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Financial Econometrics (PE-IV) FISAC Term Paper

"Mapping The Multivariate Time-Series Relationship Between INR Currency Value (Against USD) And NIFTY50 Index"

Submitted By:

Shwetabh Saxena

200953262

Computer and Communication

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Abstract

This paper explores the multivariate time-series relationship between the Indian Rupee (INR) currency value against the US Dollar (USD) and the NIFTY50 stock market index in the Indian economy. The study investigates whether a correlation exists between these key economic indicators and to what extent. Using datasets from Yahoo! Finance for the period from 03/01/2022 to 06/11/2023 with a weekly frequency, the analysis employs the ARIMA(p, d, q) algorithm. Granger causality tests assess whether these factors forecast each other. Methodology involves data downloading, merging, visualization, and stationarity checks using Augmented Dickey-Fuller tests. Differencing makes the time series stationary, and autocorrelation and partial autocorrelation functions determine p and q values. Various ARIMA models are fitted, and the best-performing model, ARIMA(1, 1, 7), is identified based on root mean squared error. The conclusion emphasizes the impact of currency exchange on the stock market index, even in a predominantly bank-based financial system like India. Suggestions for improvement include expanding the scope to include panel-data evaluation, incorporating additional variables like GDP, and extending the analysis to include data from 2021.

Introduction

The health of the economy is often linked with the currency value. The currency value of the country (most commonly measured against USD), is a showcase of the global economic power of the country, as it is a shadow of its stance in the global trades. Moreover, another indicator of the economy of a country is the stock market index of the country. It gives a general idea of the trend of the country's economy. It is almost logical to club these two important aspects affecting the economy together to gain a complete picture. But the question arises, do these factors affect each other?

In most developed countries with market-based economies, the correlation between the currency value and the stock index of that country in a market-based economy is fairly logical. The strength of the market gauged by the stock market index clearly shows that the country is doing better in the global trades, having an effect of the exchange value of the currency. However, such a correlation is not always this obvious for predominantly bank-based financial systems, such as in developing countries. Several of these countries have a mixed financial system (bank and market), and these makes the analysis and the correlation of such factors fairly complicated.

India is such an economy, where there is a market-based aspect in its financial system, but is predominantly bank based. In cases such as India, as mentioned, there needs to be a further analysis if such a correlation even exists, and if it does, to what extent?

Literature Review

The academic paper of [1], using the S&P 500 as a proxy investigates the complex relationship between exchange rate movements and returns on the US stock market. Since the 1970s, various research have produced conflicting results, making it difficult to determine why this link exists. The authors evaluate data from January 2000 to December 2019 using novel approaches. According to their analysis, changes in market returns are impacted by fluctuations in the Australian, Canadian, and euro currencies, which also have an impact on the S&P 500. Bivariate GARCH models are one of the limitations. The paper offers a unique empirical analysis that adds to our understanding of how exchange rates affect stock returns, which is what makes it original.

This paper [2] analyses the relationship between stock prices and important macroeconomic factors in India, such as the prime lending rate, the narrow and broad money supply, the rupee-dollar exchange rate, and the index of industrial production, is examined in this review of the literature. Using sophisticated econometric methods such as cointegration, unit root testing, and error-correction models, the study places its findings against the background of notable macroeconomic shifts, especially in the financial sector of India from the early 1990s. Understanding the dynamic interaction between stock prices and macroeconomic variables in the changing Indian economy is aided by this study.

The goal of this paper [3] is to project the future of the Indian stock market by thoroughly examining its current state. The study applies an ARIMA model to forecast future stock indices using monthly closing stock indices data from 2007 to 2012. This is an important tool for comprehending and influencing India's economic performance. The study emphasizes how important it is to comprehend the state of the market, particularly for researchers, investors, and economists. The model's accuracy in predicting future unobserved values is improved by the validation process using data from 2013, providing insightful information for well-informed investment decisions.

This paper [4] tackles the difficult task of forecasting currency rates in modern financial markets. This study assesses the prediction capabilities of ARIMA, Neural Network, and Fuzzy Neuron models with a focus on the Indian Rupee (INR) versus the USD, GBP, EUR, and JPY. The study adds to the continuing investigation of statistical and econometric techniques for improving accuracy in forecasting foreign currency prices, a crucial concern for traders and financial practitioners, by using daily RBI reference exchange rates from January 2010 to April 2015.

Research Design

The datasets for INR currency value and NIFTY50 index were taken from Yahoo! Finance. The following links can be referred to for the same:

INR currency value: https://finance.yahoo.com/quote/INR=X/history/

NIFTY50 index: https://finance.yahoo.com/quote/%5ENSEI/history?p=%5ENSEI

The dataset was taken from 03/01/2022 – 06/11/2023 range, in the interest of keeping the impact of COVID-19 fluctuations on the economy out of the analysis, and to keep the data relevant so that the resulting analysis is also relevant. A weekly frequency was taken, to find the sweet spot between having enough training examples for the model parameter fitting and to ensure enough significant digits change between each training example (the currency value doesn't change drastically in a daily frequency, and a monthly frequency would result in only 18 training examples).

Because this a multivariate time-series analysis, the algorithm ARIMA(p, d, q) is explored. Since this model converges into VAR for (p, 0, 0), and into MA for (0, 0, q), finding an optimal model will be easy in Python code in this all-in-one algorithm. Moreover, both of the factors, INR currency value and NIFTY50 index, will have their own models treating the other as an independent variable. Further analysis will be done after the models are constructed.

An important aspect is to find whether these factors forecast each other or not. This will be done using the granger causality test. Furthermore, since this study is done from scratch and no model is already present, the tests for stationarity won't be done using graphical or unit root method, rather, Augmented Dickey-Fuller (ADF) test will be used. The p-value computed should be lower than 0.05 to be considered as stationary. This analysis will be included in the methodology.

Methodology

1. First, we need to download the datasets and then merge them properly. The links to the dataset are included in "Research design" section. Taking them from 03/01/2022 – 06/11/2023 in a weekly frequency, we need to select the closing index column and the closing currency value column and merge them in one .csv file.
2. Next, we need to see our data (Figure 1). We have 97 training examples to use.

```
dataset
```

date	index	value
2022-03-01	17812.69922	74.467300
2022-10-01	18255.75000	73.972298
2022-01-17	17617.15039	74.452202
2022-01-24	17101.94922	74.994301
2022-01-31	17516.30078	74.643898
...	...	...
2023-09-10	19751.05078	83.262398
2023-10-16	19542.65039	83.122299
2023-10-23	19047.25000	83.282501
2023-10-30	19230.59961	83.247299
2023-06-11	19411.75000	83.158501

97 rows × 2 columns

(Figure 1)

3. Now, we need to ensure there is correlation between the two factors. We can do this by running a Granger Causality test. The null hypothesis states that "the factor x doesn't forecast factor y" while the alternate hypothesis is "the factor x forecasts factor y". We will determine the p-value and compare it with the significance factor 0f 0.05 (95% confidence). If the p-value is lesser, then the null hypothesis is incorrect, hence, factor x forecasts y.

```python
grangercausalitytests(dataset[['index', 'value']], maxlag=[2])
print()
grangercausalitytests(dataset[['value', 'index']], maxlag=[2])
print()
```

```
Granger Causality
number of lags (no zero) 2
ssr based F test:         F=5.3935  , p=0.0061  , df_denom=90, df_num=2
ssr based chi2 test:   chi2=11.3863 , p=0.0034  , df=2
likelihood ratio test: chi2=10.7540 , p=0.0046  , df=2
parameter F test:         F=5.3935  , p=0.0061  , df_denom=90, df_num=2


Granger Causality
number of lags (no zero) 2
ssr based F test:         F=0.5460  , p=0.5812  , df_denom=90, df_num=2
ssr based chi2 test:   chi2=1.1526  , p=0.5620  , df=2
likelihood ratio test: chi2=1.1457  , p=0.5639  , df=2
parameter F test:         F=0.5460  , p=0.5812  , df_denom=90, df_num=2
```

(Figure 2)

In Figure 2, we first check whether INR value determines any future values of NIFTY50 index. We find that the p = 0.0061, which is lower than 0.05, which mean INR value is a good determinant of the future value of NIFTY50 index (as null hypothesis is rejected). On the other hand, the reverse is not found to be true, the p = 0.5812 which means the null hypothesis isn't rejected. Moving further, only one model will be constructed, where index is determined using the INR currency value.

4. Now we need to clean our dataset. Here is the summary of the type of data and whether any missing values are present or not. As we can see in figure 3, there are no missing values.

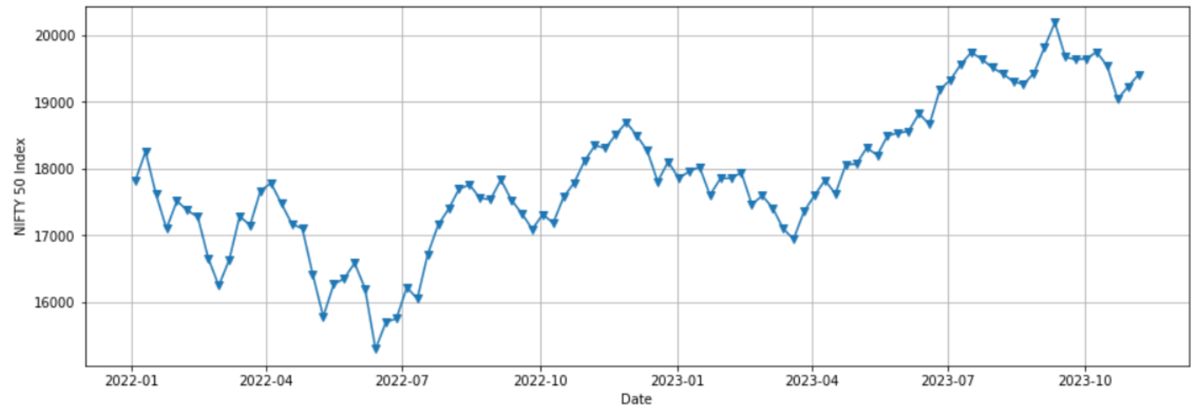
```python
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 97 entries, 2022-03-01 to 2023-06-11
click to scroll output; double click to hide type
---  ------  --------------  -----
 0   index   97 non-null     float64
 1   value   97 non-null     float64
dtypes: float64(2)
memory usage: 2.3 KB
```

(Figure 3)

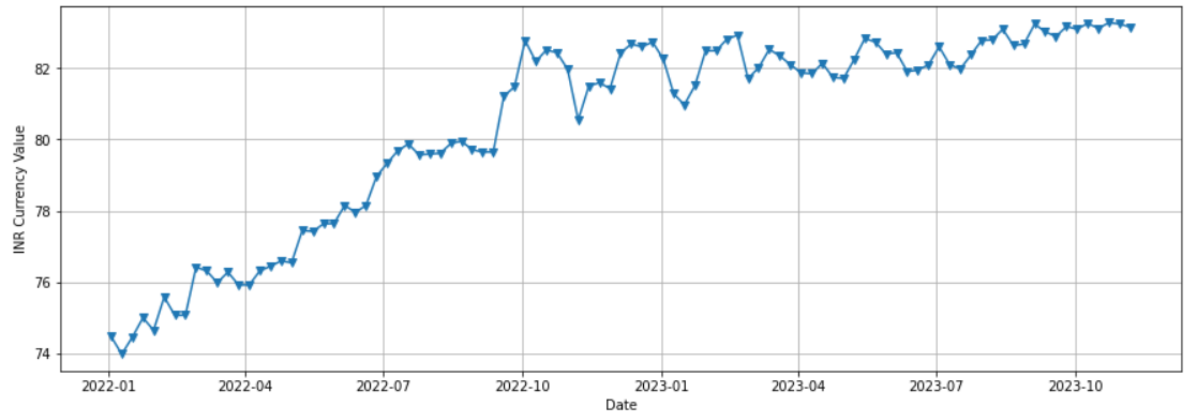
5. Next step is to visualise the dataset.

```
plt.figure(figsize=(15, 5))
plt.plot(dataset['index'], marker='v')
plt.xlabel("Date")
plt.ylabel("NIFTY 50 Index")
plt.grid()
plt.show()
```



(Figure 4)

```
plt.figure(figsize=(15, 5))
plt.plot(dataset['value'], marker='v')
plt.xlabel("Date")
plt.ylabel("INR Currency Value")
plt.grid()
plt.show()
```

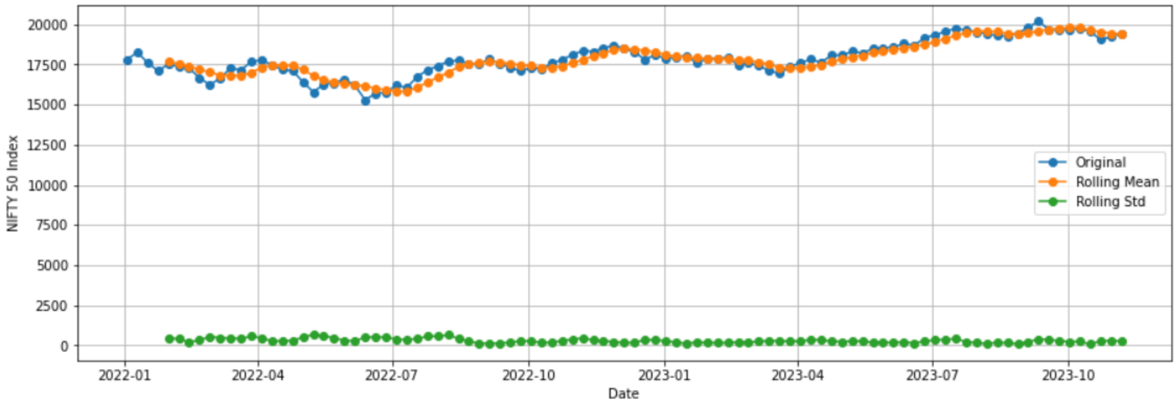


(Figure 5)

There is some noticeable trend, but no seasonal variations or any cyclicity whatsoever.

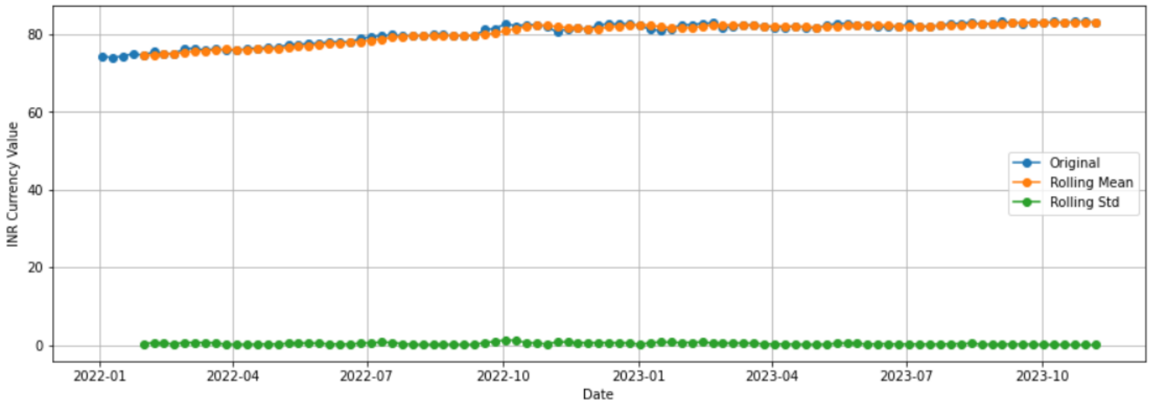
6. Now we need to check for stationarity. Refer to figure 6 and 7, it is clear that there is no constant mean or standard deviation, which means they aren't stationary.

```
plt.figure(figsize=(15, 5))
plt.plot(dataset['index'], marker='o', label='Original')
plt.plot(dataset['index'].rolling(window = 5).mean(), marker='o', label='Rolling Mean')
plt.plot(dataset['index'].rolling(window = 5).std(), marker='o', label='Rolling Std')
plt.xlabel("Date")
plt.ylabel("NIFTY 50 Index")
plt.grid()
plt.legend()
plt.show()
```



(Figure 6)

```
plt.figure(figsize=(15, 5))
plt.plot(dataset['value'], marker='o', label='Original')
plt.plot(dataset['value'].rolling(window = 5).mean(), marker='o', label='Rolling Mean')
plt.plot(dataset['value'].rolling(window = 5).std(), marker='o', label='Rolling Std')
plt.xlabel("Date")
plt.ylabel("INR Currency Value")
plt.grid()
plt.legend()
plt.show()
```



(Figure 7)

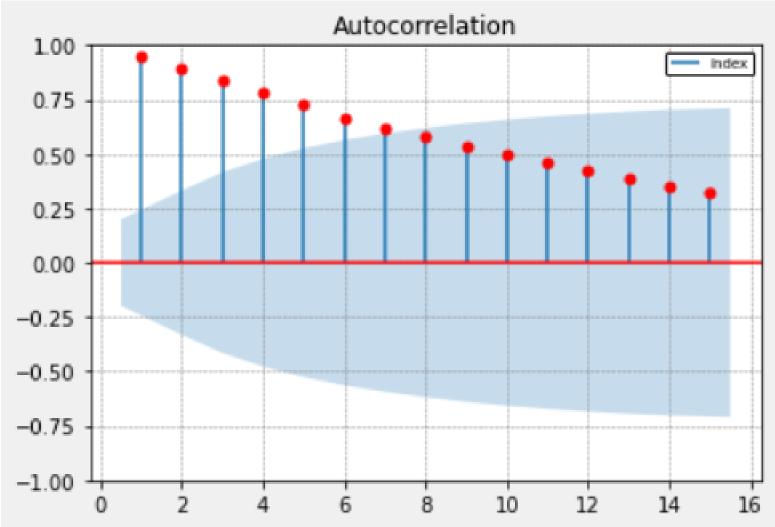
7. Thus, we need to make these time-series stationary. Most common method is differencing; thus, we will first apply first differencing. Luckily in Pandas, we can easily access the method .diff() of DataFrames to find the first differences. Applying the ADF test helper function from statsmodels.tsa.stattools:

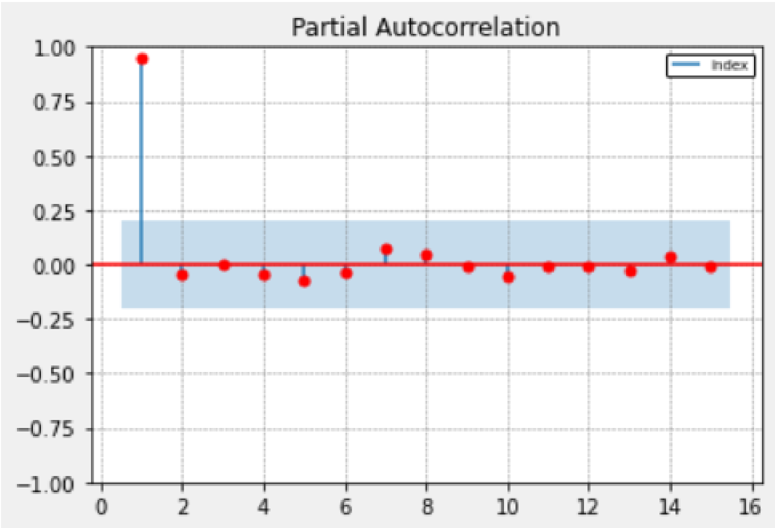
```
    Augmented Dickey-Fuller Test on "index"
    -----------------------------------------------
ADF Statistic: -9.250169
p-value: 0.000000
Critical Values:
        1%: -3.501
        5%: -2.892
        10%: -2.583
Stationary


    Augmented Dickey-Fuller Test on "value"
    -----------------------------------------------
ADF Statistic: -6.407840
p-value: 0.000000
Critical Values:
        1%: -3.504
        5%: -2.894
        10%: -2.584
Stationary
```

(Figure 8)

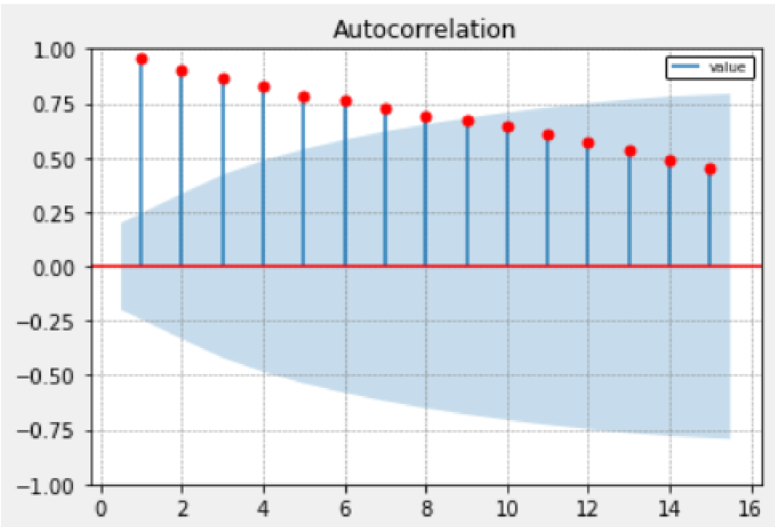
Thus, we can conclude the first differencing works to make the data stationary. Moreover, we have the first parameter of our model, d, which is differencing, which is equal to 1.

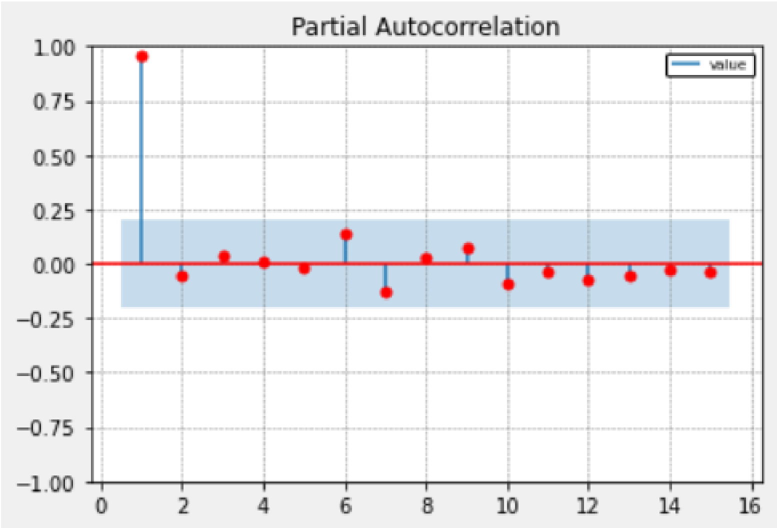
8. Next, we need to plot the ACF and PACF of each variable to determine the value of p, q constants in the ARIMA model.


Autocorrelation
index
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10
12
14
16


Partial Autocorrelation
index
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10
12
14
16

(Figure 9)


Autocorrelation
value
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
2
4
6
8
10
12
14
16



(Figure 10)

Here the confidence level was set 95%. The shaded portions signifies which lags will not have a significant affect on the future values. For NIFTY50 index, 6 lags are significant and for INR currency value, 7 lags are significant in ACF plot. That means q can be equal to 6 or 7. While in PACF both only have 1 lag significant, therefore, p = 1.

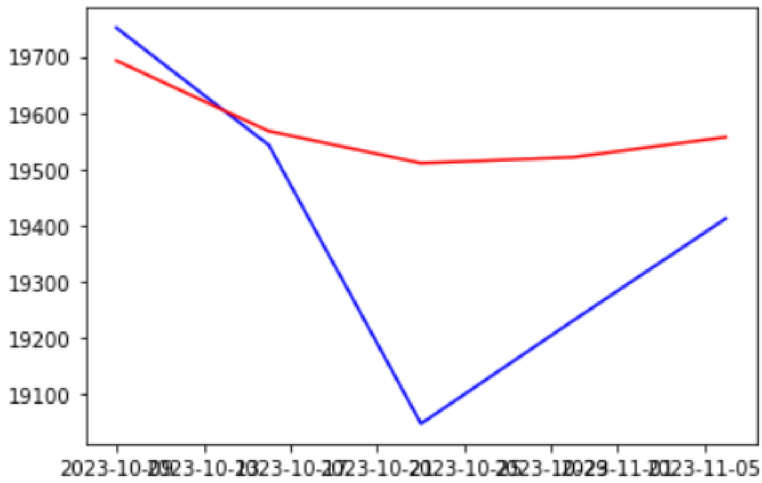
9. Now we can finally fit the ARIMA model and evaluate their performance. We will try the following orders of (p, d, q):
    a. (1, 1, 6): One of the most likely models according to analysis
    b. (1, 1, 7): Another likely model according to analysis
    c. (2, 1, 6): To check with more lag terms
    d. (2, 1, 7): To check with more lag terms
    e. (1, 1, 0): To check for AR model
    f. (0, 1, 1): To check for MA model

Results And Analysis

The following table summarizes the findings of each model's metric. For this paper, the metric used was root mean squared error, the most common metric used for time series analysis.

Model	**RMSE**
(1, 1, 6)	333.38
(1, 1, 7)	*254.42*
(2, 1, 6)	425.25
(2, 1, 7)	266.96
(1, 1, 0)	337.98
(0, 1, 1)	337.57

It is clear the most successful model is ARIMA(1, 1, 7), with RMSE score of 256.42. Figure 11 shows the prediction of the test values:




```
Root Mean Squared Error 254.4272952940381
```

(Figure 11)

Except for the sudden dip 23/10/2023, the values are pretty close together, suggesting that this model is viable for forecasting. It is unclear as to why the model predicted a sudden dip. Such an anomaly can be explored further, maybe according to the trend there was supposed to be a dip. The coefficients of the models are as follows (figure 12):

```
                 coef
------------------------
value       -168.7150
ar.L1          0.2653
ma.L1         -0.1733
ma.L2         -0.0777
ma.L3         -0.0969
ma.L4          0.1761
ma.L5         -0.0557
ma.L6         -0.1033
ma.L7         -0.0581
sigma2      9.118e+04
```

(Figure 12)

We can make a prediction for 13/11/2023, take the INR value at that date and check to see how closely our model will predict the value. Figure 13 shows the result:

```
pred = model_fit.forecast(steps = 1, exog = [83.2989])
print(pred[0], [19443.55])
print("Root Mean Squared Error", math.sqrt(mean_squared_error([19443.55], pred)))
```

```
19426.247743469045 [19443.55]
Root Mean Squared Error 17.302256530954764
```

(Figure 13)

The RMSE is at 17.30! it means that our prediction was very close. The actual value of the index was at 19443.55 while the model determined 19426.24. This reveals that the model has given significant results.

Conclusion And Further Scope

In conclusion, the ARIMA(1, 1, 7) model has given the best results with the least RSME score. A prediction made for 13/10/2023 also boasted very favourable and promising results. It is clear that even in a bank-based financial system like India, the currency exchange does have an impact on the Stock Market Index.

There are a few ways to improve this model. The paper limited the scope of the problem statement to a time-series evaluation, while a panel-data evaluation of the same can be conducted to find out the cross-sectional relationship between NIFTY50 index and INR currency value. It is also clear through the granger causality tests that there no impact of index upon the value, hence it is futile to further work upon the same. Also, 2021 can be included in the analysis to include more training examples. More dependent variables like GDP can be included in the analysis of NIFTY50 index.

References

[1] Banerjee, Debadrita. “Forecasting of Indian Stock Market Using Time-Series ARIMA Model.” IEEE Xplore, 1 Jan. 2014, ieeexplore.ieee.org/abstract/document/6970973.

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[3] Pethe, Abhay, and Ajit Karnik. “Do Indian Stock Markets Matter? Stock Market Indices and Macro-Economic Variables.” Economic and Political Weekly, vol. 35, no. 5, 2000, pp. 349–356, www.jstor.org/stable/4408881.

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