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Forecasting Canadian Dollar against the US Dollar via Combined Approaches

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Abstract

The purpose of this study is to forecast the Canadian-US dollar exchange rate using both independent and combination models. The fourth model is multivariate, as opposed to the first three, which are univariate. The multivariate model is NARDL, whereas the univariate models are ARIMA, Nave, and Exponential Smoothing. The NARDL is a recent contribution to the literature because it was rarely used for projecting exchange rates in previous studies. The data of exchange rate and other macroeconomic variables ranges from M12011 to M122021. To prevent bias, the authors combine the combination and equally weighted techniques. With a MAPE score of 0.130, the NARDL + Naive model combination outperforms three other solo and combined models.

Keywords: *Forecasting, NARDL, ARIMA, Naïve, Combined models*

1. Introduction:

Economists have begun to explore the relationship between the floating exchange system and major macroeconomic indices since its implementation [1-11]. This is because these indicators are crucial for any country. According to academics and the literature, success in these macroeconomic metrics is only possible if the country has a competitive exchange rate [12]. If the exchange rate float freely and uncontrollably then the economic system may collapse due to uncertainty and devaluation or appreciation of domestic currency without any information. The imports and exports can be hit badly due to uncertain determination of the exchange with the other trading currencies. It happens in many economies earlier as we can see in Sri Lanka, Turkey, and Pakistan where the exchange rate fluctuates rapidly which brings economic shocks to the local economy.

The mixed-market economy in Canada is well entrenched. Its nominal GDP is ninth globally, and its PPP GDP is fifteenth globally. The service sector, which employs around three-quarters of the population, dominates Canada's economy, as it does in other wealthy nations. Natural resources in Canada are predicted to be worth US$33.98 trillion in 2019, ranking third in the world. It is the third-largest exporter of crude oil globally and has the third-largest known oil reserves. In terms of overall natural gas exports, it comes in fifth place.

According to a Reuters poll, analysts expect the Canadian dollar to gain in the coming year as the US Federal Reserve and the Bank of Canada end their rate-hike cycles in 2023. GDP figures showed that the Canadian economy was more resilient than financial markets and the Bank of Canada (BoC) had anticipated for May, the Canadian dollar briefly increased against

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the pound and a few other currencies, which could have implications for future interest rates. However, the Canadian Dollar's recovery faded swiftly along with the U.S. Dollar's, allowing GBP/CAD to regain its footing before the weekend and positioning it well for potential gains at the start of the new week.

Academic professionals concentrate their efforts on anticipating exchange rates due to their numerous advantages. A predicted exchange rate minimizes uncertainty and enables better decision-making. Forecasting currency market volatility is crucial for reducing economic loss. Precise forecasting aids in accurate financial instrument pricing and increased hedging. Exact estimations are also included in value-at-risk models. Financial and corporate decision-makers regard forecasting as a vital tool [13].

All time series' efficacy could not be retrieved using a single Non-linear model (Khashei et al., 2009). It is tough to establish which forecasting approach is best. As a result, a variety of forecasting approaches are employed in this study to reach meaningful results. According to [14], economists and academic professionals use a variety of approaches to forecasting the future direction of currency rates. This encourages practitioners to employ a wide range of methods, including NARDL models and univariate models.

2. Literature review

Experts integrated ANN models, time series models, and well-known machine learning approaches to analyze the exchange rate in the past. Poon and Granger [15] anticipated USD parity with the British pound, Japanese yen, and the Deutschemark using a variety of time series models. According to the study, more accurate projections are produced when multiple models are used. MacDonald and Marsh demonstrated [16] the usage of two forecasting models working together. The researchers suggested that by combining ARIMA-ANN with MLP, ARIMA-MLP outperforms other models, whether used alone or in combination.

The task of analyzing the traits of 16 models was handed to Matroushi [17]. The statistics show that no one model works well; rather, the "mixed model" performs better than all of them. The successful model illustrates the value of these models in "mixed modeling" by utilizing volatility, Neural Network Regression, and several time series techniques. Dunis and Chen [18] projected currency parity by combining the three-layer ANN model with the Autoregressive integrated moving average model. For the calculation, US/Euro exchange rates were utilized between 2010 and 2013. The results showed that the selected linked models outperformed the standalone ones. Wang [19] claim that combining 20 sets of Nave and cubic regression approaches produces better forecasting results than doing so alone.

Authors have experimented with combining time series, ANN, and machine learning models for exchange rate projection, as seen by the publication of past literature. To improve prediction outcomes, this work will emphasize the necessity of combining non-linear ARDL techniques with univariate time series. This study will show whether integrated models perform better than standalone ones or not. It would be an addition to the literature on Finance which open the doors for future researchers.

Data:

The data on the exchange rate of Canadian Dollars has been taken from the IMF statistics website in monthly frequency from M12011 to M122021. The figures for 2021 have been suppressed owing to forecasting purposes. The macroeconomic fundamentals have been chosen for NARDL analysis. The selected macroeconomic fundamentals have been extensively used by the previous researchers in their studies It is also illustrated in [Table 1].

3. Methodology

In total, three univariate and one multivariate model have been selected by the author due to their uniqueness and characteristics. It is postulated that any single model isn't fit for every time series due to their limitations therefore the author is willing to lessen their weaknesses by combining with the other univariate model to predict the time series more efficiently. All models with the combination and their evaluation criteria have been discussed briefly below;

(a) ARIMA

ARIMA model is accepted by researchers at large, because of its effective and efficient forecasting of time series. ARIMA is used to produce the mean equation for volatility investigation. In every time series, the ARIMA model possesses the term error or residual value over timeε_t. In the ARIMA model lags of forecasts errors represent as moving average (MA), and lags of difference series appear in an equation called Auto-Regressive (AR). If the time series is stationary at level then it will be ARMA Model but if stationary at difference then the integrated difference (I) will be included in the ARMA model which subsequently converts into ARIMA.

(b) Naïve:

Simple forecasting formulas rely solely on historical data. There is no attempt to identify any conceivable underlying causal connections between the variables being studied. There are two recognized categories of naive models. Basic projection models are included in one category. Although these models require current observational data as inputs, no statistical analysis is carried out. The intricacy of the models in the second group necessitates their utilization of a computer. The simple Nave model, which relies on the most recent observation to forecast future observations, was employed in this research.

(c) Exponential Smoothing

It is widely used for forecasting. It is a different technique from than ARIMA approach where the model used a linear combination of the preceding value of time series for future value forecast. It has been observed that in time series data recent values will be more useful than older ones for future forecasts. However distant values still may possess some useful information for the development of future values. It succeeds in this by giving declining weights to lagged values geometrically.

(d) NARDL

This model is different if compare with the above-mentioned three models in the sense that it forecasts the time series with the help of other explanatory or control variables which isn't the case for ARIMA, ES, and Naïve. Shahriari [20] created a nonlinear ARDL model that uses positive and negative parts to identify asymmetric impacts in the long and short term/run. NARDL model holds some competitive advantages over traditional ARDL, therefore, it gains more insight from the researchers, first of all, there is no need for a large sample to find out the results, the small sample is also enough for the analysis. They can be utilized secondarily regardless of whether the regressor is stationary at the level or the first difference (i.e., I (0) or I (1)). They are, however, meaningless if I am the regressor (2). It is suitable for our research issue since it allows us to evaluate both short- and long-run asymmetries as well as latent co-integration.

(e) Explanatory Variables

The following variables are also taken in monthly frequency for NARDL analysis.

Table 1. Explanatory variables

Variables Name
Money Supply
Interest Rate
Inflation
Industrial Production Index
Trade Balance
Foreign Reserves
Oil Price
Gold Price

(f) Combination Techniques

In his study on "The combination of forecasts," Shin et al., [21] determined that projections should be given equal weight when determining the best course of action. Granger and Ramanathan introduced a viable alternative technique in 1984, the linear product of individual forecasts, weighted by the matrix of prior predictions and the direction of past values as determined by OLS (assuming unbiasedness). Non-consistent weights are preferred by some researchers over constant, equal weights. By changing the model regimen and STAR model transition, Armstrong and Deutsch et al., [22][23] proposed another scheme that is related to the time-dependent non-linear behavior. The writers forecast the value of a currency using var-cor and the equal weighting technique for the reasons outlined above. The reason for selecting the two different methods of combining different models is to avoid biasedness.

(g) MAPE

There are varieties of measures that have been applied by previous researchers to find out the accuracy of forecasting of the selected model. Some of them include MAE, MAPE, RMSE, MAD, etc. Relatively, MAPE is the most commonly used proxy to find out the accuracy of performance in the context of forecasting therefore the author chooses the MAPE to examine and compare the performance of models. The thumb rule is that the lesser the MAPE value, the more accurate the forecasting is. It also enables us to find out the weakest model in this regard if compare to the other models.

4. Empirical results:

(a) Unit Root Test:

It is important in the analysis of time series that the prerequisites have been fulfilled. The most important pre-requisite of time series analysis is the issue of stationarity, therefore, two diagnostic tests have been included in this study to avoid biasedness i.e., the ADF test and the PP test. The below results show that all variables are found stationary at the level and 1^{st} difference which concludes that the selected time series are reliable for the analysis.

Table 2. Unit root test results

Variables	ADF Test		PP Test	
	Level	1st Diff.	Level	1st Diff.
Exchange Rate	-1.689	-9.994**	-1.639	-8.659**
Gross Domestic Product	-1.025	-8.666**	-12.589**	--
Money Base Growth	-1.958	-10.121**	-2.336	7.222**
Inflation	-1.264	-10.021**	-2.265	-7.526**
Interest Rate	-2.326	-10.695**	-2.254	-6.326**
Oil Price	-2.664	-8.256**	-2.214	-7.362**
Trade Balance	-7.111**	--	-7.111**	--
Foreign Reserves	-2.598	-7.847**	-2.598	-9.022**

(b) Forecasting Exchange Rate from Univariate Model

As previously mentioned, there are three selected univariate models: Nave, Exponential Smoothing, and ARIMA. The ARIMA (1,1,2) model best fits the data on the exchange rate, according to Table 2. The selection criteria are based on the law of parsimony. When utilizing an exponential smoothing technique, the additive trend model is the most crucial model to forecast the Canadian Dollar versus the US Dollar. The coefficients and criteria values are as follows:

Table 3. Individual models results

Models	Best Fitted Model	R-Sq		A.I.C		Schwarz Criterion
ARIMA	ARIMA (1,1,2)	0.01998		-1.5466		-1.2249
ES Model	Trend	α	β	Φ	γ	A.I.C.
	Additive Trend	1.0000	0.0000	0.0000	0.0000	1.444

(c) NARDL Analysis:

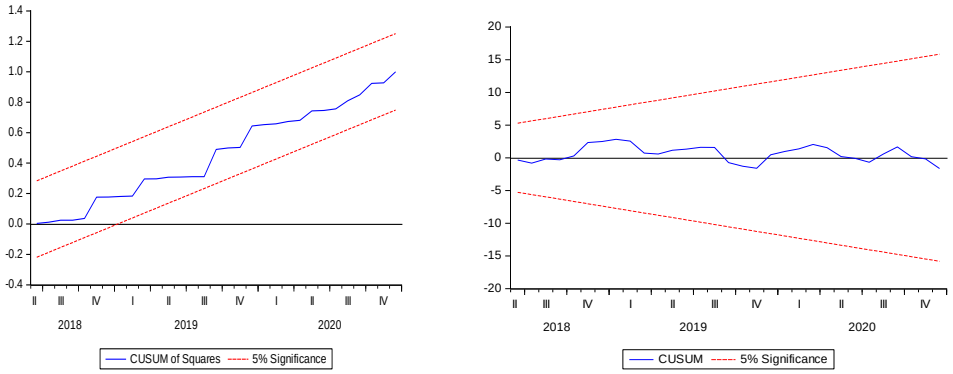
Table 4. NARDL coefficients

Variables	Estimates	S.E	T-Stats
Foreign Reserves-Positive	-0.000094	0.000032	-2.55951**
Foreign Reserves-Negative	-0.005528	0.000001	-3.455921*
Oil Price_ Positive	0.005512	0.002655	0.682282
Oil Price_Negative	0.022121	0.002559	0.256851
Interest Rate_Positive	0.228549	0.785459	0.125518
Interest Rate_Negative	-1.245150	0.485951	-2.204028**
Gross Domestic Product_Positive	-0.006859	0.026928	-0.515521
Gross Domestic Product _Negative	-0.054869	0.021558	-0.945458
Gold Price- Positive	-0.000859	0.000456	-1.712528
Gold Price_ Negative	-0.000125	0.000215	-0.926585
F-Statistics		R-Squared	
Bound Test	3.4525	I0 Bound: 3.91	I1 Bound 3.85 (10%)
Diagnostic Tests			P-Value
Breusch-Godfrey Serial Correlation LM Test			0.1999
Harvey Test for Heteroscedasticity			0.6261
RESET Test			0.5232

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

The NARDL results, which show how the linear and nonlinear behavior of macroeconomic fundamentals about the exchange rate of the Canadian Dollar vs the US Dollar, are presented in Table 4. The findings imply that foreign reserves and the exchange rate for the Canadian dollar have a considerable and asymmetric relationship. The Canadian dollar has been observed to strengthen as foreign reserves increase while weakening as they decrease. The second macroeconomic component that has an impact on the exchange rate is the interest rate. The Canadian dollar has been more volatile as a result of the drop-in interest rates. Strangely, the gold price, oil price, & GDP do not impact the exchange rate in either way which indicates that Canadian policymakers have developed such policies which are favorable to keep the exchange rate stable.

The diagnostic tests further refer that there isn't any issue of autocorrelation, heteroskedasticity, normality, or omission in the data set therefore it is concluded that the findings are valid. The stability of the NARDL model is further demonstrated in the graphics below using the CUSUM and CUSUMQ models.



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

(d) Forecasting Accuracy:

Table 5. MAPE values of all models

Individual	AR	N	ES			ND
	3.353	2.475	1.890			0.1666
Equal Weightage Method	2-Way Combinations					
	AR-ES	AR-N	AR-ND	ES-N	ES-ND	N-ND
	3.124	1.493	1.816	2.258	2.380	0.130
	3-Ways Combination				4-Way Combination	
	AR-ES-N	AR-ES-ND	ES-N-ND	AR-N-ND	AR-N-ES-ND	
	2.112	2.025	3.014	1.695	1.999	
Var-Cor Method		2-Way Combinations				
	AR-ES	AR-N	AR-ND	ES-N	ES-ND	N-ND
	2.222	1.205	4.556	5.320	2.595	0.333
	3-Ways Combination				4-Way Combination	
	AR-ES-N	AR-ES-ND	ES-N-ND	AR-N-ND	AR-N-ES-ND	
	0.584	1.587	1.982	1.247	2.364	

As discussed earlier, Table 4 shows the results of MAPE values from individuals and a combination of different models which have been selected in this study. In total, there are twenty-six models from which eleven models have combined with equal weights models and the other eleven models are combined via variance-covariance types of combination. The rest of the four models are univariate models. It is found that in the case of single models, NARDL has the least MAPE value i.e., 0.1666 whereas, in the case of a combination of models, the combined NARDL and Naïve model results in 0.130 MAPE value, under equal weightage criteria of combination, which is the least MAPE value among all individual and combined models in terms of forecasting the exchange rate. The above results affirm the postulation of Granger and Poor (2003) who claims that the combined models forecast better than individual models. This study also adds to the body of knowledge showing the NARDL is capable of anticipating the exchange rate. Researchers may apply the same method to forecast any other time series in the future.

5. Conclusion

This study's goal is to forecast the Canadian-US dollar exchange rate using both independent and combination models. The fourth model is multivariate, whereas the first three are univariate. The multivariate model is NARDL, and the three univariate models are ARIMA, Nave, and Exponential Smoothing. The NARDL is a recent contribution to the literature because it was rarely used for projecting exchange rates in earlier studies. Additionally, the combination of NARDL with univariate time series approaches will be useful for future studies. To prevent bias, the authors mix the combination via var-cor and equally weighted methods. With a MAPE score of 0.130, the NARDL and Naive model combo outperforms all other models irrespective of their combination. It backs up Poon and Granger's (2003) claim that combining many models can result in more exact forecasts than using just one model. The research assists legislators, FOREX markets, hedgers & policymakers in modifying regulations to reduce unanticipated risk and uncertainty.

6. Future research

It is recommended the future researchers apply the same methodology on any other time series to validate the methodology. The other time series refers to inflation, interest rate, employment rate, GDP, etc. It is further recommended that future authors may include some other models with the NARDL for forecasting and combined them via equal weights and var-cor method or any other method as postulated by Poon and Granger (2003).

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