Predicting Foreign Exchange Rates Using ARIMA

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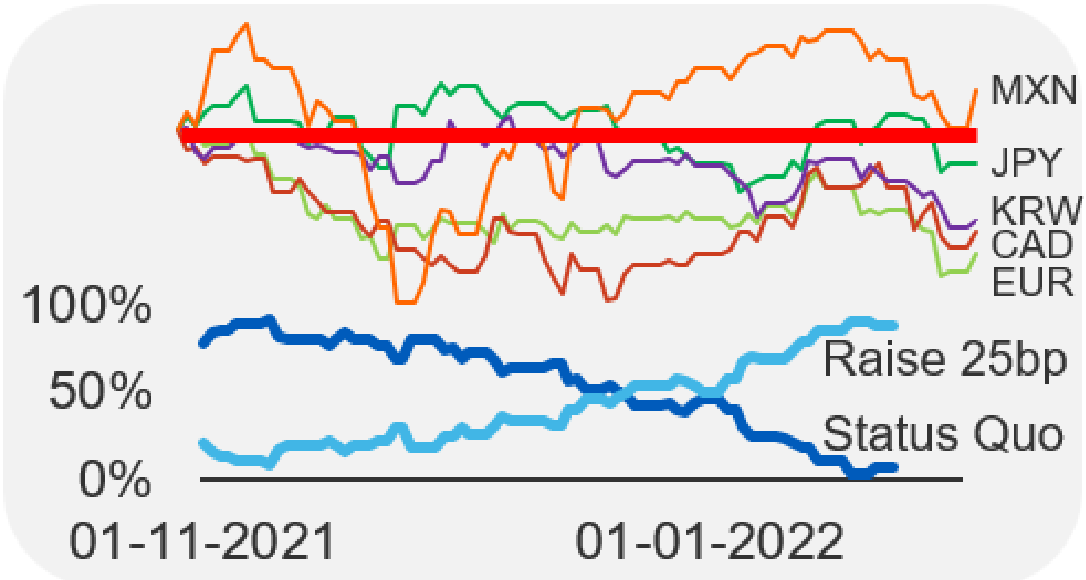

Fig. 1. Foreign Exchange Rates.

In this project, our main objective is to predict foreign exchange rates as accurately as possible. We select appropriate time-series analysis model after explanatory data analysis step and apply the model to our data. We perform data preprocessing not only for the consistency among foreign exchange rates but also for the purpose of converting the original data into stationary data. Considering our data sets matches univariate ARIMA, we implement several univariate ARIMA. In addition, another objective is to deliver our EDA process and forecasting results via R Shiny App that accommodates users by providing easy user interface. The only thing users need to do is to select currency and forecasting time span. Due to data suitability, we use univariate ARIMA. However, for more accurate forecasting, monetary policy variables and other real economic variables should be included in our model, which will be our future works.

Additional Key Words and Phrases: Foreign Exchange Rates, ARIMA, R Shiny, Akaike Information Criterion (AIC), DF Test

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1 INTRODUCTION

Foreign Exchange rates (from now on, FX rates) play a significant role in various economic activities by affecting transaction conditions. Therefore, it is essential for an agent from individual travelers to big companies which engage in various international trades to predict FX accurately [4] [5]. Considering that FX is determined mainly by its demand and supply associated with international trades and the primary key currency is USD, we set and test diverse time-series models for the United States and its major trade partners and find which model setting best predicts the future movements of FX rates. The countries we are interested in have monthly trade records with the United States exceeding $10 billion and 'floating rates system': Canada, Mexico, Euro Zone, Japan, and South Korea. China is excluded due to the government's intervention in the FX market, even if it is one of the biggest trade partners of the United States.

In this regard our main goal is to find models which successfully predict the future movements of the five FX rates. To achieve it, first, the original data is checked through EDA process so that a model suitable for the time-series analysis can be selected. Subsequently, the results and forecasts of the time series analysis model are derived. Lastly, the results of this project will be implemented on the R Shiny App so that users can easily access and use them.

2 METHOD

2.1 Data Source

we got FX dataset from Yahoo Finance and only considered data on business day. And Then, we used Jupyter Notebook to use Python API to get the average monthly FX.

2.2 Software Description

The software we used R Shiny Package. The Shiny package is useful tool for creating easy interactive web applications in R. It allows for a better data visualization by creating dashboards, data reports, and a bunch of visual plots. Just like any other web application, Shiny allows the usage of HTML elements to customize the different components of the webpage. One of the major advantages of Shiny is that we can create a web application without the knowledge of CSS, HTML or Javascript. Shiny uses R programming to handle its client-side and server-side functionalities. The client side (UI) controls what components are displayed and allow for user interaction. The server side controls the data and backend functionalities such as data loading, data wrangling and communicating with the UI. The Shiny server side makes use of Reactive programming paradigm which allows the automatic update of UI output when an input is changed.

2.3 Method used

We used AUTO-ARIMA and RSHINY package given in RStudio. In case of AUTO ARIMA package, after loading necessary dataset, we preprocessed the data first. And then, we fit our dataset to ARIMA model, and forecast the target variable with our ARIMA model. In terms of RShiny App, we used 'library(shiny)' to use a user interface object, a server function, and a call to the shinyApp. we used function to use both given interface and server in shiny pacakge with a preprocessed dataset. we defined 'ui' as the interface, and 'server' as the server, and then called 'shinyApp(ui = ui, server = server)' to run RShiny.

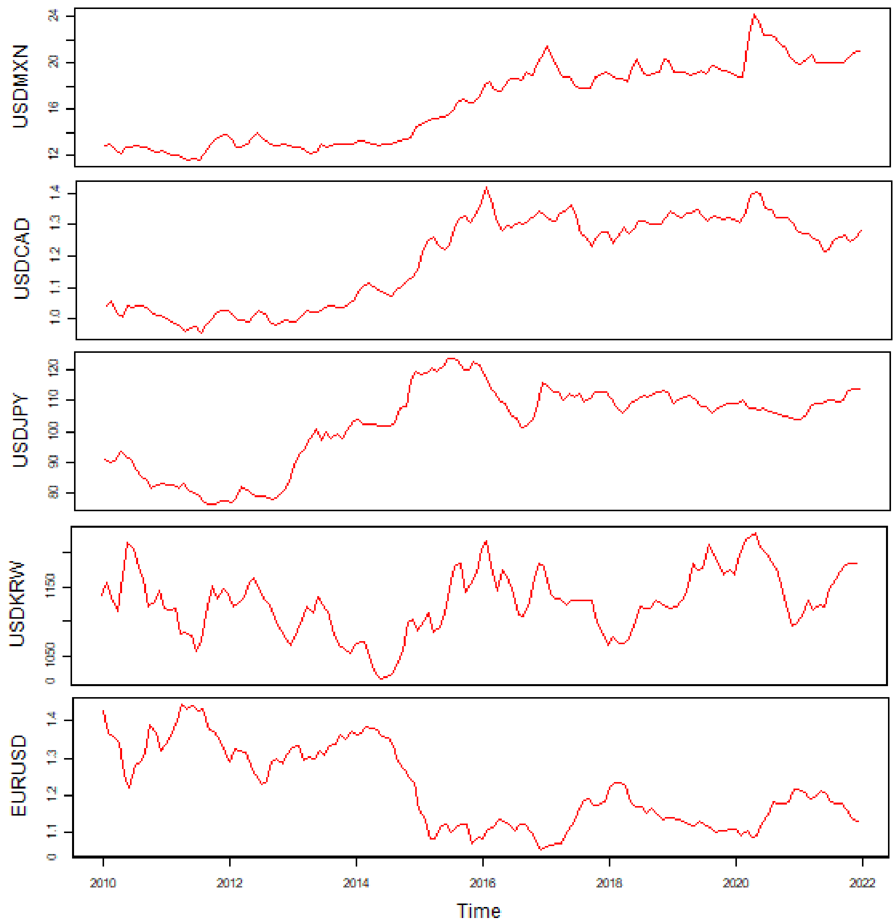

Fig. 2. The long-term time-series of the five FX rates.

2.4 Time-series analysis: Stationarity Check, ARIMA

For time-series data to be inputs of time-series analysis models, they must be stationary. In addition, several time-series can be cointegrated each other, which can cause a spurious regression. Since FX rates are defined in terms of US dollar and for this reason, there exists co-movement between them. Considering the existence of cointegration, the multivariate time-series analysis does not seem to be desirable. Specifically, it can be found that all currencies are depreciated against US dollar from 2014 to 2016 and appreciated from 2016 to 2017 as seen in 2). Note that only is EURUSD denominated as the value of US dollar in terms of EU, which means that the value of EUR can be understood inversely compared to the other currencies. In this project, univariate ARIMA models are applied due to the aforementioned reason.

In univariate ARIMA, autoregressive order, moving average order, and time difference are determined so that the Akaike Information Criterion value become the minimum among several combinations. Since the non-stationarity found in (partial) autocorrelation function graph in all FX rates is considerably alleviated by the first time-difference as in 3 and **??**, the univariate ARIMA models in this project takes the first order time difference in common. If there exists

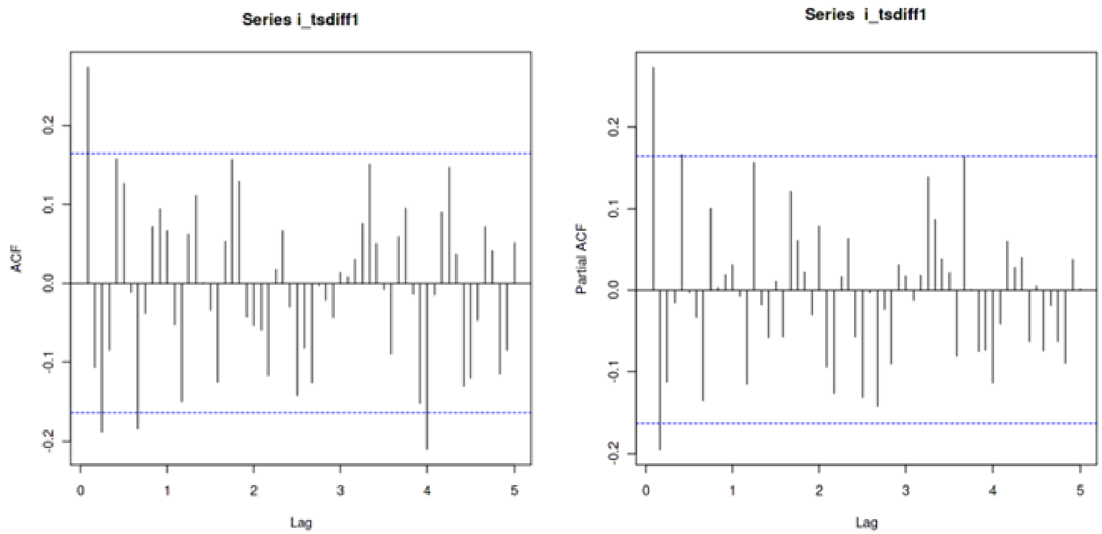

Fig. 3. Autocorrelation Function Example (USDCAD).

a unit root in given time-series, an ARIMA cannot be applied to the data. As such, it is necessary for the data to be free from unit root problem before applying ARIMA. If the first order time difference is valid, the null hypothesis of augmented Dickey-Fuller test is highly likely to be rejected. Before the first order time difference, the augmented DF test p-value for USDCAD is 0.835, which indicates the null hypothesis (there exists unit root) is not rejected whereas after the first order time difference applied, the p-value of the test becomes 0.01. In the same way, the univariate ARIMA models for the other FX rates are fitted to each data set after the first order time difference. For AR and MA orders, it appears that each FX rate has a different optimal AR and MA order. From the estimated univariate ARIMA models, the forecasts for each FX rate is provided later in this report.

3 RESULTS AND DISCUSSION

The results of multiple univariate analysis of various forex rates are as follows. The ARIMA models have predicted the forex rates for 12 months for each currency.

```
Series: i_ts
ARIMA(1,1,2)

Coefficients:
         ar1      ma1      ma2
      0.8533  -0.5697  -0.4150
s.e.  0.0591   0.0888   0.0757

sigma^2 estimated as 317.5:  log likelihood=-614.02
AIC=1236.03   AICc=1236.32   BIC=1247.88
```

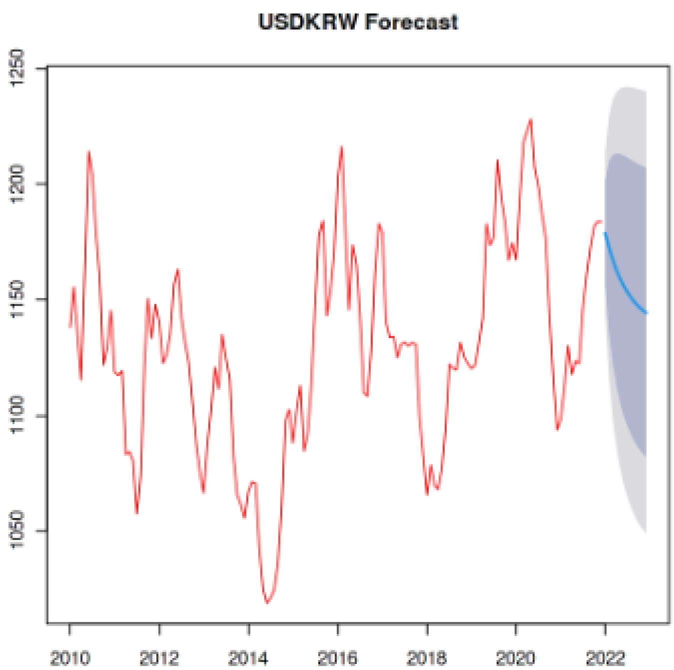

Fig. 4. 12 Month forecast for USDKRW.

```
Series: i_ts
ARIMA(1,1,1)

Coefficients:
          ar1     ma1
      -0.6357  0.7908
s.e.   0.2310  0.1853

sigma^2 estimated as 0.2439:  log likelihood=-101.06
AIC=208.13   AICc=208.3   BIC=217.02
```

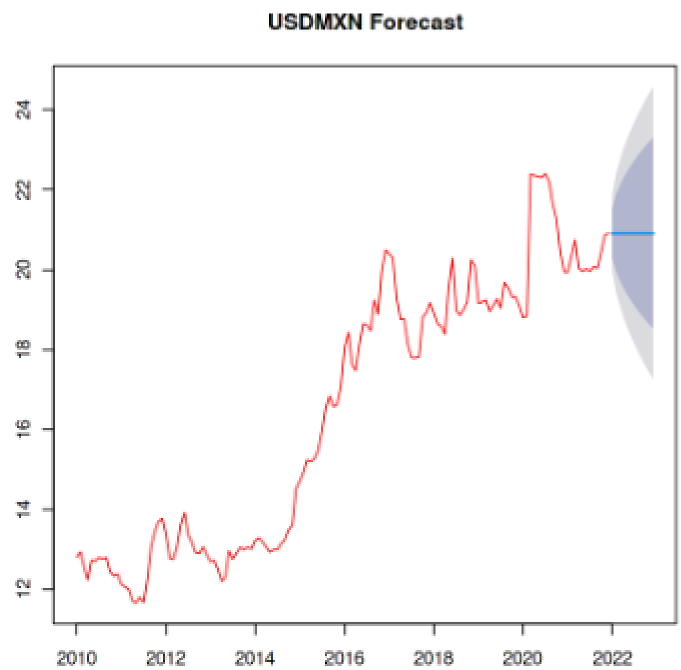

Fig. 5. 12 Month forecast for USDMXN.

```
Series: i_ts
ARIMA(1,1,0)

Coefficients:
         ar1
      0.2356
s.e.  0.0829

sigma^2 estimated as 0.0005329:  log likelihood=336.48
AIC=-668.95   AICc=-668.87   BIC=-663.03
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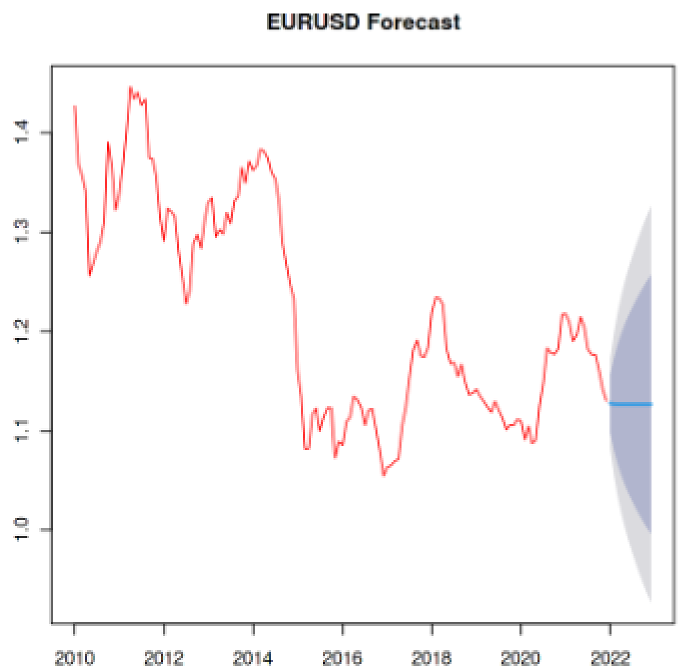

Fig. 6. 12 Month forecast for EURUSD.

```
Series: i_ts
ARIMA(2,1,2)

Coefficients:
         ar1      ar2      ma1     ma2
      0.6714  -0.8192  -0.4331  0.6618
s.e.  0.1050   0.1294   0.1514  0.1716

sigma^2 estimated as 0.0003564:  log likelihood=366.54
AIC=-723.08   AICc=-722.65   BIC=-708.27
```

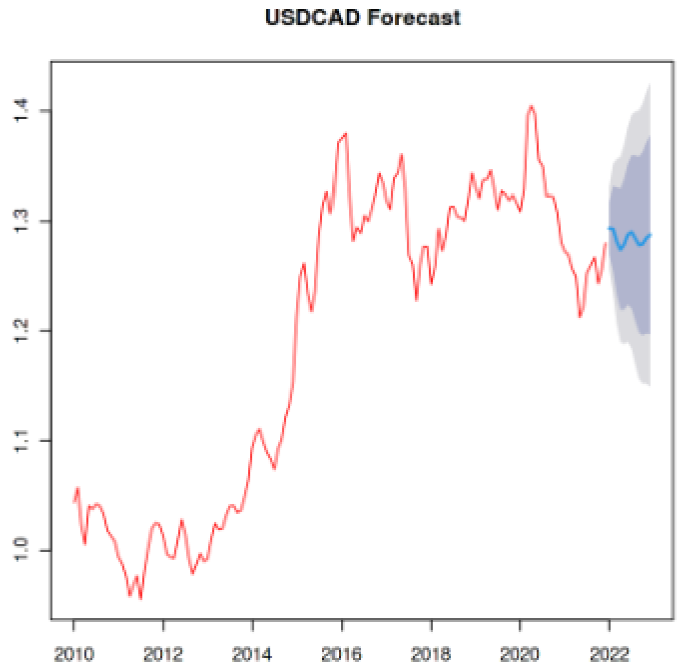

Fig. 7. 12 Month forecast for USDCAD.

```
Series: i_ts
ARIMA(2,1,0)(1,0,0)[12]

Coefficients:
         ar1     ar2    sar1
      0.2516  0.1303  0.1866
s.e.  0.0826  0.0828  0.0829

sigma^2 estimated as 3.742:  log likelihood=-296.02
AIC=600.04   AICc=600.33   BIC=611.89
```

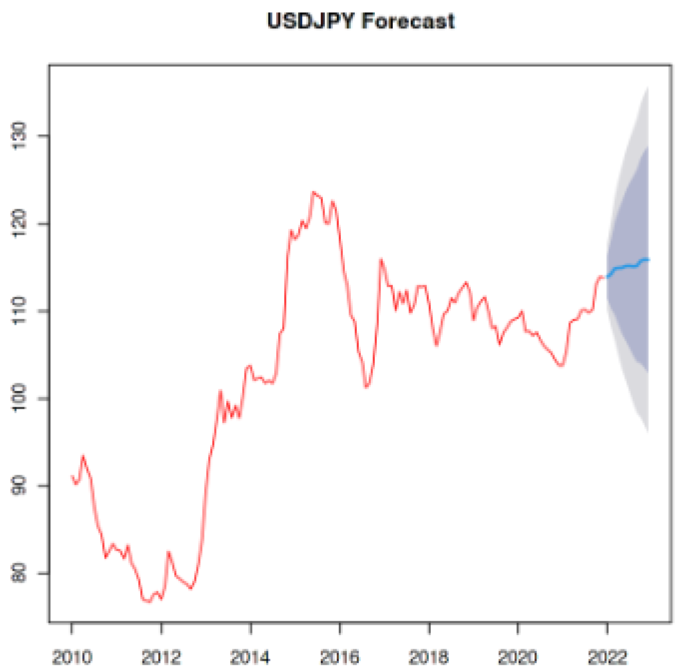

Fig. 8. 12 Month forecast for USDJPY.

Each original foreign exchange rate shows different stochastic process. As such, each one is converted into a stational process in the different ways. To be specific, Korean won does not have a long-term trend (depreciation) while the others has either a long-term trend or drift terms from the plots of the original time-series. That is, Korean won fluctuated around the long-term mean unlike the others. In addition, all univariate ARIMA are different from each other. Japanese Yen has seasonal ARIMA autoregressive order, which is not the case of others. However, all models include i=1, which matches the fact that the existence of unit root in each augmented Dickey-Fuller test is not rejected under the 5% significance level in our analysis. After first-differentiation of each original time-series, all unit root tests reject the existence of unit root. From the estimated univariate ARIMA models, Canadian dollar and Korean won are expected to be appreciated in the short run (over the next 3 month). On the other hand, Japanese yen is predicted to be slightly depreciated against US dollar in the same period. If the forecast period is increased to 12 months, Korean won is still expected to be stronger while Canadian dollar becomes neutral. The Japanese yen is expected to slowly weaken not only in the same short term but also over the next 12 months. For the other foreign exchange rates, it is predicted that there will be no up-and-down fluctuations for all time-horizon. Even the Korean won is expected to stop its bullish trend against the U.S. dollar from early next year. The Euro and Mexican Peso, as seen in the forecast plots, follows a steady non-seasonal pattern.

4 CONCLUSION

This project discusses the motivation behind study and forecasting of Foreign Exchange rates. The data exploration focused on understanding the temporal trends of several currencies with respect to the US Dollar. The limitation of the initial data to apply auto regressive models is resolved by a first order differencing and validated using ACDF tests. Univariate ARIMA models are used to forecast the future forex prices and they have provided a good estimate of the forex rates. Based on the analysis of the data that contains little data from 2022, once the predicted results are compared with the actual exchange rate flows in 2022 and evaluated, the exchange rate against all the dollars is weak from the beginning of this year. This suggests that it is necessary to try multivariate ARIMA along with exogenous variables that explain the strength of the U.S. The variables discussed in the data exploration such as inflation rate, 3 MT Bill rate can be integrated in the multivariate ARIMA models to provide a more accurate forex rate. On the contrary, various theories such as Random Walk theory [3] have argued that financial market prices are volatile and are unpredictable since the historical data is not relevant to the present. For future works, both the avenues, multi variate analysis and random walk literature[1], can be given importance to find better results. Recently various Deep learning techniques such as Recurrent Neural Networks and Autoencoders-LSTM models have shown promising results in the forecasting [2].

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