A Time Series Approach for Interest Rate Forecasting - DFCU

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1 The First Task - A Univariate Approach for 6-Month LIBOR

The following document contains a description of the time series models researched and implemented with regards to predicting future rates for DFCU (6-Month LIBOR in this regard). Monthly data was received from July 2011 to November 2020. The focus, at this moment, is to use these historical 6-Month LIBOR rates provided by DFCU, to forecast three months into the future, that is, forecasting rates for December 2020, January 2021, and February 2021. If these rates are received, the model will automatically update to provide forecasts for the next quarter (which at this moment will be unknown). This task is particularly difficult since interest rates mainly arise from two features that characterize their evolution over time. First, like other financial variables, interest rates vary widely from day to day, which make them difficult to link to economic fundamentals such as monetary or fiscal policy. Second, as evident from the 10-year US Treasury yields since 1971, interest rates have not fluctuated around a stable average level over this period. Instead of "mean reversion" around a constant average, they exhibit slow-moving trends, such as the rise during the "Great Inflation" period of the 1970s, and the long-lasting decline since then.

At this moment in time, the data from DFCU is greatly influenced by the COVID-19 pandemic. This increases the difficulty of this task and caution should be taken when future rates are predicted. This document will include a description of the 6-Month data as well as a practical implementation of four traditional time series models including a deep learning model. These are; Auto Regressive Integrated Moving Average (ARIMA), Facebook's Prophet, the Holt-Winters Triple Exponential Smoothing, and a Recurrent Neural Network with Long Short-Term Memory (LSTM).

1.1 The 6-Month LIBOR Data

The data was split into a training and test set where the training data is all the data from 2011 including 2020-08-01 meaning that the test set only takes on three months (one quarter). Table 1 and Table 2 provides the split. A graph of the movement over time based on 6-Month LIBOR is provided in Figure 1. A description of the data is given in Table 3. **The steep drop in LIBOR from 2019 to 2020 should be noted, as this is considered an extreme event. Modelling this will be tricky as traditional time series models will assume that the trend will jump into a negative direction**.

Table 1: 6-Month LIBOR Training Data (Most Recent)

Date	Rate
2020-04-01	1.20
2020-05-01	1.20
2020-06-01	0.71
2020-07-01	0.38
2020-08-01	0.27

Table 2: 6-Month LIBOR Test Data

Date	Rate
2020-09-01	0.27
2020-10-01	0.27
2020-11-01	0.27

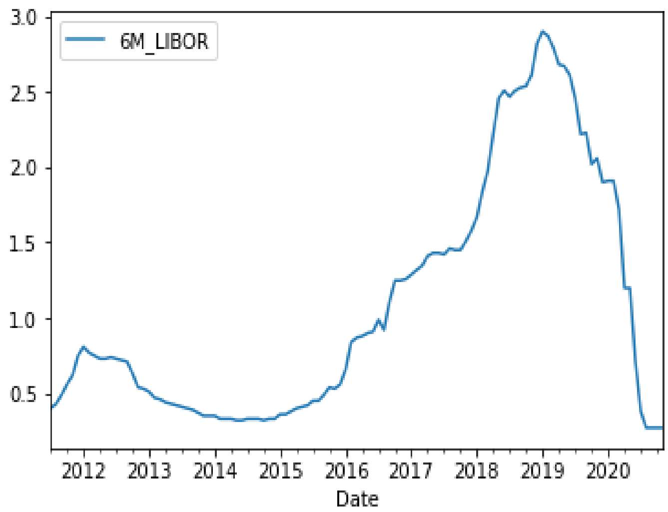

Figure 1: 6-Month LIBOR.

Table 3: 6-Month LIBOR Data Description

Description	Value
count	113
mean	1.08
std	0.80
min	0.27
25%	0.41
50%	0.74
75%	1.51
max	2.90

1.2 The ARIMA Model

Information on this model can be found at `https://otexts.com/fpp2/non-seasonal-arima.html`. Essentially, this model is a combination of an autoregression and a moving average model that takes on no seasonality component. It is important to understand that the ARIMA is not capable of perfectly predicting any time series data. It is merely a starting point in any time series forecasting. ARIMA models are applied in some cases where data show evidence of non-stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied one or more times to eliminate the non-stationarity. Non-seasonal ARIMA models are generally denoted $ARIMA(p, d, q)$ where parameters p, d, and q are non-negative integers.

The $AR(p)$ part is a regression model that utilizes the dependent relationship between a current observation and observations over a previous period. The $I(d)$ (integrated) part is a differencing of observations (subtracting an observation from an observation at the previous time step) in order to make the time series stationary. The $MA(q)$ part is a Moving Average model that uses the dependency between an observation and a residual error from a moving average model applied to lagged observations. It is important in this case to understand that a stationary series has constant mean and variance over time and will allow our model to predict that the mean and variance will be the same in future periods. The values for p, q, and d was chosen from a grid-search done by the *pmdarima* package in python. The model chosen was $ARIMA(1, 1, 4)$ and thereafter was run on the training data and forecasted on the index values of the test data. The following output for the three months forecasted into the future, was obtained in Table 4.

Table 4: ARIMA Prediction

Date	Test data	Prediction
2020-09-01	0.27	0.160134
2020-10-01	0.27	0.017678
2020-11-01	0.27	0.132234

1.3 The Facebook Prophet Model

Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well. More information can be obtained at `https://peerj.com/preprints/3190/`. The following output for the three months forecasted into the future, was obtained in Table 5. This model did not do well (refer to the Figure 2). The model focuses too much on trying to predict the trend. Which is extremely difficult in the case of the steep drop in LIBOR from 2019.

Table 5: Facebook Prophet Prediction

Date	Test data	Prediction
2020-09-01	0.27	2.240117
2020-10-01	0.27	2.235745
2020-11-01	0.27	2.247882

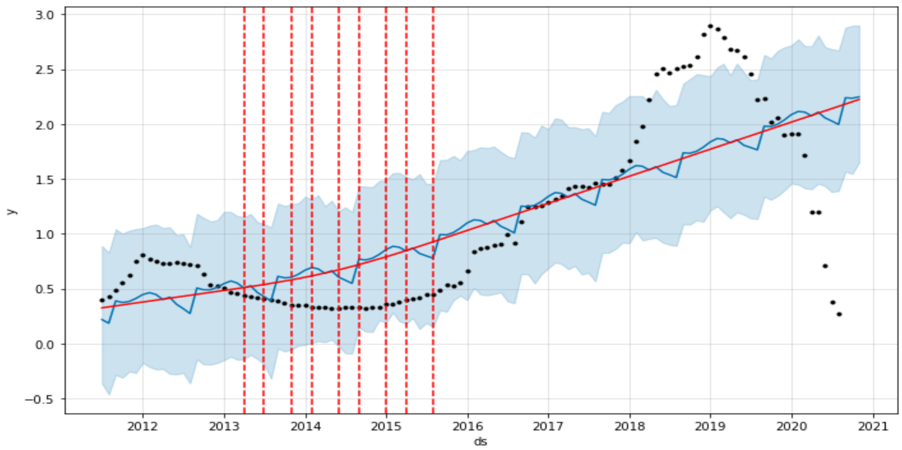

Figure 2: Facebook Prophet Prediction for 6-Month LIBOR.

1.4 Holt-Winters Triple Exponential Smoothing

In Double Exponential Smoothing (aka Holt's Method) a smoothing factor, β, is introduce that addresses trend.

$l_t = (1-\alpha)l_{t-1} + \alpha x_t$ =level
$b_t = (1-\beta)b_{t-1} + \beta(l_t - l_{t-1})$ =trend
$y_t = l_t + b_t$ =fitted model
$\hat{y}_{t+h} = l_t + hb_t$ =forecasting model (h = periods into the future)

This forecasting model is simply a straight sloped line extending from the most recent data point. With Triple Exponential Smoothing (the Holt-Winters Method) a smoothing factor γ, is introduced that addresses seasonality.

$l_t = (1-\alpha)l_{t-1} + \alpha x_t$ =level
$b_t = (1-\beta)b_{t-1} + \beta(l_t - l_{t-1})$ =trend
$c_t = (1-\gamma)c_{t-L} + \gamma(x_t - l_{t-1} - b_{t-1})$ seasonal $y_t = (l_t + b_t)c_t$ =fitted model
$\hat{y}_{t+m} = (l_t + mb_t)c_{t-L+1+(m-1)modL}$ =forecasting model (m = periods into the future)

Here L represents the number of divisions per cycle. In our case we would use $L = 12$. In general, higher values for α, β and γ (values closer to 1), place more emphasis on recent data (**this is particularly important in our case, as a stronger emphasis will be placed on the data from 2019 to 2020**). More information on this model can be found at `https://otexts.com/fpp2/holt-winters.html`. Figure 3 indicates the way in which this model is following and forecasting the trend from the 6-Months LIBOR data (based on the additive and multiplicative methods). Table 6 provides forecasted values based on this model for the test set, and Table 7 provides forecasted values three months into the future (unseen data).

Table 6: Holt-Winters (Multiplicative) Prediction on the Test set

Date	Test data	Prediction
2020-09-01	0.27	0.274660
2020-10-01	0.27	0.269524
2020-11-01	0.27	0.274978

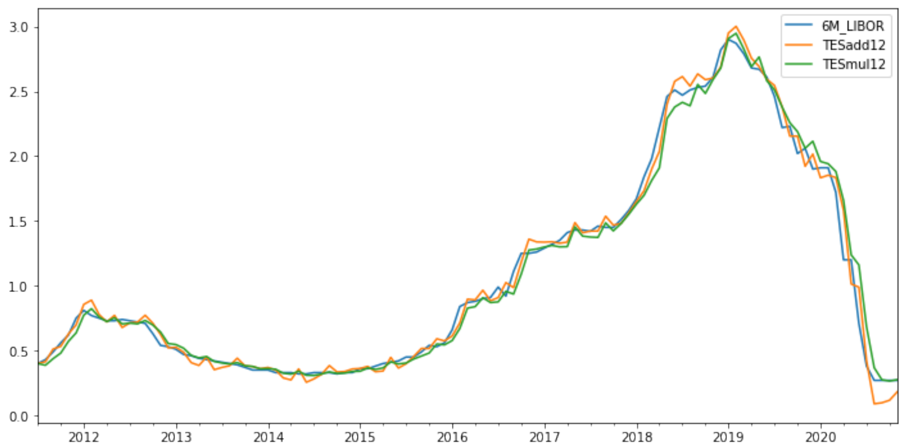

Figure 3: Holt-Winters for 6-Month LIBOR.

Table 7: Holt-Winters (Multiplicative) Future 3-Months Forecasts

Date	Rate
2020-12-01	0.277171
2021-01-01	0.285714
2021-02-01	0.290362

1.5 Recurrent Neural Network with Long Short-Term Memory (LSTM)

A basic RNN (`https://builtin.com/data-science/recurrent-neural-networks-and-lstm`) has a major disadvantage, such that it only really "remembers" the previous output. This is remedied by a LSTM process. A short explanation of this model can be found at `machinelearningmastery.com/gentle-introduction-long-short-term-memory-networks-experts`.

Two models were deployed, one with 175 neurons and another with 200 neurons. Table 8 provides an output of the 175 neuron case and Table 9 provides an output of the 200 neuron case.

Table 8: RNN (175 Neurons) Prediction on the Test set

Date	Test data	Prediction
2020-09-01	0.27	0.470922
2020-10-01	0.27	0.366758
2020-11-01	0.27	0.293778

Table 9: RNN (200 Neurons) Prediction on the Test set

Date	Test data	Prediction
2020-09-01	0.27	0.335195
2020-10-01	0.27	0.225997
2020-11-01	0.27	0.150152

2 To Do

Give mathematical descriptions of each model and provide outputs based on 3-Month future forecasts for each model. ~~Compare these models maybe to short-term interest rate models such as Black-Derman-Toy and Cox-Ingersoll-Ross~~. Choose the best time series model (it looks like the Holt-Winters method and the RNN-LSTM). Calculate RMSE values for each of the model (although we can logically see which model performs better than others, for instance the RNN-LSTM is doing much better than Facebook's Prophet model, therefore the top two models by inspection is Holt-Winters and the RNN-LSTM). Build a GUI. ~~Build multivariate time series models (Vector Autoregression (VAR), VARMA, RNN-LSTM) to forecast Interbank, Prime, Central Bank, and 6-Month TBill rates to include their intercorrelations (once a model has been chosen for forecasting 6-Month LIBOR). Consider short-term interest rate models in this case also~~. ~~Do additional forecasting for the other deposit and lending rates~~.

An interesting article to consider for univariate time series analysis: `https://thenewstack.io/when-holt-winters-is-better-than-machine-learning/`

2.1 Cox-Ingersoll-Ross

The following output, in Table 10, was obtained from Rebecca Herbert. This output is based on a Cox-Ingersoll-Ross model that was applied to the 6-Month LIBOR dataset. Clear indication that the model is not forecasting these values properly, and therefore Black-Derman-Toy will not be considered.

Table 10: Cox-Ingersoll-Ross Prediction on the Test set

Date	Test data	Prediction
2020-09-01	0.27	1.196087
2020-10-01	0.27	1.195116
2020-11-01	0.27	1.194142

2.2 A Segmentation Approach

The following output, in Table 11, was obtained from Teboho Morule. This output is based on a segmentation model that was applied to the 6-Month LIBOR dataset. Clear indication that the model is not forecasting these values properly, and therefore will not be considered.

Table 11: A Segmentation Approach on the Test set

Date	Test data	Prediction
2020-09-01	0.27	2.186
2020-10-01	0.27	2.210
2020-11-01	0.27	2.235

3 A Multivariate Approach

Monthly data was received from July 2011 to November 2020. The focus now is to use these historical Interbank, Prime, Central Bank, and 6-Month TBill rates provided by DFCU, to forecast three months into the future, that is, forecasting these rates for December 2020, January 2021, and February 2021. If these rates are received, the model will automatically update to provide forecasts for the next quarter (which at this moment will be unknown). The models that would be considered is: VAR, VARMA, and RNN-LSTM.

3.1 The Data

The data was split into a training and test set where the training data is all the data from 2011 including 2020-08-01 meaning that the test set only takes on three months (one quarter). Figure 1 displays these rates. Figure 2 displays the intercorrelations between these variables. Table 12 provides a description of the data. Table 13 and Table 14 provides the data split.

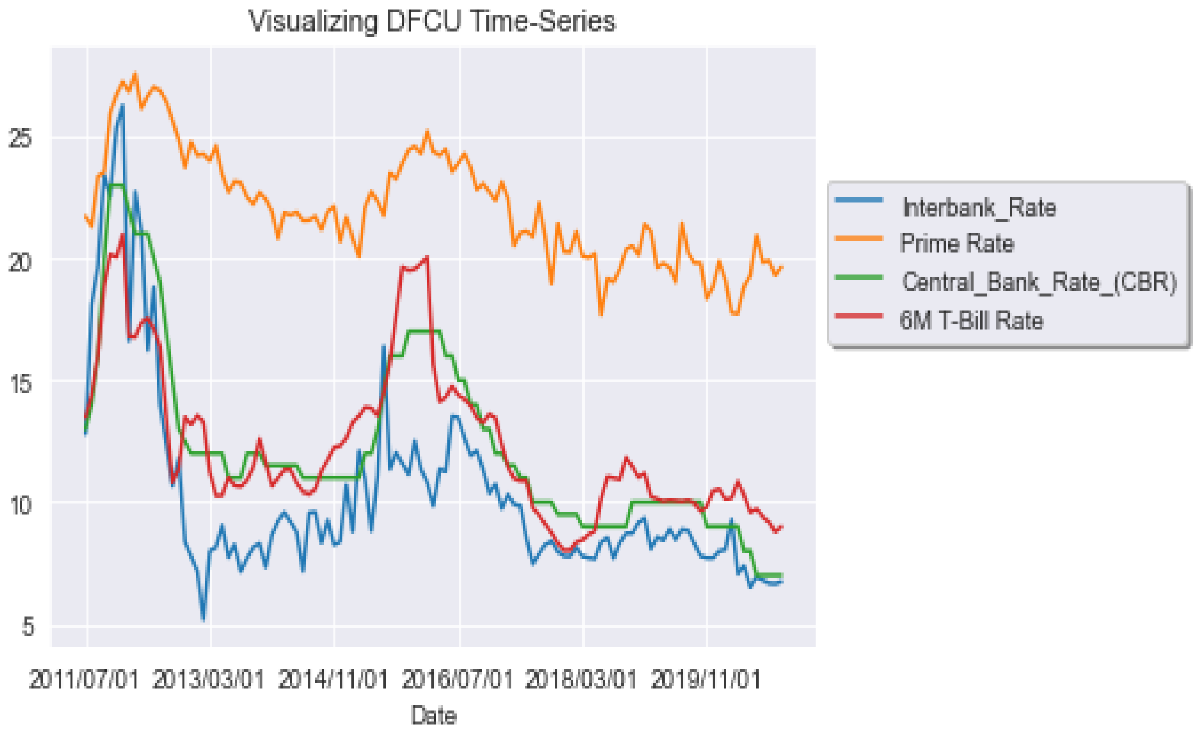

Figure 4: Multivariate Interest Rates.

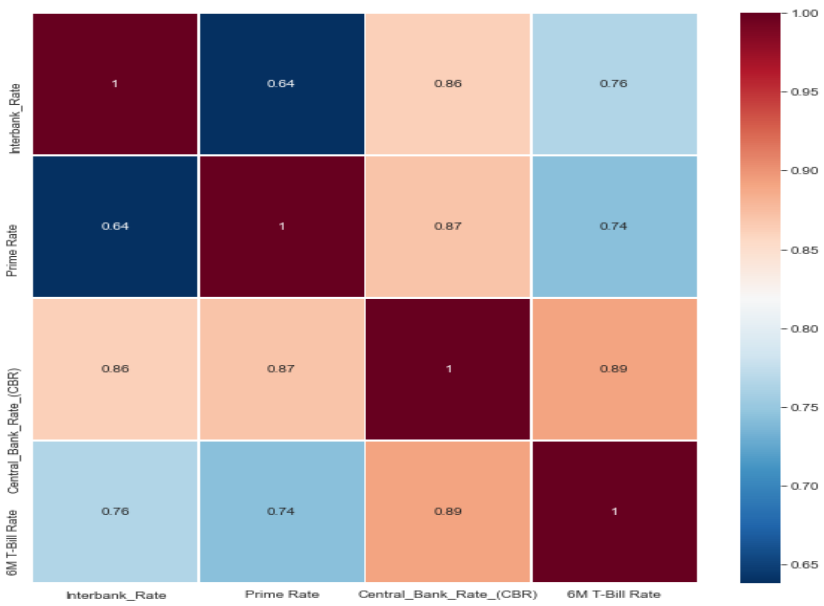

Figure 5: Correlation Matrix.

Table 12: Data Description

Description	Interbank Rate	Prime Rate	Central Bank Rate	6-Month T-Bill Rate
count	113	113	113	113
mean	10.36	22.10	12.35	12.40
std	4.09	2.33	3.765	3.14
min	5.19	17.68	7.00	8.02
25%	7.99	20.23	10.00	10.17
50%	8.82	21.87	11.50	11.29
75%	11.33	23.71	14.00	13.85
max	26.27	27.58	23.00	20.98

Table 13: Training Data (Most Recent)

Date	Interbank Rate	Prime Rate	Central Bank Rate	6-Month T-Bill Rate
2020-04-01	7.06	17.73	9.0	10.85
2020-05-01	7.39	18.84	8.0	10.30
2020-06-01	6.51	19.30	8.0	9.58
2020-07-01	6.93	20.93	7.0	9.72
2020-08-01	6.80	19.84	7.0	9.40

Table 14: Test Data

Date	Interbank Rate	Prime Rate	Central Bank Rate	6-Month T-Bill Rate
2020-09-01	6.67	19.91	7.0	9.18
2020-10-01	6.65	19.30	7.0	8.78
2020-11-01	6.74	19.64	7.0	8.99

3.2 The RNN-LSTM Model

A RNN-LSTM model was deployed using 180 neurons and the results can be seen in Table 15. These values should be compared to the values in the test set as can be found in Table 14.

Table 15: Predictions: RNN-LSTM

Date	Interbank Rate	Prime Rate	Central Bank Rate	6-Month T-Bill Rate
2020-09-01	6.066124	19.692776	8.0	9.244319
2020-10-01	6.059742	19.781519	8.0	9.267845
2020-11-01	6.075719	19.843602	8.0	9.290086

3.3 The VAR Model

Information on the VAR model can be found at `https://online.stat.psu.edu/stat510/lesson/11/11.2`. A prediction output of the model is given in Table 16. These values should be compared to the values in the test set as can be found in Table 14.

Table 16: Predictions: VAR

Date	Interbank Rate	Prime Rate	Central Bank Rate	6-Month T-Bill Rate
2020-09-01	6.044104	19.455855	8.0	9.605679
2020-10-01	6.060990	19.391881	8.0	9.741250
2020-11-01	6.241085	19.420869	8.0	9.869946

3.4 The VARMA Model

The Vector Autoregression Moving-Average (VARMA) method models the next step in each time series using an ARMA model. It is the generalization of ARMA to multiple parallel time series, e.g. multivariate time series. The notation for the model involves specifying the order for the $AR(p)$ and $MA(q)$ models as parameters to a VARMA function, e.g. $VARMA(p,q)$. A VARMA model can also be used to develop VAR or VMA/VARMAX models. The method is suitable for multivariate time series without trend and seasonal components. A prediction output of the model is given in Table 17. These values should be compared to the values in the test set as can be found in Table 14.

Table 17: Predictions: VARMA

Date	Interbank Rate	Prime Rate	Central Bank Rate	6-Month T-Bill Rate
2020-09-01	6.858860	19.707892	7.0	9.250184
2020-10-01	6.606173	19.333609	7.0	9.389419
2020-11-01	6.579198	19.167993	8.0	9.646705

4 A Multivariate Approach - Excluding Central Bank Rate

Consider the following output whereby the CBR is excluded. The reason for this experiment is, that the CBR is an external variable for the bank and does not depend on the interbank or prime rate or Tbill (even though it is creating extreme correlations with these three variables which "could" influence the way in which these models do their predictions). The CBR usually depends on external macro-economic variables (such as long-term government bonds) and values for which we do not have data at the moment. However, it is still possible to forecast this value without this needed data due to historical trends. Therefore, this section will be a short experiment on whether or not the final model should be designed including or excluding this variable.

4.1 The RNN-LSTM Model

A RNN-LSTM model was deployed using 180 neurons and the results can be seen in Table 18. These values should be compared to the values in the test set as can be found in Table 14.

Table 18: Predictions: RNN-LSTM Excluding CBR

Date	Interbank Rate	Prime Rate	6-Month T-Bill Rate
2020-09-01	7.323246	19.969176	9.671943
2020-10-01	7.700356	20.122179	9.933665
2020-11-01	7.994509	20.280796	10.169930

4.2 The VAR Model

A VAR(1) model was deployed and the results can be seen in Table 19. These values should be compared to the values in the test set as can be found in Table 14.

Table 19: Predictions: VAR Excluding CBR

Date	Interbank Rate	Prime Rate	6-Month T-Bill Rate
2020-09-01	7.073730	19.829341	9.544920
2020-10-01	7.319932	19.858391	9.709154
2020-11-01	7.544031	19.917153	9.882817

4.3 The VARMA Model

A VARMA(1,2) model was deployed and the results can be seen in Table 20. These values should be compared to the values in the test set as can be found in Table 14.

Table 20: Predictions: VARMA Excluding CBR

Date	Interbank Rate	Prime Rate	6-Month T-Bill Rate
2020-09-01	7.758819	20.146652	9.592479
2020-10-01	7.468509	20.103655	9.748194
2020-11-01	7.470416	20.160939	9.937903

4.4 Comments

This approach does not provide satisfactory results.

5 The Other Rates

The remaining rates to model are: FCY-6-Month Fixed Deposits, LCY-6-Month Fixed Deposits, Demand Deposits, Savings Deposits, Demand Deposits-Foreign, Savings Deposits-Foreign, and Lending-Foreign. A Pearson-correlation analysis is applied to the matrix of these rates, and the output can be seen Figure 6. Clear indication that no two variables are highly correlated, however, Foreign Savings and Demand Deposit rates show correlation of > 0.5, which suggests that these rates could be modelled using a multivariate approach that captures this intercorrelation while the other rates could be modelled by several univariate approaches.

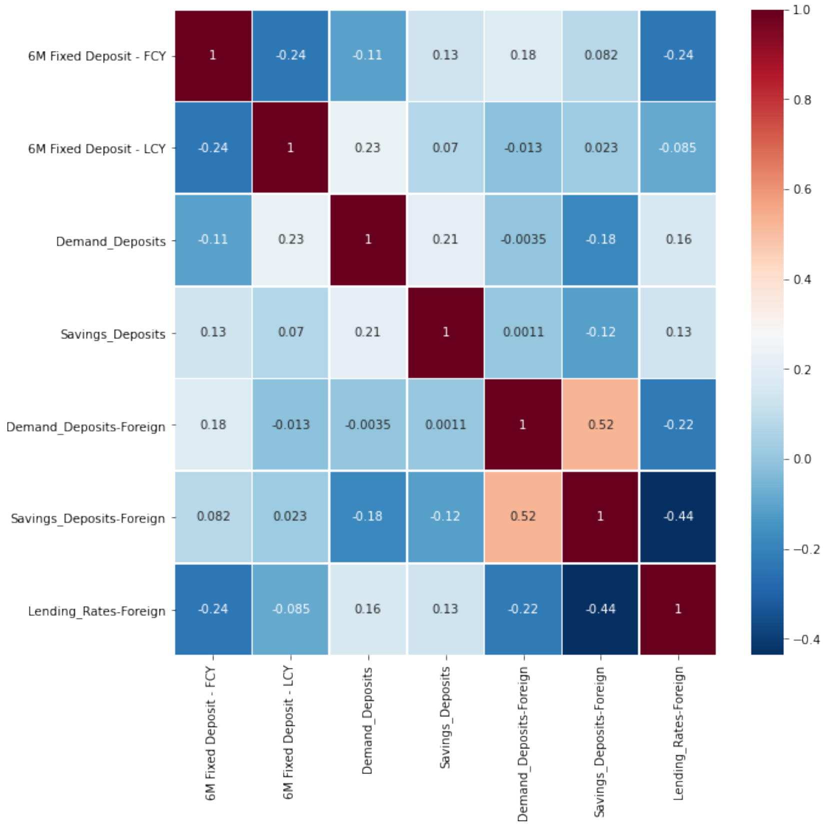

Figure 6: Correlation Matrix of the Other Rates.

5.1 A Multivariate Approach for Foreign Savings and Foreign Demand Deposit Rates

5.1.1 The Data

The data was split into a training and test set where the training data is all the data from 2011 including 2020-05-01 meaning that the test set only takes on six months (two quarters). Table 21 and Table 22 provides the split.

Table 21: Foreign Deposits Training Data (Most Recent)

Date	Demand Deposits-Foreign	Savings Deposits-Foreign
2020-01-01	1.016022	1.806707
2020-02-01	1.007826	1.837016
2020-03-01	1.003999	1.799879
2020-04-01	1.004470	1.797346
2020-05-01	1.000000	1.810000

Table 22: Foreign Deposits Test Data

Date	Demand Deposits-Foreign	Savings Deposits-Foreign
2020-06-01	0.999724	1.839378
2020-07-01	1.005567	1.782455
2020-08-01	1.006846	1.799005
2020-09-01	1.015677	1.798685
2020-10-01	1.019156	1.787105
2020-11-01	1.020000	1.800000

5.1.2 The RNN-LSTM Model

A RNN-LSTM model was deployed using 180 neurons and the results can be seen in Table 23. These values should be compared to the values in the test set as can be found in Table 22.

Table 23: Predictions: RNN-LSTM

Date	Demand Deposits-Foreign	Savings Deposits-Foreign
2020-06-01	1.000566	1.734244
2020-07-01	0.994543	1.687675
2020-08-01	0.988226	1.657951
2020-09-01	0.983216	1.638594
2020-10-01	0.979611	1.625870
2020-11-01	0.977128	1.617472

5.1.3 The VAR Model

A VAR(1) model was deployed and the results can be seen in Table 24. These values should be compared to the values in the test set as can be found in Table 22.

Table 24: Predictions: VAR

Date	Demand Deposits-Foreign	Savings Deposits-Foreign
2020-06-01	1.014664	1.779305
2020-07-01	1.016498	1.756580
2020-08-01	1.014226	1.739291
2020-09-01	1.011022	1.725948
2020-10-01	1.007966	1.715576
2020-11-01	1.005364	1.707485

5.2 A Univariate Approach for 6-Month Fixed Deposit - FCY

5.2.1 The Data

The data was split into a training and test set where the training data is all the data from 2011 including 2020-08-01 meaning that the test set only takes on three months (one quarters). Table 25 and Table 26 provides the split.

Table 25: FCY Training Data (Most Recent)

Date	FCY
2020-04-01	3.184
2020-05-01	2.959
2020-06-01	2.342
2020-07-01	2.563
2020-08-01	1.749

Table 26: FCY Deposits Test Data

Date	FCY
2020-09-01	1.756
2020-10-01	2.050
2020-11-01	1.990

5.2.2 The RNN-LSTM Model

A RNN-LSTM model was deployed using 200 neurons and the results can be seen in Table 27. These values should be compared to the values in the test set as can be found in Table 26.

Table 27: Predictions: RNN-LSTM

Date	FCY
2020-09-01	2.110215
2020-10-01	2.310559
2020-11-01	2.422262

5.2.3 The Holt-Winters Model

A Holt-Winters Exponential Smoothing model was deployed using a multiplicative trend and additive seasonality where the results can be seen in Table 28. These values should be compared to the values in the test set as can be found in Table 26.

Table 28: Predictions: Holt-Winters

Date	FCY
2020-09-01	2.122491
2020-10-01	2.126086
2020-11-01	2.186017

5.2.4 The Auto-ARIMA Model

An ARIMA model was deployed and the chosen model by the package was $ARIMA(3, 0, 0)$ where the results can be seen in Table 29. These values should be compared to the values in the test set as can be found in Table 26. This model seems to perform the best.

Table 29: Predictions: Auto-ARIMA

Date	FCY
2020-09-01	2.061060
2020-10-01	2.132137
2020-11-01	1.942984

5.3 A Univariate Approach for 6-Month Fixed Deposit - LCY

5.3.1 The Data

The data was split into a training and test set where the training data is all the data from 2011 including 2020-08-01 meaning that the test set only takes on three months (one quarters). Table 30 and Table 31 provides the split.

Table 30: LCY Training Data (Most Recent)

Date	LCY
2020-04-01	4.156069
2020-05-01	4.856081
2020-06-01	4.530000
2020-07-01	2.293817
2020-08-01	2.290000

Table 31: LCY Deposits Test Data

Date	LCY
2020-09-01	2.29
2020-10-01	2.29
2020-11-01	2.29

5.3.2 The RNN-LSTM Model

A RNN-LSTM model was deployed using 200 neurons and the results can be seen in Table 32. These values should be compared to the values in the test set as can be found in Table 31.

Table 32: Predictions: RNN-LSTM

Date	LCY
2020-09-01	2.607592
2020-10-01	2.802512
2020-11-01	2.923707

5.3.3 The Holt-Winters Model

A Holt-Winters Exponential Smoothing model was deployed using a additive trend and multiplicative seasonality where the results can be seen in Table 33. These values should be compared to the values in the test set as can be found in Table 31.

Table 33: Predictions: Holt-Winters

Date	LCY
2020-09-01	2.256888
2020-10-01	2.200776
2020-11-01	2.259076

5.3.4 The Auto-ARIMA Model

An ARIMA model was deployed and the chosen model by the package was $ARIMA(1, 0, 3)$ where the results can be seen in Table 34. These values should be compared to the values in the test set as can be found in Table 31.

Table 34: Predictions: Auto-ARIMA

Date	LCY
2020-09-01	2.952974
2020-10-01	2.711431
2020-11-01	2.551050

5.4 A Univariate Approach for Demand Deposits

5.4.1 The Data

The data was split into a training and test set where the training data is all the data from 2011 including 2020-08-01 meaning that the test set only takes on three months (one quarters). Table 35 and Table 36 provides the split.

Table 35: Demand Deposits Training Data (Most Recent)

Date	Demand Deposits
2020-04-01	1.560544
2020-05-01	1.545066
2020-06-01	1.484946
2020-07-01	1.479703
2020-08-01	1.490895

5.4.2 The RNN-LSTM Model

A RNN-LSTM model was deployed using 200 neurons and the results can be seen in Table 37. These values should be compared to the values in the test set as can be found in Table 36.

Table 36: Demand Deposits Test Data

Date	Demand Deposits
2020-09-01	1.62000
2020-10-01	1.63178
2020-11-01	1.56000

Table 37: Predictions: RNN-LSTM

Date	Demand Deposits
2020-09-01	1.541517
2020-10-01	1.575737
2020-11-01	1.598972

5.4.3 The Holt-Winters Model

A Holt-Winters Exponential Smoothing model was deployed using a additive trend and multiplicative seasonality where the results can be seen in Table 38. These values should be compared to the values in the test set as can be found in Table 36.

Table 38: Predictions: Holt-Winters

Date	Demand Deposits
2020-09-01	1.568884
2020-10-01	1.504265
2020-11-01	1.571695

5.4.4 The Auto-ARIMA Model

An ARIMA model was deployed and the chosen model by the package was $ARIMA(1, 0, 2)$ where the results can be seen in Table 39. These values should be compared to the values in the test set as can be found in Table 36.

5.5 A Univariate Approach for Savings Deposits

5.5.1 The Data

The data was split into a training and test set where the training data is all the data from 2011 including 2020-08-01 meaning that the test set only takes on three months (one quarters). Table 40 and Table 41 provides the split.

5.5.2 The RNN-LSTM Model

A RNN-LSTM model was deployed using 200 neurons and the results can be seen in Table 42. These values should be compared to the values in the test set as can be found in Table 41.

Table 39: Predictions: Auto-ARIMA

Date	Demand Deposits
2020-09-01	1.485578
2020-10-01	1.479830
2020-11-01	1.475717

Table 40: Savings Deposits Training Data (Most Recent)

Date	Savings Deposits
2020-04-01	2.483134
2020-05-01	2.410000
2020-06-01	2.379262
2020-07-01	2.457242
2020-08-01	2.454946

Table 41: Savings Deposits Test Data

Date	Savings Deposits
2020-09-01	2.480000
2020-10-01	2.451691
2020-11-01	2.510000

Table 42: Predictions: RNN-LSTM

Date	Savings Deposits
2020-09-01	2.608577
2020-10-01	2.718500
2020-11-01	2.798295

5.5.3 The Holt-Winters Model

A Holt-Winters Exponential Smoothing model was deployed using a multiplicative trend and multiplicative seasonality where the results can be seen in Table 43. These values should be compared to the values in the test set as can be found in Table 41.

Table 43: Predictions: Holt-Winters

Date	Savings Deposits
2020-09-01	2.479842
2020-10-01	2.361802
2020-11-01	2.499874

5.5.4 The Auto-ARIMA Model

An ARIMA model was deployed and the chosen model by the package was $ARIMA(1, 0, 1)$ where the results can be seen in Table 44. These values should be compared to the values in the test set as can be found in Table 41.

Table 44: Predictions: Auto-ARIMA

Date	Savings Deposits
2020-09-01	2.437474
2020-10-01	2.428852
2020-11-01	2.420260

5.6 A Univariate Approach for Lending-Foreign

5.6.1 The Data

The data was split into a training and test set where the training data is all the data from 2011 including 2020-08-01 meaning that the test set only takes on three months (one quarters). Table 45 and Table 46 provides the split.

Table 45: Lending-Foreign Training Data (Most Recent)

Date	Lending-Foreign
2020-04-01	6.20
2020-05-01	4.24
2020-06-01	5.47
2020-07-01	5.33
2020-08-01	5.94

5.6.2 The RNN-LSTM Model

A RNN-LSTM model was deployed using 200 neurons and the results can be seen in Table 47. These values should be compared to the values in the test set as can be found in Table 46.

Table 46: Lending-Foreign Test Data

Date	Lending-Foreign
2020-09-01	5.90
2020-10-01	6.29
2020-11-01	5.29

Table 47: Predictions: RNN-LSTM

Date	Lending-Foreign
2020-09-01	6.513259
2020-10-01	6.958243
2020-11-01	7.308893

5.6.3 The Holt-Winters Model

A Holt-Winters Exponential Smoothing model was deployed using a multiplicative trend and multiplicative seasonality where the results can be seen in Table 48. These values should be compared to the values in the test set as can be found in Table 46.

Table 48: Predictions: Holt-Winters

Date	Lending-Foreign
2020-09-01	5.593237
2020-10-01	5.932394
2020-11-01	5.893723

5.6.4 The Auto-ARIMA Model

An ARIMA model was deployed and the chosen model by the package was $ARIMA(0,1,1)$ where the results can be seen in Table 49. These values should be compared to the values in the test set as can be found in Table 46.

Table 49: Predictions: Auto-ARIMA

Date	Lending-Foreign
2020-09-01	5.555489
2020-10-01	5.516658
2020-11-01	5.477827