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Forecasting Chinese Yuan/USD Via Combination Techniques During COVID-19

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Abstract

This study aims to forecast the exchange rate of the Chinese Yuan against the US Dollar by a combination of different models as proposed by Poon and Granger (2003) during the Covid-19 pandemic. For this purpose, we include three uni-variate 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 Chinese Yuan against the US dollar by two combination criteria i.e. var-cor and equal weightage. After finding out the individual accuracy, the models are then assessed through equal weightage and var-cor methods. Our results suggest that Naïve outperforms all individual & combination of time series models. Similarly, the combination of NARDL and Naïve model again outperformed all of the individual as well as combined models except the Naïve model, with the lowest MAPE value of 0764. The results suggesting that the Chinese Yuan exchange rate against the US Dollar is dependent upon the recent observations of the time series. Further evidence shows that the combination of models plays a vital role in forecasting which commensurate with the literature.

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

JEL Classification Code: E37, E47, F47

1. Introduction

The World Health Organization (WHO) announced the first case in China affected by a coronavirus (Covid-19) on 31 December 2019. A few weeks later, the number of diseases became immense, creating chaos. There have been catastrophic declines in the Chinese stock market, culminating in a financial crisis. The pandemic was recently announced by the World Health Organization and has spread to more than 190 countries worldwide. Due to the coronavirus pandemic, the whole world experienced economic loss, and the crisis boiled over and became the cause for a much larger global financial crisis. Vast and extensive studies shed light on the economic and social effects of the crisis triggered by this pandemic in this context, and literature examined how financial variables react to the emergence of this pandemic.

Albulescu (2020) discussed the effect on crude oil prices of the Covid-19 pandemic while monitoring the impact of financial instability and economic policy uncertainty in the United States (US). The results indicated the marginal negative effect of Covid-19 on the long-term price of crude oil. Zhang et al. (2020) analyzed the effects of coronavirus on global financial markets and showed a huge increase in global market volatility as a result of the outbreak. They found that, before and after the pandemic declaration, global capital markets linkages show different trends, and policy responses introduce additional uncertainties in global financial markets.

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Besides, Al-Awadhi et al. (2020) examined whether Chinese stock market results are influenced by the Covid-19 pandemic and found that Covid-19 has major negative effects on stock returns. Onali (2020) recently found that the rise in confirmed deaths in the US had a positive effect on the Dow Jones Index's conditional heteroscedasticity. On the other hand, a detailed analysis examined the causes and determinants of (what drives) volatility in exchange rates. In financial crises, for example, different factors influence exchange rate volatility (Coudert et al. 2011; Choudhry & Hassan, 2015). In this context, we are drawing attention to the performance of some significant forecasting models during the time period of the Covid-19 pandemic in the context of currency markets.

Business interactions between nations are becoming increasingly frequent as economic globalization continues to grow. The status of the exchange rate is very significant as foreign trade and financial activities are closely related to the exchange rate (Goh et al., 2020). The relationship between the exchange rate and export trade has been studied by Ding and Ying (2011). The results have shown that shifts in the exchange rate have an effect on different macro-economic indicators. At present, China's economy occupies an important position in the global economy. For more than ten years, China's monetary policy has been to keep the exchange rate of the Yuan/US Dollars stable by creating parity between the two currencies. This policy was against the balance of the market and caused some political difficulties. This strategy allows the Yuan to remain low and, thanks to it, the attractiveness of the Chinese industries to be maintained. In 2015, China had begun to change its strategy and has a long-term plan to compete with US dollars as an international currency. However, the Chinese market and the Chinese bank are not prepared to change policy abruptly. Since January 2013, China has followed the Base III regulation approach to credit risk and market risk and the basic approach to operational risk. We, therefore, need to build a system that allows us to predict the future exchange rate of the Yuan/US Dollars by considering the effect of macro-economic fundamentals. Many people in previous years have been interested in the macroeconomic exchange rate model.

Traditionally, it is possible to categorize exchange rate prediction techniques into two types: fundamental analysis and technical analysis. The basic analysis assumes that the shift in the exchange rate is triggered by the change in the two countries' purchasing power ratio (Grossmann & Simpson, 2010). In recent years, the fundamental economic factors influencing exchange rates have been continuously evolving as a result of the increasingly complicated international economic and financial climate. Hu (2005) indicated that trade conditions, national openness, and the level of domestic technology had an effect on the RMB's rate of exchange. By means of fundamental analysis, it is hard to predict the exchange rate of the RMB. However, there is a consistent internal structure of the exchange rate as a time sequence, no matter how the exchange rate mechanism shifts. The premise of technical research is that in time series there is a nonlinear structure of correlation. It is therefore easy to incorporate the use of implied time-series information to render a trend analysis, and a significant improvement has been experienced in the exchange rate time series forecast model.

2. Literature Review

Many prediction studies suggest that the complex characteristics of exchange rate time series can not effectively fit and be analyzed by a single model (Zhang, 2003). Besides, different models have similarities in data mining and analysis. To improve predictive capacity, a large number of scholars have mixed different predictive models (Alpaslan & Cagcag, 2012; Rojas et al., 2008; Wong et al, 2010 and Zhao and Yang, 2009).

Aladag et al. (2009) proposed a new hybrid approach by combining Elman's recurring neural networks (ERNN) and ARIMA models to predict non-linear time series like the Canadian Lynx data. Egrioglu et al. (2011) had built a hybrid model of seasonal ARIMA, self-regressive conditional heteroscedasticity (ARCH), and ANN to predict non-linear time series. Considering that some time series have long memory characteristics, Aladag et al. (2012) combined the self-regressive fractionally integrated moving average (ARFIMA) models with the FNN to predict Turkish tourism data. Valenzuela et al. (2008) had shown that the prediction of the ARIMA-ANN hybrid model is more accurate than a single model.

Matroushi (2011) proposed two combined models for the 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.

By incorporating ARIMA, ANN, and the ARIMA-ANN combined hybrid model, Mucaj et al. (2017) predicted the time series of USD/ALL. The results concluded that the combined hybrid model ARIMA-ANN performed better than the models ARIMA and ANN for forecasting. Amat et al. (2018) found that better prediction estimates perform better than individual models by combining typical exchange rate models with machine learning and Taylor Rule models. Compared to random walk models, Zhang et al. (2020) speculated on the exchange rate by combining the fundamental models with machine learning. The analysis showed that the random walk models are outclassed by the combined modeling of basic models with machine learning.

To date, no one has forecasted the exchange rate through a combination of univariate time series and non-linear ARDL techniques before and during Covid. The above-mentioned research gap motivates the authors to launch a pioneering study in which we can predict one of the major currency's future observations through a combination of non-linear multivariate models, i.e. NARDL and univariate time series techniques.

3. Methodology

3.1. Data

The authors collect the monthly data of the Chinese currency i.e. Yuan Exchange rate against 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 the in-sample 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 Base Growth rate, Trade Balance, Gross Domestic Product, Interest Rate, Inflation Rate, Oil Prices, and Gold Prices. The reason for selecting the above explanatory variable is the evidence of a significant relationship between exchange rate and above mentioned macro-economic fundamentals in the literature.

3.2. Methodological Approaches

We specifically have two types of models in the literature of forecasting time series, i.e. linear and non-linear. The model predicts future findings in linear models by taking into account various linear combinations of the sample, while the models were developed to question and hypothesize the notion of linearity between explanatory and control variables in the case of non-linear models. (Khashei & Bijari, 2010).

3.2.1. ARMA/ARIMA

The model of Box and Jenkins (1994) is one of the most widely used templates for future forecast values. The ARIMA model used the past and present values to predict the potential values of the time series. The ARIMA model is an integrated model where the time series becomes stationary after following the first or second difference. It takes and decomposes the historical data into the Autoregression process. ARIMA models are written as ARIMA (a, b, c, where a defines the order of the autoregressive model according to the Bo-Jenkins rule, b defines 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 ARMA model (*a*, *b*).

The Indian Rupee exchange rate time series was forecasted by Joshi et al. (2020) against the US Dollars using the ARIMA model. The authors concluded that the most suitable results were given by ARIMA (1, 1, 5). The Jordanian Dinar exchange rate against the US Dollar was predicted by Al-Gounmein et al. (2020). The findings concluded that ARIMA offered better forecasting (1, 0, 1). Besides, Deka et al. (2019) applied ARIMA methodology to forecast the Turkish Lira exchange rate against the US Dollar and considered it acceptable. Asadullah et al. (2020) also considered ARIMA to be acceptable for forecasting the Pakistani Rupee exchange rate against the US Dollar. Alshammari (2020) also applied this model for the forecasting of the exchange rate.

3.2.2. Naïve

This model implies that for the last available period, the time series forecast values will be equal to the real-time series values, i.e., $y(t + 1) = Y(t)$, which also applies to the exponential smoothing model where $\alpha = 1$. For comparison with other models with the same characteristics, the Naïve 1 model is also used as a benchmark, i.e. Smoothing Exponential & ARIMA.

To model the US Dollar/Euro Exchange Rate as a metric, Dunis et al. (2008) used the Naïve model. Newaz (2008) ranked the Naïve model as 7th in forecasting the Saudi Riyal to the Indian Rupee exchange rate. Khalid (2008) forecasted the exchange rates of three countries by using the Naïve random walk model technique.

3.2.3. Exponential Smoothing Model

For forecasting purposes, the ES model (Gardner, 1985) is commonly used in economics and finance. According to Brooks (2004), it is distinct from the ARIMA process, where the model used an earlier linear combination of the previous time series value for the estimation of future values. For forecasting future time series, the new values would be more useful than the old values for previous time-series outcomes. However, for the creation of future values, distant values can still have some useful information. In the exponential smoothing model, the ordinary model is the single exponential smoothing model parameter, i.e., next forecast = last forecast + the share of the last error. The single parameter model, however, is only valid for the time series and has no seasonal and trend effects.

3.2.4. NARDL

The recently developed Non-linear ARDL model by Shin et al. (2014) uses positive and negative partial sum decompositions, allowing long and short-term asymmetric effects to be observed. The NARDL models offer several other advantages compared to the classical co-integration models. Firstly, in small samples, they perform better in evaluating co-integration relations. Secondly, regardless of whether the regressors are stationary at a degree or the first difference (i.e., $I(0)$ or $I(1)$), they can be enforced. However, they cannot be implemented if the regressors are $I(2)$.

By using the NARDL method, Qamruzzaman et al. (2019) examined the asymmetric relationship between the exchange rate and FDI in the context of Bangladesh by applying the NARDL model. Le et al. (2019) examined the asymmetric impact of exchange rate fluctuations on the trade balance. Bahmani et al. (2015) had used the NARDL approach to control the effect of the exchange rate. They found that the exchange rate had an asymmetric effect on the trade balance variance. Besides, Turan et al. (2018) employed the current account case and found that the budget deficit is greatly influenced by shifts in the current account deficit. The author has chosen to use the Non-Linear Auto Regressive Distributive Lag (NARDL) technique in this analysis to analyze the non-linear relationship between the exchange change rate and various explanatory variables due to the comprehensive application and benefits of the above technique as explained in Table 1.

3.2.5. Combination Techniques

Armstrong (2001) concluded that the combination of forecasts is that you should weigh forecasts equally when you are uncertain about which method is best. Another quick method suggested by Granger and Ramanathan (1984) is a linear mixture of individual forecasts combining weights from the matrix of past predictions and the vector of past observations (ordinary least square - assuming unbiasedness). Some researchers prefer to use unequal weights instead of fixed equivalent weights for a combination of purposes. Deutsch et al. (1994) altered the fixed weights in their analysis using regimen switching models and smooth transition autoregressive (STAR) models, and a time-dependent weighting scheme was proposed in a non-linear way. For the above purposes, to combine forecasting of the exchange rate, the authors use var-cor and equal weighting techniques.

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

4.1. Empirical Results

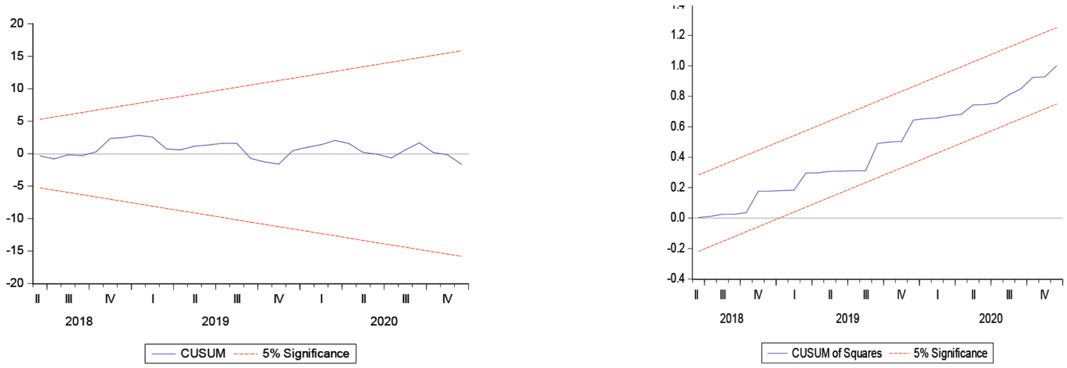
The first step towards different univariate and multivariate series analyses is to warrant that the time series does not own any upward or downward tendency. There should not be any seasonality issue that eventually leads to non-stationary problems. To overcome this problem, the authors tested each time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

Table 1 depicts that the time series of the exchange rate of the Chinese Yuan versus US Dollars was not stationary at a level with t-value of –2.6567 and –2.6441 at ADF and PP tests respectively as can be easily observed in Figure 1. The authors took the first difference to adjust the trend, which indicates that the time series is now stationary with the t-value of –7.8951 & –7.9248 in both Augmented Dickey-Fuller and Phillip Peron tests as shown in Table 2.

Table 2 also illustrates the result of the unit root test of explanatory variables which indicates that all explanatory variables are found to be stationary in level or at 1st difference. The results validate that it has fulfilled the assumption of the NARDL model because if any of the variables are found to be stationary at the second difference then we cannot run the NARDL model or we have to drop that specific variable.

Table 3 depicts the ARIMA model results which indicate that the ARIMA (1, 1, 10) model is the best-suited model for the purpose of the forecasting exchange rate of the Chinese currency Yuan against the US Dollar. The R-squared, Akaike, and Schwarz criterion values are 0.101766, –2.5282, and –2.4282 respectively. Table 3 also 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 Winters' additive trend has been spotted, and the best-fitted model A.I.C results as –50.072. The additive 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 @ value is maximum, concluding that the impact of historical values on future trends will die out quickly. The null values of Φ, β, and g indicate that historical values & recent observations on future values are insignificant.

Table 4 interprets the results of long-term coefficients that define the relationship between exchange rate and macro-economic fundamentals. The bound test shows the value of 3.0793 which is higher than the upper and lower bound



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

Figure 1: CUSUM and CUSUMQ–NARDL

Table 2: Unit Root Test of Explanatory Variables

Variables	Augmented Dickey-Fuller Test		Phillip Peron Test	
	Level	1st Diff.	Level	1st Diff.
ER	–2.6567	–7.8951**	–2.6441	–7.9248**
GDP	–1.9350	–14.926**	–13.221**	–
MS	–3.8276	–12.457**	–3.9036**	–
INF	–3.8828**	–	–3.0103	–15.8740**
IR	–1.7314	–7.3442**	–1.9647	–7.2751**
OP	–2.6640	–8.5447**	–2.2434	–8.3373**
TB	–5.4350**	–	–5.2024	–
FR	–1.9756	–7.8199**	–2.1608	–8.2985**

Table 3: Univariate Models Forecasting Results

Models	Selected Models	*R*-Squared		Akaike-Info		Schwarz Criterion
ARMA/ARIMA Model	ARIMA (1,1,10)	0.11350		4.50828		4.60817
Exponential Smoothing Model	**Trend**	**α**	**β**	**Φ**	**γ**	**A.I.C.**
	Winters' Additive Trend	1.0000	0.000	—	0.000	–50.072

and hence, provides significant evidence of a long-term relationship. The results indicate that the decrease in one unit of oil price leads to a decrease in exchange rate by 1.748 units therefore it can be concluded that China's economy has a significant outflow for the import of oil. It is also found that the increase in trade balance and decrease in trade balance leads to a decrease in the exchange rate by 0.003 units and 0.0001 units respectively. Moreover, it is also unusual to find out a case of linear relationship but in this case, we have found a linear relationship among the exchange rate of the Chinese Yuan against US Dollars and the Gold Price. The increase in gold price decrease the exchange rate by 0.00089 units and a decrease in the Gold price of one unit increases the exchange rate by 0.00089 units.

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**
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
GP–POS	–0.00089	0.0003	–2.2894**
GP_NEG	–0.00089	0.0003	–2.2410**
F-Statistics	79.738	*R*-Squared	0.9724
Bound Test	3.0793	I0 Bound: 1.83	I1 Bound 2.94
Diagnostic Tests		*P*-Value	
Breusch-Godfrey Serial Correlation LM Test		0.8205	
Heteroscedasticity Test: Harvey		0.1395	
RESET Test		0.6200	

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

The *F*-statistics show a value of 79.378 with a significant *p*-value. It is important to explain that the authors have dropped the Interest rate and money growth base rate because due to the integration of the above-mentioned explanatory variables, the assumptions of NARDL were not fulfilling. Table 4 also shows the values of diagnostic results. All three tests' insignificant values indicate that there is no issue of serial correlation & heteroscedasticity in the data set. Furthermore, the RESET test also shows the fitness of the model for the analysis.

Table 5 illustrates the results of accuracy of individual models i.e. ARIMA, Exponential Smoothing, Naïve, and NARDL. The results indicate that the Naïve model outperforms all individual models with the MAPE value of 0.715. The second-best model is NARDL with the MAPE value of 1.246 which outperforms the ARIMA and Exponential smoothing model. The superiority of Naïve provides evidence that the exchange rate of the Chinese Yuan against the US Dollar mainly emphasizes the recent observations.

By combining different individual models, the results of Table 5 show that the optimal model for forecasting exchange rate under equal weightage model is the combination of NARDL and Naïve model via two-ways combination. The MAPE value of the combination of the Naïve and NARDL model is 0.98, 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.

Furthermore, Table 5 represents individuals' combination by integrating the var-cor method. 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 than all other combinations of models i.e. 0.764. The authors also found stability by running the CUSUM and CUSUMQ criteria as shown below figure which indicates that the model is stable at 5% significance.

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 by various techniques. The best model is the Naïve model which individually outperforms all individuals and a combination of different techniques under equal weightage method and var-cor method with the least MAPE value of 0.715 during the tenure of Covid-19. It is also noticeable that combination of models as suggested by Poon and Granger (2003) plays a vital role in forecasting as the combination of Naïve and NARDL model has outperformed all combinations and individual models forecasting except

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

Individual	**AR**	**N**	**ES**		**ND**	
	2.521	0.715	1.484		1.246	
Equal Weightage Method	**Two-Way Combinations**					
	AR-ES	**AR-N**	**AR-ND**	**ES-N**	**ES-ND**	**N-ND**
	2.002	1.618	1.883	2.199	1.365	0.98
	Three-Ways Combination				**Four-Way Combination**	
	AR-ES-N	**AR-ES-ND**	**ES-N-ND**	**AR-N-ND**	**AR-N-ES-ND**	
	1.573	1.750	1.148	1.494	1.4914	
Var-Cor Method		**Two-Way Combinations**				
	AR-ES	**AR-N**	**AR-ND**	**ES-N**	**ES-ND**	**N-ND**
	2.342	1.0762	1.2532	1.218	1.388	0.764
	Three-Ways Combination				**Four-Way Combination**	
	AR-ES-N	**AR-ES-ND**	**ES-N-ND**	**AR-N-ND**	**AR-N-ES-ND**	
	1.638	1.577	1.089	0.984	1.232	

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

the Naïve model, therefore, it also validates the decision of authors to introduce NARDL for the forecasting of the exchange rate during Covid.

4.2. Discussion

This study aims to forecast the exchange rate of the Chinese Yuan versus the US dollar by the proposed method of Poon and Granger (2003), i.e., combining different individual models, under the tenure of Covid. For this purpose, the authors include three uni-variate time series models, i.e., ARIMA, Naïve, Exponential smoothing model & 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. It is also an addition to the literature as the authors forecast the above-mentioned exchange rate for the first time during the Covid-19 pandemic by combining a unique set of univariate and multivariate techniques with the focus of assumption of non-linearity. The authors applied two techniques to avoid biases, i.e., equal weight and var-cor.

The data of the Chinese Yuan against the US Dollar has been taken from M1 2011 to M12 2020. The results proved the selection of authors' right, i.e., NARDL & Naïve under var-cor combination outperforms all remaining individual models, i.e., ARIMA, Naïve, and exponential smoothing except individual Naïve model. On the other hand, the Naïve model is counted as the most optimal model with a MAPE value of 0.715. It means the Chinese Yuan exchange rate against the US Dollar is dependent upon the recent observations of the time series during the tenure of Covid-19. Further evidence shows that the combination of models plays a vital role in forecasting, as stated by Poon and Granger (2003). The findings will be helpful for the concerned authorities to make their policies accordingly as it has been declared from resources that Covid will have to be us for an undefined time period therefore we may face lockdowns and recession in the future too. Due to the above reason, such findings may play a vital role for Chinese economists and policymakers.

5. Conclusion and Limitations

In short, this paper focuses on two objectives. First, testing efficiency of the combination of univariate time series models and nonlinear autoregressive distributive lag model for the first time. Second, to find out the accuracy of different individual and combination of models in the context of the forecasting exchange rate of Chinese Yuan against the US Dollar during the tenure of covid. The authors concluded that the combination of NARDL and Naïve outperforms other combinations which supports the selection of the NARDL model in this study, however; Naïve outperforms all individual and combination of models.

It is recommended by the authors that the exchange rate of the Chinese Yuan against the US dollar depends upon the recent observations, however, the macro-economic fundamentals have also an effect on the exchange rate. The findings provide evidence that the Chinese government has spent on gold under proper protocols & uniform policies, therefore, it shows a linear relationship. The oil price also plays a vital role in determining the equilibrium of exchange rate, however, the impact of the trade balance on the exchange rate is inconclusive. The reason behind inconclusive behavior is maybe the inflow or outflow relevant to gold transactions which may be counted in the trade balance. Therefore, the investors or FOREX market should emphasize these factors before taking any decision. This study is relevant to the Chinese Yuan exchange rate against the US Dollars under the Covid, The future researchers may test other time series by employing this framework or criteria or include other important statistical techniques.

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