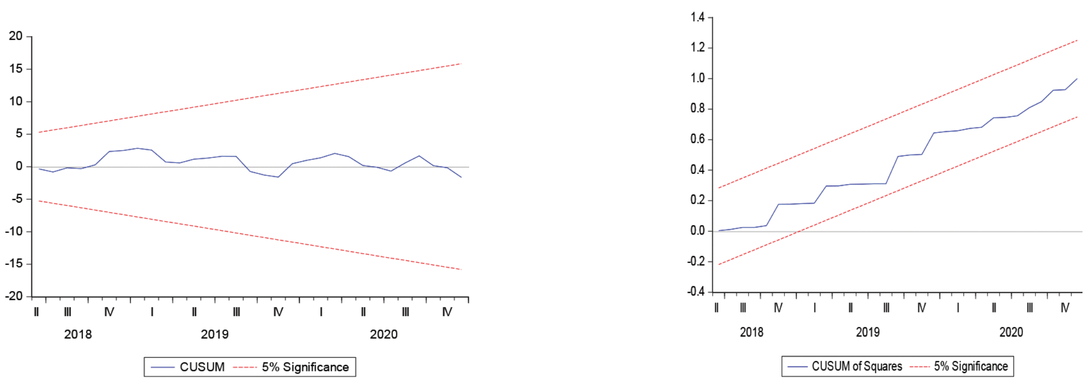
Table 9 represents individual combinations by integrating the var-cor method where the weightage is assigned as per unlikely equal weightage method, each model according to their MAPE. Under the var-cor method, a total of eleven, i.e., six two-ways, four three-ways, and one four-way combination, are applied. The combination of Naïve and NARDL has given the lowest MAPE value compared with all other combinations of models.

In a nutshell, the authors run a total of twenty-six different models for forecasting the exchange rate, in which four are individual, and the remaining are the combinations of various models. The best model is the combination of Naïve and NARDL models under equal weightage method by applying a two-way combination with the least MAPE value of 0.612.

Table 5: Accuracy of Individual & Combined Models (MAPE Value)

Individual	**AR**	**N**	**ES**		**ND**	
	2.97	0.932	4.02		0.292	
Equal Weightage Method	**Two-Way Combinations**					
	AR-ES	AR-N	AR-ND	ES-N	ES-ND	N-ND
	3.495	1.951	1.631	2.476	2.156	0.612
	Three-Ways Combination				**Four-Way Combination**	
	AR-ES-N	AR-ES-ND	ES-N-ND	AR-N-ND	AR-N-ES-ND	
	2.64	2.42	1.748	1.398	2.0535	
Var-Cor Method	**Two-Way Combinations**					
	AR-ES	AR-N	AR-ND	ES-N	ES-ND	N-ND
	3.999	2.1548	2.3005	2.99	3.274	0.7186
	Three-Ways Combination				**Four-Way Combination**	
	AR-ES-N	AR-ES-ND	ES-N-ND	AR-N-ND	AR-N-ES-ND	
	2.967	2.155	2.605	1.689	2.714	

AR = Auto Regressive Integrated Moving Average, N = Naïve, ES = Exponential Smoothing Model, ND = Non-Linear Auto-Regressive Distributive Lag.



(a) CUSUM **(b)** CUSUMSQ

Figure 1: CUSUM and CUSUMQ –NARDL

5. Conclusion

This study aims to forecast the exchange rate by the proposed method of Poon and Granger (2003), i.e., combining different individual models. For this purpose, the authors include three univariate time series models, i.e., ARIMA, Naïve, and Exponential smoothing model, and one multivariate model, i.e., NARDL. This research paper covers the research gap of combining univariate time series and the NARDL model for the first time. The authors applied two techniques i.e., equal weight and var-cor, to avoid biases. Each model is calculated by the same weight; however, in the var-cor case, every individual model has a unique weightage according to its MAPE values. The US Dollar data against the Pakistani Rupee has been taken from M1 2011 to M12 2020. The results proved that NARDL outperforms all individual models, i.e., ARIMA, Naïve, and exponential smoothing. By applying a combination of different models via different techniques, the combination of NARDL and Naïve models outperforms all individual and combined models by scoring the least MAPE value, i.e., 0.612. It means the Pakistani Rupee exchange rate against the US Dollar is dependent upon the macro-economic fundamentals and recent observations of the time series. Further evidence shows that the combination of models plays a vital role in forecasting, as stated by Poon and Granger (2003).

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