

Extracting Data From Fred Data Base

```

import pandas_datareader.data as web
import pandas as pd
from datetime import datetime
from pandas.tseries.offsets import MonthBegin

start = datetime(2014,1,1)
end = datetime(2025,11,30)

fred_df = pd.DataFrame()
fred_df['USD_INR'] = web.DataReader('DEXINUS', 'fred', start, end)
fred_df['CPI_USA'] = web.DataReader('MEDCPIM158SFRBCLE', 'fred', start, end)
fred_df['Crude_Oil'] = web.DataReader('DCOILWTICO', 'fred', start, end)
fred_df['Trade_Balance_India'] = web.DataReader('XTEXVA01INM667S', 'fred', start, end)
fred_df['US_Rate_EFFR'] = web.DataReader("FEDFUNDS", "fred", start, end)

```

Interpolating missing Data with Previous Values and averaging out the data on monthly basis

```

fred_df.reset_index(inplace=True)
fred_df['USD_INR'] = fred_df['USD_INR'].interpolate(method='linear', limit_direction='both')
fred_df['Crude_Oil'] = fred_df['Crude_Oil'].interpolate(method='linear', limit_direction='both')
fred_df.resample('ME',on = 'DATE').mean()
fred_df.dropna(inplace=True)

```

Converting all dates to start of the month

```

fred_df['DATE']=pd.to_datetime(fred_df['DATE'],format='%m%Y',errors='coerce')
fred_df = fred_df.dropna(subset=['DATE'])
fred_df['DATE'] = fred_df['DATE'] - MonthBegin(1)
fred_df.rename(columns={'DATE':'Date'},inplace=True)
fred_df

```

	Date	USD_INR	CPI_USA	Crude_Oil	Trade_Balance_India	US_Rate_EFFR
0	2013-12-01	62.310	2.406327	95.140	2.678252e+10	0.07
64	2014-03-01	59.860	2.214932	99.690	2.634899e+10	0.09
86	2014-04-01	60.110	2.545627	99.690	2.799275e+10	0.09
129	2014-06-01	60.050	2.404904	106.060	2.600628e+10	0.09
152	2014-07-01	61.200	1.751737	97.860	2.795354e+10	0.09
...
2956	2025-04-01	84.580	2.695123	60.590	3.802151e+10	4.33
2999	2025-06-01	85.580	3.367945	66.640	3.736336e+10	4.33
3022	2025-07-01	87.540	3.368096	68.390	3.627925e+10	4.33
3043	2025-08-01	88.165	2.384737	65.155	3.592263e+10	4.22
3065	2025-09-01	88.690	1.078007	62.590	3.489003e+10	4.09

102 rows × 6 columns

Extracting RBI Repo Rate From Website

```

"""
import pandas as pd
import requests
import io
url = 'https://basunivesh.com/rbi-repo-rate-history-from-2000/'
header = {
    "User-Agent": "Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/91.0.4472.124 Safari/537.36"
}
response = requests.get(url, headers=header)
tables = pd.read_html(io.StringIO(response.text))
repo_df = tables[0]
repo_df.columns = repo_df.iloc[0]
repo_df = repo_df[1:].reset_index(drop=True)
repo_df['Date'] = repo_df['Date'].str.replace('-', ' ', regex=False)
repo_df['Date'] = pd.to_datetime(repo_df['Date'], dayfirst=True)
repo_df['RBI Repo Rate'] = repo_df['RBI Repo Rate'].str.replace('%', ' ', regex=False).astype(float)

```

```
repo_df.to_excel('RBI_Repo_Rate.xlsx', index=False)
"""

'nimport pandas as pd\nimport requests\nimport io\nurl = \'https://basunivesh.com/rbi-repo-rate-history-from-2000/\'\nheaders = {\n    "User-Agent": "Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/91.0.4472.124 Safari/537.36"\n}\nresponse = requests.get(url, headers=headers)\ntables = pd.read_html(io.StringIO(response.text))\nrepo_df = tables[0]\nrepo_df.columns = repo_df.iloc[0]\nrepo_df = repo_df[1:].reset_index(drop=True)\nrepo_df['Date'] = repo_df['Date'].str.replace('-', '\\-', regex=False)\nrepo_df['Date'] = pd.to_datetime(repo_df['Date'], dayfirst=True)
```

Was getting blocked by website so downloaded html to extract the data for the same

```
import pandas as pd
import io
from bs4 import BeautifulSoup
file_path = 'RBI Repo Rate History from 2000 to 2025 (5th December 2025).html'
with open(file_path, 'r', encoding='utf-8') as f:
    html_content = f.read()
tables = pd.read_html(io.StringIO(html_content))
repo_df = tables[0]
repo_df.columns = repo_df.iloc[0]
repo_df = repo_df[1:].reset_index(drop=True)
repo_df['Date'] = repo_df['Date'].str.replace('-', '\\-', regex=False)
repo_df['Date'] = pd.to_datetime(repo_df['Date'], dayfirst=True, errors='coerce')
repo_df = repo_df.dropna(subset=['Date'])
repo_df['Date'] = repo_df['Date'] - MonthBegin(1)
repo_df['RBI Repo Rate'] = repo_df['RBI Repo Rate'].astype(str).str.replace('%', '', regex=False).astype(float)
repo_df
```

	Date	RBI Repo Rate
0	2025-12-01	5.25
1	2025-09-01	5.50
2	2025-06-01	5.50
3	2025-04-01	6.00
4	2025-02-01	6.25
...
104	2000-06-01	9.60
105	2000-06-01	9.30
106	2000-06-01	9.10
107	2000-06-01	9.00
108	2000-06-01	9.10

109 rows × 2 columns

Importing data from excel about Foreign Exchange Reserves

```
import pandas as pd
import warnings
warnings.simplefilter(action='ignore', category=UserWarning)
df = pd.read_excel('Foreign Exchange Reserves.xlsx', skiprows=3)
reserves_df = df.iloc[2:].copy()
new_column_names = list(df.columns)
new_column_names[13] = 'Total_Reserves_USD'
reserves_df.columns = new_column_names
reserves_df['Year'] = pd.to_numeric(reserves_df['Year'], errors='coerce')
reserves_df = reserves_df.dropna(subset=['Year']).reset_index(drop=True)
reserves_df['Date'] = pd.to_datetime(
    reserves_df['Year'].astype(int).astype(str) + '-' + reserves_df['Month'].astype(str) + '-01',
    format='%Y-%b-%d')
)
reserves_df = reserves_df[['Date', 'Total_Reserves_USD']]
reserves_df
```

	Date	Total_Reserves_USD
0	2025-12-01	687734.274
1	2025-11-01	687929.818
2	2025-10-01	689732.836
3	2025-09-01	700088.694
4	2025-08-01	695358.144
...
425	1990-07-01	3553
426	1990-06-01	3685
427	1990-05-01	3701
428	1990-04-01	3625
429	1990-03-01	3962

430 rows × 2 columns

Importing Indian CPI data from Excel

```
import pandas as pd
cpi_df=pd.read_excel('rbi_cpi_IND.xlsx',skiprows=5)
cpi_df=cpi_df[1:]
clmns=list(cpi_df.columns)
clmns[1]='Date'
clmns[5]='Ind_CPI'
cpi_df.columns=clmns
cpi_df=cpi_df[['Date','Ind_CPI']]
cpi_df = cpi_df.dropna(subset=['Date','Ind_CPI'])
cpi_df['Date']=pd.to_datetime(cpi_df['Date'],errors='coerce') - MonthBegin(1)
cpi_df['Ind_CPI']=pd.to_numeric(cpi_df['Ind_CPI'],errors='coerce')
cpi_df
```

	Date	Ind_CPI
1	2025-10-01	0.71
2	2025-09-01	0.25
3	2025-08-01	1.44
4	2025-07-01	2.07
5	2025-06-01	1.61
...
139	2014-04-01	8.33
140	2014-03-01	8.48
141	2014-02-01	8.25
142	2014-01-01	7.88
143	2013-12-01	8.60

143 rows × 2 columns

Merging all dataframes into one and cleaning the data.

```
from typing_extensions import final
dfs=[fred_df,repo_df,reserves_df,cpi_df]
final_df=dfs[0]
for nxt in dfs[1:] :
    final_df = pd.merge(final_df, nxt, on='Date',how='outer')
final_df = final_df.fillna()
final_df = final_df.where(final_df['Date']>'2014-01-01')
final_df.dropna(inplace=True)
final_df.set_index('Date',inplace=True)
final_df
#final_df.to_excel('final_df.xlsx',index=False)
```

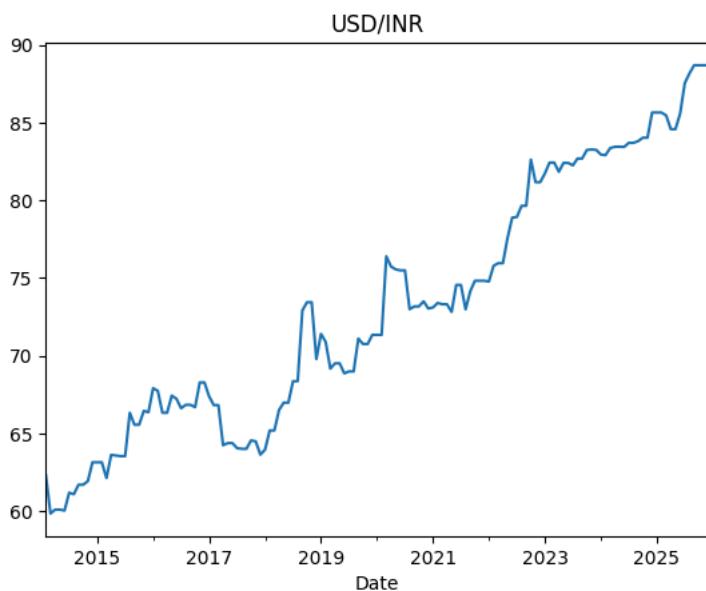
```
/tmp/ipython-input-978572063.py:6: FutureWarning: Downcasting object dtype arrays on .fillna, .ffill, .bfill is deprecated and will be removed in a future version. You can use astype('float64') to silence this warning.
final_df = final_df.ffill()
```

Date	USD_INR	CPI_USA	Crude_Oil	Trade_Balance_India	US_Rate_EFFR	RBI Repo Rate	Total_Reserves_USD	Ind_CPI
2014-02-01	62.310	2.406327	95.140	2.678252e+10	0.07	8.00	294360.200	8.25
2014-03-01	59.860	2.214932	99.690	2.634899e+10	0.09	8.00	304223.200	8.48
2014-04-01	60.110	2.545627	99.690	2.799275e+10	0.09	8.00	310986.300	8.33
2014-05-01	60.110	2.545627	99.690	2.799275e+10	0.09	8.00	312207.000	6.77
2014-06-01	60.050	2.404904	106.060	2.600628e+10	0.09	8.00	316138.000	7.39
...
2025-08-01	88.165	2.384737	65.155	3.592263e+10	4.22	5.50	695358.144	1.44
2025-09-01	88.690	1.078007	62.590	3.489003e+10	4.09	5.50	700088.694	0.25
2025-10-01	88.690	1.078007	62.590	3.489003e+10	4.09	5.50	689732.836	0.71
2025-11-01	88.690	1.078007	62.590	3.489003e+10	4.09	5.50	687929.818	0.71
2025-12-01	88.690	1.078007	62.590	3.489003e+10	4.09	5.25	687734.274	0.71

143 rows × 8 columns

Plot for USD/INR for given period

```
import matplotlib.pyplot as plt
final_df['USD_INR'].plot(title='USD/INR')
plt.show()
```



```
y = final_df['USD_INR']
x = final_df.copy()
```

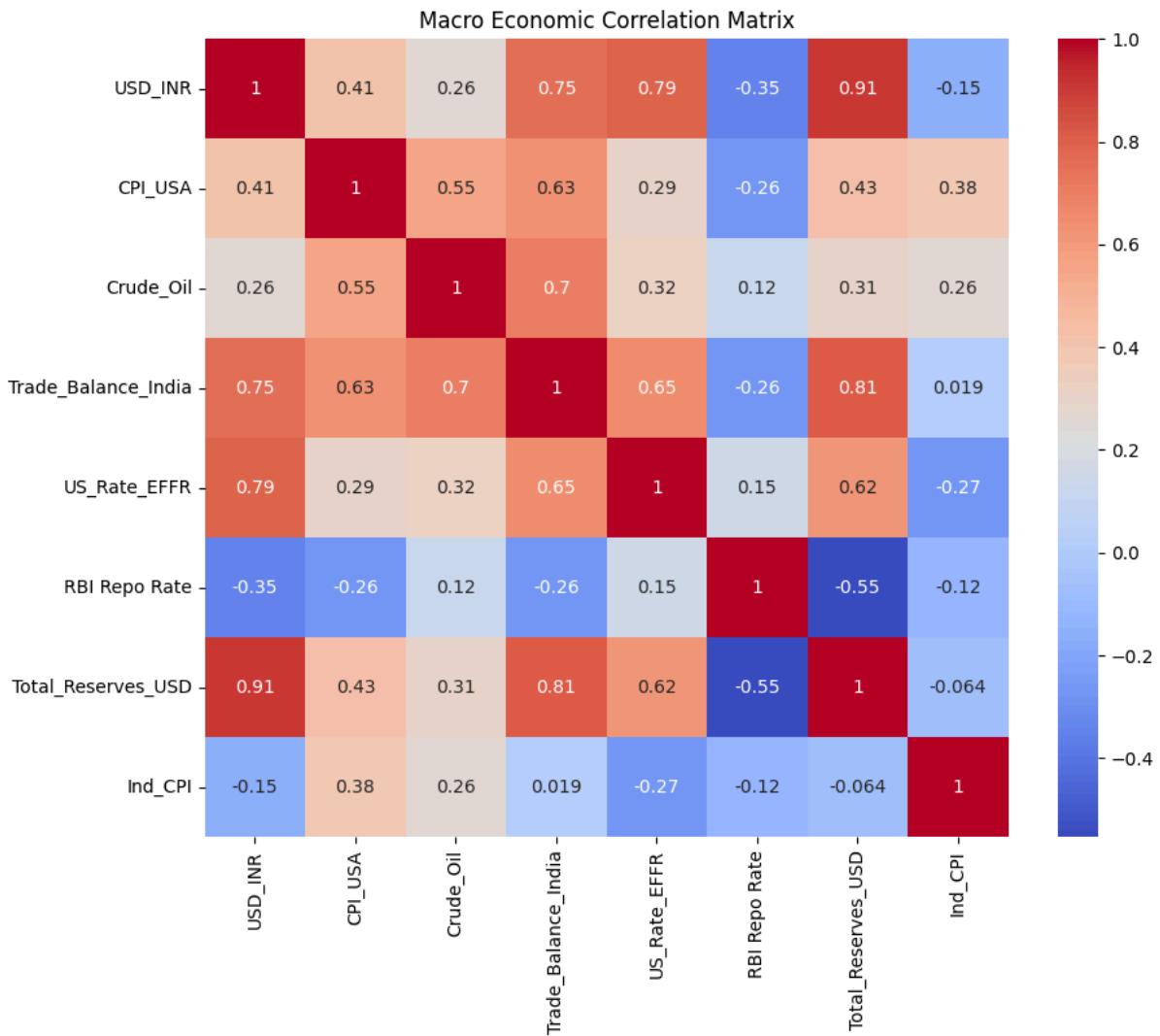
Scaled down the data for correlation

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
x_scaled = pd.DataFrame(
    scaler.fit_transform(x),
    columns=x.columns,
    index=x.index
)
```

Plot of correlation Matrix

```
import seaborn as sns
plt.figure(figsize=(10, 8))
```

```
sns.heatmap(x_scaled.corr(), annot=True, cmap='coolwarm')
plt.title("Macro Economic Correlation Matrix")
plt.show()
```



```
x_scaled = x_scaled.drop(columns=['USD_INR'])
```

Calculate Variance Inflation Factor for Dataset to detect Multicollinearity in regression and found out that Trade Balance and Total reserves are highly correlated and redundant

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif["Variable"] = x_scaled.columns
vif["VIF"] = [
    variance_inflation_factor(x_scaled.values, i)
    for i in range(x_scaled.shape[1])
]
vif
```

	Variable	VIF
0	CPI_USA	2.428974
1	Crude_Oil	4.017389
2	Trade_Balance_India	11.112152
3	US_Rate_EFFR	4.515682
4	RBI Repo Rate	4.449314
5	Total_Reserves_USD	10.033527
6	Ind_CPI	1.588790

Finding the best fit line using Ordinary Least Squares based on dependent variables Found that main drivers of Exchange rate is US EFFR, US CPI, Total Reserves, surprisingly rbi rate and IND cpi are not well related to USD/INR

```
import statsmodels.api as sm
x_ols = sm.add_constant(x_scaled)
ols_model = sm.OLS(y,x_ols).fit()
print(ols_model.summary())
```

```
OLS Regression Results
=====
Dep. Variable:      USD_INR    R-squared:           0.931
Model:              OLS     Adj. R-squared:        0.928
Method:             Least Squares F-statistic:       261.4
Date:      Sun, 08 Feb 2026   Prob (F-statistic):  3.17e-75
Time:          10:51:01    Log-Likelihood:     -311.05
No. Observations:    143    AIC:                  638.1
Df Residuals:        135    BIC:                  661.8
Df Model:                 7
Covariance Type:    nonrobust
=====
            coef    std err      t      P>|t|      [0.025      0.975]
-----
const      73.0614    0.183   398.511    0.000     72.699    73.424
CPI_USA      0.8750    0.286     3.062    0.003     0.310     1.440
Crude_Oil     -0.4286    0.367    -1.166    0.246    -1.155     0.298
Trade_Balance_India  -1.3751    0.611    -2.250    0.026    -2.584    -0.166
US_Rate_EFFR      3.1501    0.390     8.086    0.000     2.380    3.921
RBI Repo Rate      0.1958    0.387     0.506    0.614    -0.569     0.961
Total_Reserves_USD  6.4585    0.581    11.121    0.000     5.310    7.607
Ind_CPI      -0.1190    0.231    -0.515    0.607    -0.576     0.338
=====
Omnibus:           0.180   Durbin-Watson:        0.419
Prob(Omnibus):      0.914   Jarque-Bera (JB):     0.293
Skew:                -0.076   Prob(JB):         0.864
Kurtosis:               2.838   Cond. No.          8.03
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

ADF test to find if exchange rate is stationary or not. Non stationary data gives bad result in OLS as The data has a trend

```
from statsmodels.tsa.stattools import adfuller
adf_result = adfuller(y)
print(f"ADF Statistic: {adf_result[0]}")
print(f"p-value: {adf_result[1]}")
```

```
ADF Statistic: -0.1207996264162772
p-value: 0.947326996610449
```

y

	USD_INR
Date	
2014-02-01	62.310
2014-03-01	59.860
2014-04-01	60.110
2014-05-01	60.110
2014-06-01	60.050
...	...
2025-08-01	88.165
2025-09-01	88.690
2025-10-01	88.690
2025-11-01	88.690
2025-12-01	88.690

143 rows × 1 columns

dtype: float64

Converting exchange rates to Difference in exchange rate Month Over Month

```
y_diff = y.diff().dropna()
y_diff
```

```
USD_INR
Date
2014-03-01 -2.450
2014-04-01 0.250
2014-05-01 0.000
2014-06-01 -0.060
2014-07-01 1.150
...
2025-08-01 0.625
2025-09-01 0.525
2025-10-01 0.000
2025-11-01 0.000
2025-12-01 0.000
142 rows × 1 columns
dtype: float64
```

Re-Testing for ADF on Change in exchange rate MoM

```
from statsmodels.tsa.stattools import adfuller
adf_diff = adfuller(y_diff)
print(f"ADF Statistic (diff): {adf_diff[0]}")
print(f"p-value (diff): {adf_diff[1]}")
```

```
ADF Statistic (diff): -13.59328617617925
p-value (diff): 2.0173764778844083e-25
```

ADF on rest of the data

```
data_cols = ['CPI_USA', 'Crude_Oil', 'Trade_Balance_India',
            'US_Rate_EFFR', 'RBI Repo Rate', 'Total_Reserves_USD', 'Ind_CPI']

for col in data_cols:
    stat, p, *_ = adfuller(final_df[col].dropna())
    print(col, round(p,4))

CPI_USA 0.4995
Crude_Oil 0.0972
Trade_Balance_India 0.7871
US_Rate_EFFR 0.3756
RBI Repo Rate 0.2836
Total_Reserves_USD 0.8724
Ind_CPI 0.7011
```

Converting data into change in MoM

```
exog = final_df[['CPI_USA', 'Crude_Oil', 'Trade_Balance_India',
                  'US_Rate_EFFR', 'RBI Repo Rate', 'Total_Reserves_USD', 'Ind_CPI']]

exog_diff = exog.diff().dropna()
```

Recalculating ADF on MoM Difference

```
for col in exog_diff.columns:
    stat, p, *_ = adfuller(exog_diff[col])
    print(col, round(p,4))

CPI_USA 0.0
Crude_Oil 0.0
Trade_Balance_India 0.0
US_Rate_EFFR 0.0657
RBI Repo Rate 0.0008
Total_Reserves_USD 0.0
Ind_CPI 0.0001
```

Scaling down the MoM change data using Standard Scaler

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
exog_scaled = pd.DataFrame(
    scaler.fit_transform(exog_diff),
    columns=exog_diff.columns,
    index=exog_diff.index
)
```

Reindexing data after MoM change

```
y_diff = final_df['USD_INR'].diff().dropna()
y_final = y_diff.loc[exog_diff.index]
```

SARIMAX model (past value=1, no of difference=1, error terms =0) on MoM change of data showing total reserves is one of the most important factor for USD/INR. The variable ar.L1 has a P-value of 0.000 and The coefficient -0.5459 means that if the USD_INR rate jumped up significantly last month, there is a strong mathematical tendency for it to pull back this month.

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
model = SARIMAX(
    y_final,
    exog=exog_scaled,
    order=(1,1,0),
    enforce_stationarity=False,
    enforce_invertibility=False
)

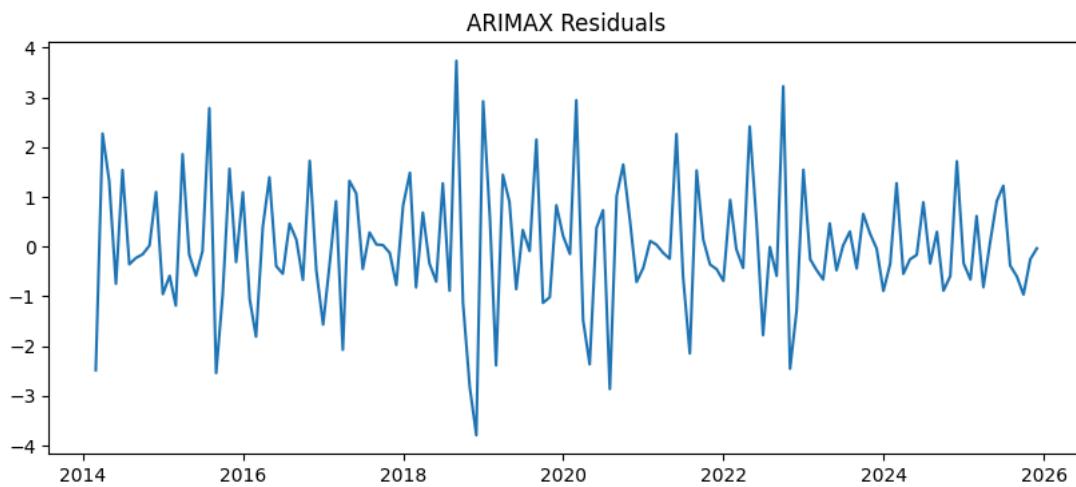
result = model.fit()
print(result.summary())
```

```
SARIMAX Results
=====
Dep. Variable:      USD_INR    No. Observations:             142
Model:              SARIMAX(1, 1, 0)    Log Likelihood:          -228.431
Date:                Sun, 08 Feb 2026    AIC:                  474.863
Time:                 10:51:01        BIC:                  501.338
Sample:            03-01-2014    HQIC:                  485.621
                           - 12-01-2025
Covariance Type:    opg
=====
            coef    std err        z     P>|z|      [0.025]     [0.975]
-----
CPI_USA       -0.0606    0.078   -0.778     0.437     -0.213      0.092
Crude_Oil      0.1517    0.104    1.463     0.143     -0.051      0.355
Trade_Balance_India -0.1426    0.103   -1.379     0.168     -0.345      0.060
US_Rate_EFFR     -0.0959    0.085   -1.127     0.260     -0.263      0.071
RBI Repo Rate    -0.1214    0.082   -1.473     0.141     -0.283      0.040
Total_Reserves_USD -0.1929    0.105   -1.843     0.065     -0.398      0.012
Ind_CPI         0.1081    0.114    0.950     0.342     -0.115      0.331
ar.L1           -0.5459    0.063   -8.643     0.000     -0.670     -0.422
sigma2          1.5302    0.176    8.683     0.000      1.185      1.876
=====
Ljung-Box (L1) (Q):      7.67    Jarque-Bera (JB):        4.69
Prob(Q):                  0.01    Prob(JB):                  0.10
Heteroskedasticity (H):    0.81    Skew:                      0.16
Prob(H) (two-sided):      0.48    Kurtosis:                  3.84
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

Plotting ARIMAX Residuals

```
import matplotlib.pyplot as plt
plt.figure(figsize=(10,4))
plt.plot(result.resid)
plt.title("ARIMAX Residuals")
plt.show()
```



Forcasting next 6 MoM chnage in USD/INR around forecasted mean within confidance interval

```

forecast = result.get_forecast(
    steps=6,
    exog=exog_scaled.iloc[-6:])
)
forecast_mean = forecast.predicted_mean
forecast_ci = forecast.conf_int()
print(forecast_mean)

2026-01-01    0.220969
2026-02-01   -0.278084
2026-03-01   -0.231957
2026-04-01    0.126668
2026-05-01   -0.102918
2026-06-01    0.056187
Freq: MS, Name: predicted_mean, dtype: float64

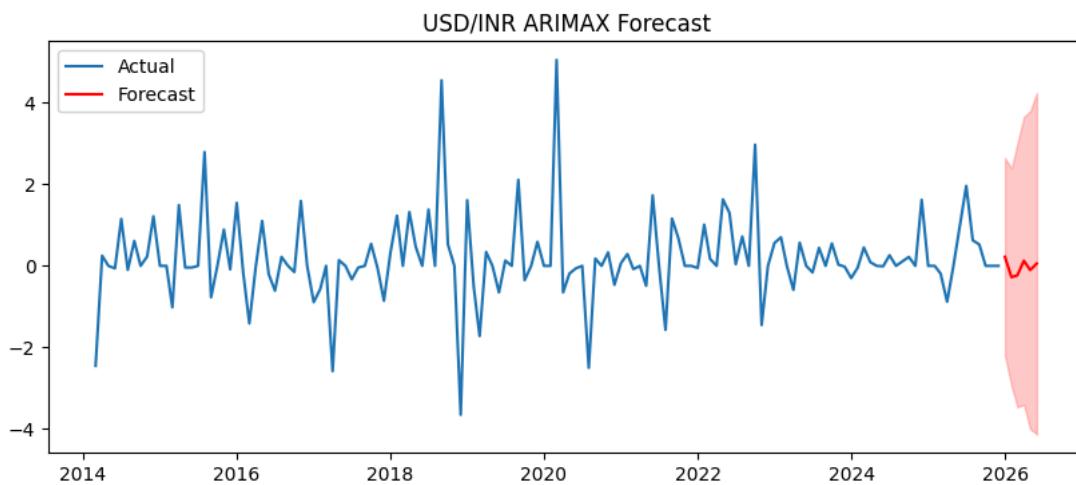
```

Plot of ARIMAX Forecast

```

plt.figure(figsize=(10,4))
plt.plot(y_final, label='Actual')
plt.plot(forecast_mean, label='Forecast', color='red')
plt.fill_between(
    forecast_ci.index,
    forecast_ci.iloc[:,0],
    forecast_ci.iloc[:,1],
    color='red',
    alpha=0.2
)
plt.legend()
plt.title("USD/INR ARIMAX Forecast")
plt.show()

```



Converting MoM change back to USD/INR using last actual value

```

last_actual = final_df['USD_INR'].iloc[-1]
usd_inr_forecast_level = last_actual + forecast_mean.cumsum()
forecast_df = pd.concat([
    final_df['USD_INR'],
    usd_inr_forecast_level
])
forecast_df.tail(7)

```

```

0
2025-12-01  88.690000
2026-01-01  88.910969
2026-02-01  88.632885
2026-03-01  88.400927
2026-04-01  88.527595
2026-05-01  88.424677
2026-06-01  88.480864

```

dtype: float64

Final Forecasted Plot Of USD/INR

```

import matplotlib.pyplot as plt

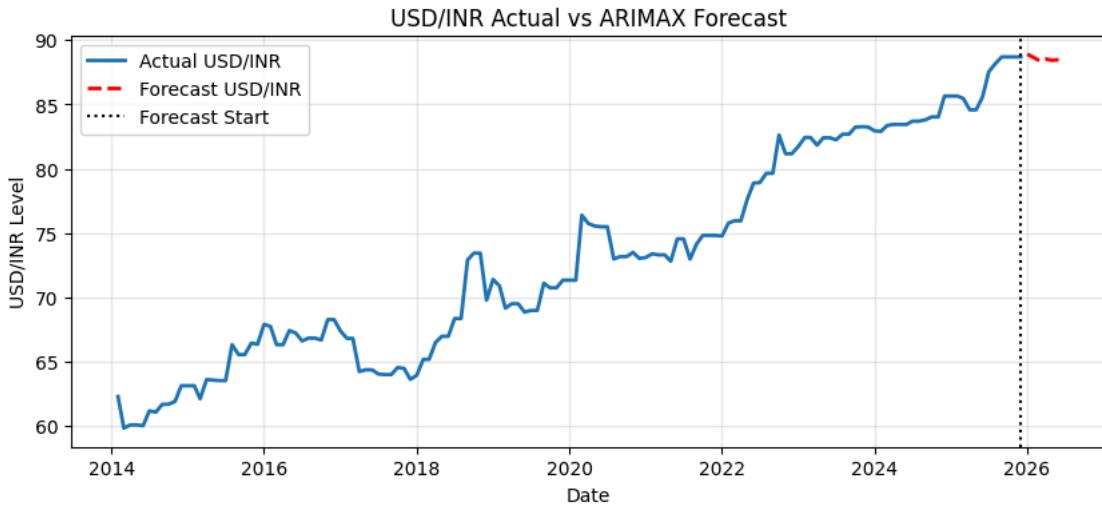
plt.figure(figsize=(10,4))

plt.plot(final_df['USD_INR'], label='Actual USD/INR', linewidth=2)
plt.plot(usd_inr_forecast_level, label='Forecast USD/INR',
         color='red', linestyle='--', linewidth=2)

plt.axvline(final_df.index[-1], color='black', linestyle=':', label='Forecast Start')

plt.title('USD/INR Actual vs ARIMAX Forecast')
plt.xlabel('Date')
plt.ylabel('USD/INR Level')
plt.legend()
plt.grid(alpha=0.3)
plt.show()

```



Training Model And Testing Again, so splitting data into train and test data

```

split_date = '2024-01-01'

y_train = y_final.loc[:split_date]
y_test = y_final.loc[split_date:]

exog_train = exog_scaled.loc[y_train.index]
exog_test = exog_scaled.loc[y_test.index]

```

SARIMAX on Test Data

```
model = SARIMAX(
    y_train,
    exog=exog_train,
    order=(1,1,0),
    enforce_stationarity=False,
    enforce_invertibility=False
)

result = model.fit()
```

Final Forecast Of Test Data

```
forecast_test = result.get_forecast(
    steps=len(y_test),
    exog=exog_test
)

y_pred = forecast_test.predicted_mean
```

Mean Absolute Error & Mean Squared error on Model

```
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print("MAE:", round(mae,3))
print("RMSE:", round(rmse,3))

MAE: 0.617
RMSE: 0.757
```

Side By Side comparison of Actual VS Forecasted FX Data

```
last_train_level = final_df.loc[y_train.index[-1], 'USD_INR']
usd_inr_forecast_test_level = last_train_level + y_pred.cumsum()
usd_inr_actual_test = final_df.loc[y_test.index, 'USD_INR']
comparison_df = pd.DataFrame({
    'Actual_USD_INR': usd_inr_actual_test,
    'Forecast_USD_INR': usd_inr_forecast_test_level
})
comparison_df = comparison_df.dropna()
print(comparison_df.head())

      Actual_USD_INR  Forecast_USD_INR
2024-02-01        82.91        83.286976
2024-03-01        83.36        83.470052
2024-04-01        83.45        82.706363
2024-05-01        83.45        83.267061
2024-06-01        83.44        83.048358
```

Plot For the same

```
import matplotlib.pyplot as plt
plt.figure(figsize=(10,4))

plt.plot(comparison_df.index,
         comparison_df['Actual_USD_INR'],
         label='Actual USD/INR',
         linewidth=2)

plt.plot(comparison_df.index,
         comparison_df['Forecast_USD_INR'],
         label='Forecast USD/INR',
         linestyle='--',
         linewidth=2)

plt.title('USD/INR: Actual vs ARIMAX Forecast (Test Period)')
plt.xlabel('Date')
plt.ylabel('USD/INR Level')
plt.legend()
plt.grid(alpha=0.3)

plt.show()
```

