

UK Econometric Analysis

June 20, 2023

1 Econometric Analysis of Macroeconomic Variables for The UK Economy: Investigating Cointegration, VAR Modeling, and Granger Causality

1.1 Summary:

This project explores the relationships among key macroeconomic variables using econometric analysis techniques. The study begins by examining cointegration between the variables, finding that there is no evidence of a long-term or equilibrium relationship. Next, a Vector Autoregressive (VAR) model is constructed with an optimal lag length of 4, providing insights into the dynamic interactions among the variables. The analysis also includes Granger causality tests, which reveal the presence of causal relationships between certain pairs of variables. Additionally, the project assesses the autocorrelation of the model residuals, finding no evidence of serial correlation. Overall, this study sheds light on the interdependencies among macroeconomic factors, contributing to a better understanding of the economic landscape and providing valuable insights for policymakers and investors.

1.2 Data Preprocessing

Dataset Source: WB

- 1- GDP: Current GDP in USD
- 2- Exports: as a percentage of GDP
- 3- Imports: as a percentage of GDP
- 4- Exchange Rate: Official exchange rate (LCU per USD, period average)

```
[1]: #First I will import the required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm

# Second step is to load the dataset
file_path = 'C:/Users/tasne/OneDrive/Desktop/My fiels/Data analysis/Python/Econ/
↳UKMacro.xlsx'
```

```
df = pd.read_excel('C:/Users/tasne/OneDrive/Desktop/My fiels/Data analysis/
↳Python/Econ/UKMacro.xlsx')
```

```
[2]: # to convert the 'Year' column to datetime format
df['Year'] = pd.to_datetime(df['Year'], format='%Y')
```

```
[5]: df.head()
```

```
[5]:
```

	Year	GDP	Exchange_Rate	Exports	Imports
0	1970-01-01	1.306719e+11	0.416667	22.065771	20.959167
1	1971-01-01	1.481139e+11	0.410920	22.149489	20.521681
2	1972-01-01	1.699650e+11	0.400390	20.879142	20.723946
3	1973-01-01	1.925380e+11	0.408171	22.713646	24.753152
4	1974-01-01	2.061314e+11	0.427756	27.138748	31.624996

```
[6]: # to calculate the GDP rate
df['GDP_Growth'] = df['GDP'].pct_change() * 100
```

```
[7]: # to remove rows with missing values in the 'GDP_Growth' column
df = df.dropna(subset=['GDP_Growth'])
```

```
[8]: # to delete the GDP before calculating the growth columns
df = df.drop(['GDP'], axis=1)
```

```
[9]: # to check the data types of each column
data_types = df.dtypes
print(data_types)
```

```
Year                datetime64[ns]
Exchange_Rate       float64
Exports             float64
Imports            float64
GDP_Growth          float64
dtype: object
```

1.3 Exploratory data analysis

```
[10]: # to generate descriptive statistics for the dataset
data_description = df.describe()
print(data_description)
```

	Exchange_Rate	Exports	Imports	GDP_Growth
count	51.000000	51.000000	51.000000	51.000000
mean	0.604577	26.395195	27.107962	6.946930
std	0.101410	2.600460	2.971417	10.684882
min	0.400390	20.879142	20.521681	-17.529021
25%	0.548089	24.547775	25.177140	-0.890668
50%	0.611927	26.113722	26.850918	6.023585

75%	0.660328	28.284787	29.099542	14.441445
max	0.783445	31.257606	32.872547	30.698497

```
[11]: import matplotlib.pyplot as plt

# to Plot Exchange_Rate
plt.figure()
plt.plot(df['Year'], df['Exchange_Rate'])
plt.xlabel('Year')
plt.ylabel('Exchange_Rate')
plt.title('Exchange_Rate over Time')

# to display the Exchange_Rate plot
plt.show()

# to plot GDP_Growth
plt.figure()
plt.plot(df['Year'], df['GDP_Growth'])
plt.xlabel('Year')
plt.ylabel('GDP Growth')
plt.title('GDP Growth over Time')

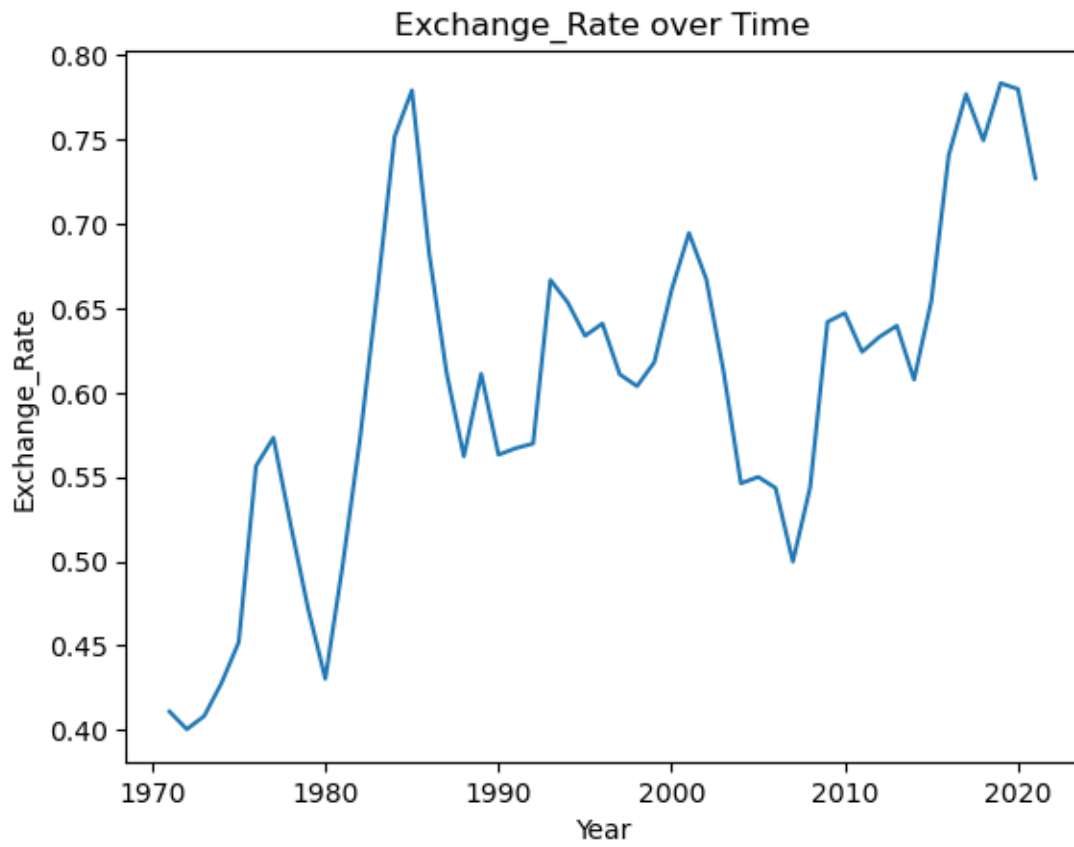
# to display the GDP Growth plot
plt.show()

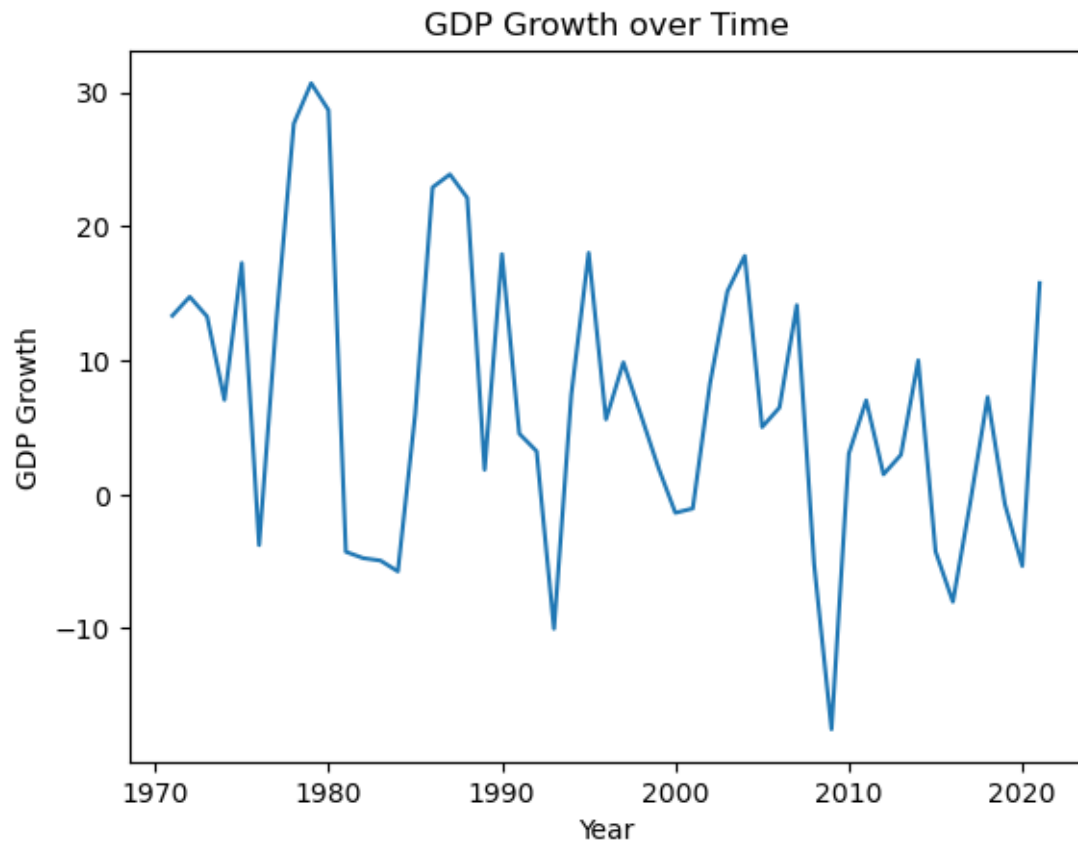
# to plot Exports
plt.figure()
plt.plot(df['Year'], df['Exports'])
plt.xlabel('Year')
plt.ylabel('Exports')
plt.title('Exports over Time')

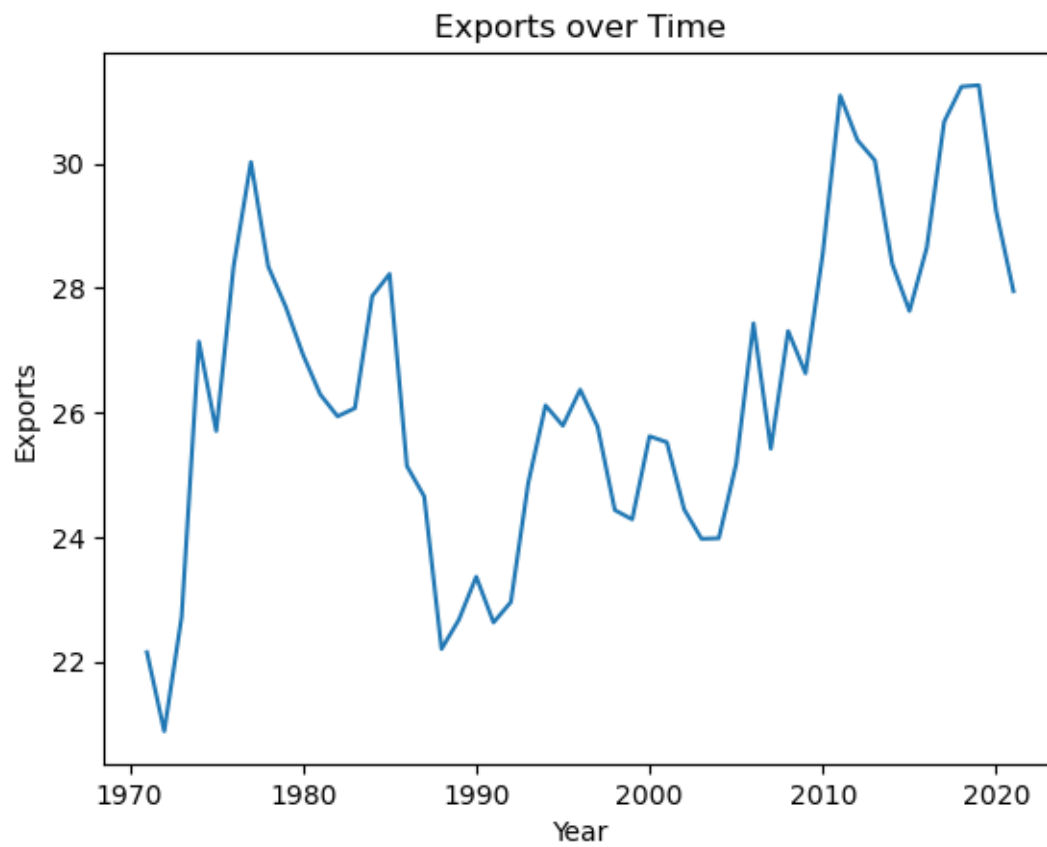
# to display the Exchange Rate plot
plt.show()

# Display the Imports plot
plt.show()

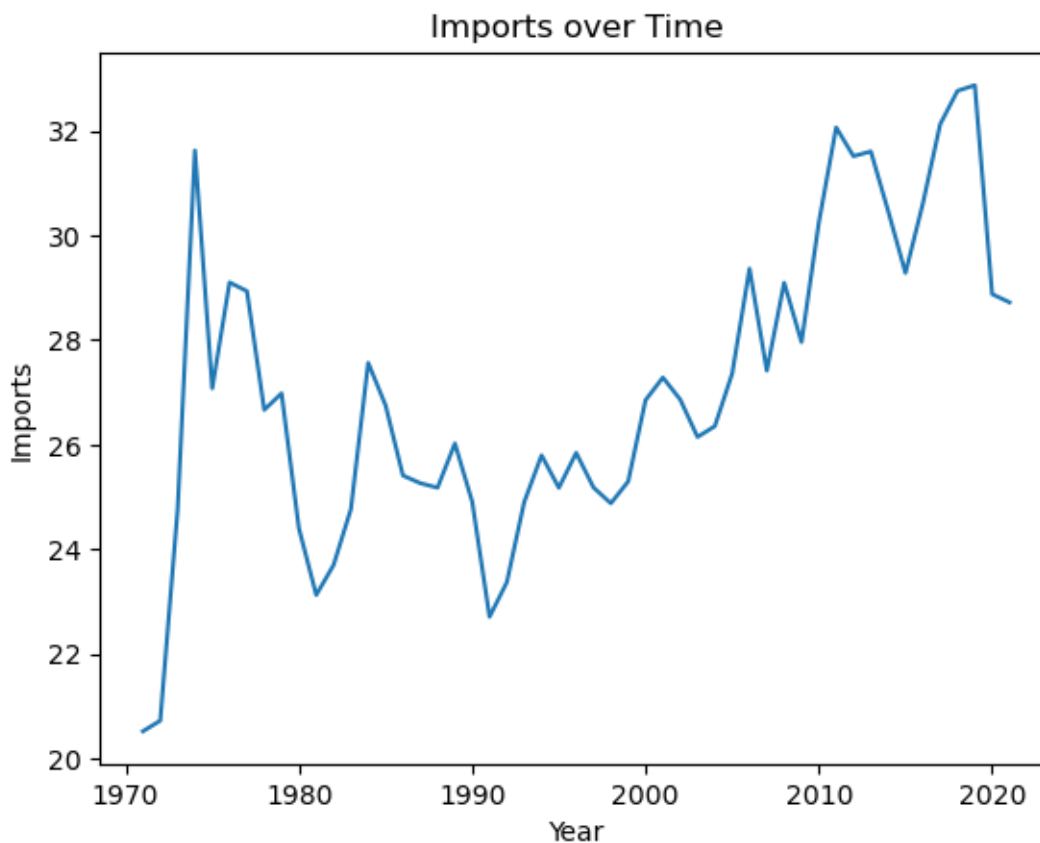
# to Plot Exports
plt.figure()
plt.plot(df['Year'], df['Imports'])
plt.xlabel('Year')
plt.ylabel('Imports')
plt.title('Imports over Time')
```







```
[11]: Text(0.5, 1.0, 'Imports over Time')
```



2 Econometric Analysis

2.1 ADF Unit root test

```
[12]: from statsmodels.tsa.stattools import adfuller

# Defining a function to perform the ADF test and print the results
def adf_test(data, variable_name):
    result = adfuller(data)
    print(f'Augmented Dickey-Fuller Test - {variable_name}')
    print(f'Test Statistic: {result[0]}')
    print(f'p-value: {result[1]}')
    print(f'Critical Values:')
    for key, value in result[4].items():
        print(f'\t{key}: {value}')

# Performing the ADF test for each variable
adf_test(df['Exchange_Rate'], 'Exchange_Rate')
```

```
adf_test(df['GDP_Growth'], 'GDP_Growth')
adf_test(df['Exports'], 'Exports')
adf_test(df['Imports'], 'Imports')
```

Augmented Dickey-Fuller Test - Exchange_Rate

Test Statistic: -1.133326141933874

p-value: 0.7016005531209161

Critical Values:

1%: -3.584828853223594

5%: -2.9282991495198907

10%: -2.6023438271604937

Augmented Dickey-Fuller Test - GDP_Growth

Test Statistic: -1.722623185640155

p-value: 0.419495635651623

Critical Values:

1%: -3.5925042342183704

5%: -2.931549768951162

10%: -2.60406594375338

Augmented Dickey-Fuller Test - Exports

Test Statistic: -2.416395661439049

p-value: 0.1371622255388582

Critical Values:

1%: -3.568485864

5%: -2.92135992

10%: -2.5986616

Augmented Dickey-Fuller Test - Imports

Test Statistic: -1.0862222311955707

p-value: 0.7205349297477012

Critical Values:

1%: -3.5812576580093696

5%: -2.9267849124681518

10%: -2.6015409829867675

2.1.1 All four variables are not stationary at their level with P values higher than .05

```
[13]: # Taking first difference for all columns in the DataFrame
df_diff = df.diff()

# Dropping the rows with any NaN values
df_diff = df_diff.dropna()

columns_without_year = [col for col in df_diff.columns if col != 'Year']

# Performing ADF test on each column excluding 'Year'
for column in columns_without_year:
    result = adfuller(df_diff[column])
    print(f'ADF Statistic for {column}: {result[0]}')
```



```

print(f'p-value for {column}: {result[1]}')
print(f'Critical Values for {column}:')
for key, value in result[4].items():
    print(f'\t{key}: {value}')
print('\n')

```

ADF Statistic for Exchange_Rate: -5.772271892883999
p-value for Exchange_Rate: 5.358108844989021e-07
Critical Values for Exchange_Rate:
1%: -3.584828853223594
5%: -2.9282991495198907
10%: -2.6023438271604937

ADF Statistic for Exports: -4.602984078203983
p-value for Exports: 0.00012754360868605738
Critical Values for Exports:
1%: -3.5812576580093696
5%: -2.9267849124681518
10%: -2.6015409829867675

ADF Statistic for Imports: -5.010661208970302
p-value for Imports: 2.1139815307203822e-05
Critical Values for Imports:
1%: -3.5812576580093696
5%: -2.9267849124681518
10%: -2.6015409829867675

ADF Statistic for GDP_Growth: -5.67917525784368
p-value for GDP_Growth: 8.564869088184162e-07
Critical Values for GDP_Growth:
1%: -3.5925042342183704
5%: -2.931549768951162
10%: -2.60406594375338

Now they all stationary after taking the first difference

2.2 checking for cointegration between the variables

```

[14]: from statsmodels.tsa.vector_ar.vecm import coint_johansen

# df_diff is the differenced DataFrame
df_test = df_diff[['Exchange_Rate', 'GDP_Growth', 'Exports', 'Imports']]

```

```
# Performing the Johansen cointegration test
result = coint_johansen(df_test, det_order=0, k_ar_diff=1)

print(f'Test statistics: {result.lr1}')
print(f'Critical values (90%, 95%, 99%): {result.cvt}')
print(f'Eigenvalues: {result.eig}')
```

```
Test statistics: [126.74264995  63.86393406  35.55832033  15.17331661]
Critical values (90%, 95%, 99%): [[44.4929 47.8545 54.6815]
 [27.0669 29.7961 35.4628]
 [13.4294 15.4943 19.9349]
 [ 2.7055  3.8415  6.6349]]
Eigenvalues: [0.73017273 0.44550655 0.34602593 0.2710213 ]
```

The test statistics are higher than the critical values at all levels (90%, 95%, and 99%) for all four series, suggesting that we cannot reject the null hypothesis of no cointegration. In other words, this implies that there is not sufficient evidence to conclude a long-term or equilibrium relationship among the variables in each series.

2.3 Selecting the optimal lag for the VAR Model

```
[15]: from statsmodels.tsa.api import VAR

df_diff_numeric = df_diff.drop(columns=['Year'])

model = VAR(df_diff_numeric)
lag_order_results = model.select_order(maxlags=4)

print(lag_order_results.summary())
```

```
VAR Order Selection (* highlights the minimums)
=====
```

	AIC	BIC	FPE	HQIC
0	-1.319	-1.160	0.2674	-1.259
1	-2.745	-1.950*	0.06446	-2.447*
2	-2.664	-1.233	0.07109	-2.128
3	-2.494	-0.4265	0.08800	-1.719
4	-2.946*	-0.2425	0.06088*	-1.933

```
-----
```

```
C:\Users\tasne\anaconda3\lib\site-
packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: An unsupported
index was provided and will be ignored when e.g. forecasting.
    self._init_dates(dates, freq)
```

Based on the VAR order selection table, the optimal lag length is 4 as it has the lowest Akaike Information Criterion (AIC) and Final Prediction Error (FPE).

2.4 fitting the VAR model

```
[16]: # Fitting the VAR model of order 4
var_model = model.fit(4)

# Printing a summary of the model results
print(var_model.summary())
```

```
Summary of Regression Results
=====
Model:                VAR
Method:               OLS
Date:                Sun, 18, Jun, 2023
Time:                04:11:30
-----
No. of Equations:      4.00000    BIC:                -0.242518
Nobs:                  46.0000    HQIC:              -1.93309
Log likelihood:        -125.333    FPE:                0.0608774
AIC:                   -2.94573    Det(Omega_mle):     0.0173032
-----
Results for equation Exchange_Rate
=====
===

```

	coefficient	std. error	t-stat
prob			

const	0.010148	0.006968	1.456
0.145			
L1.Exchange_Rate	0.865084	0.418662	2.066
0.039			
L1.Exports	-0.003995	0.009274	-0.431
0.667			
L1.Imports	-0.006631	0.008289	-0.800
0.424			
L1.GDP_Growth	0.002432	0.002060	1.181
0.238			
L2.Exchange_Rate	-1.193984	0.472805	-2.525
0.012			
L2.Exports	0.005672	0.008857	0.640
0.522			
L2.Imports	-0.007811	0.008098	-0.965
0.335			
L2.GDP_Growth	-0.002582	0.002392	-1.079
0.280			
L3.Exchange_Rate	0.109510	0.527819	0.207
0.836			
L3.Exports	-0.010358	0.009518	-1.088

0.276			
L3.Imports	0.009722	0.008022	1.212
0.226			
L3.GDP_Growth	-0.000809	0.002148	-0.377
0.706			
L4.Exchange_Rate	-0.348352	0.470961	-0.740
0.460			
L4.Exports	0.016911	0.009336	1.811
0.070			
L4.Imports	-0.013670	0.007071	-1.933
0.053			
L4.GDP_Growth	-0.002769	0.000775	-3.575
0.000			
=====			
===			

Results for equation Exports

=====			
===			
	coefficient	std. error	t-stat
prob			

const	0.226525	0.200666	1.129
0.259			
L1.Exchange_Rate	35.842793	12.056332	2.973
0.003			
L1.Exports	-0.231053	0.267056	-0.865
0.387			
L1.Imports	-0.062010	0.238699	-0.260
0.795			
L1.GDP_Growth	0.155856	0.059312	2.628
0.009			
L2.Exchange_Rate	-10.475593	13.615510	-0.769
0.442			
L2.Exports	0.347026	0.255071	1.361
0.174			
L2.Imports	-0.380912	0.233189	-1.633
0.102			
L2.GDP_Growth	0.096567	0.068876	1.402
0.161			
L3.Exchange_Rate	-29.688981	15.199755	-1.953
0.051			
L3.Exports	-0.024865	0.274098	-0.091
0.928			
L3.Imports	-0.013422	0.231013	-0.058
0.954			
L3.GDP_Growth	-0.034331	0.061850	-0.555

0.579			
L4.Exchange_Rate	-5.613100	13.562383	-0.414
0.679			
L4.Exports	-0.253174	0.268854	-0.942
0.346			
L4.Imports	0.083623	0.203625	0.411
0.681			
L4.GDP_Growth	-0.045094	0.022305	-2.022
0.043			

=====

===

Results for equation Imports

=====

===

	coefficient	std. error	t-stat
prob			

const	0.102950	0.223427	0.461
0.645			
L1.Exchange_Rate	19.218871	13.423878	1.432
0.152			
L1.Exports	-0.288629	0.297348	-0.971
0.332			
L1.Imports	-0.023726	0.265775	-0.089
0.929			
L1.GDP_Growth	0.064673	0.066039	0.979
0.327			
L2.Exchange_Rate	-14.651710	15.159912	-0.966
0.334			
L2.Exports	0.305004	0.284004	1.074
0.283			
L2.Imports	-0.233762	0.259640	-0.900
0.368			
L2.GDP_Growth	-0.006325	0.076689	-0.082
0.934			
L3.Exchange_Rate	-20.054850	16.923858	-1.185
0.236			
L3.Exports	-0.122261	0.305189	-0.401
0.689			
L3.Imports	-0.066912	0.257217	-0.260
0.795			
L3.GDP_Growth	-0.114210	0.068865	-1.658
0.097			
L4.Exchange_Rate	16.117217	15.100759	1.067
0.286			
L4.Exports	-0.322005	0.299351	-1.076

```

0.282
L4.Imports          0.093557          0.226722          0.413
0.680
L4.GDP_Growth       -0.011319          0.024835         -0.456
0.649
=====
===

```

Results for equation GDP_Growth

```

=====
===

```

	coefficient	std. error	t-stat
prob			

const	-2.414778	1.606321	-1.503
0.133			
L1.Exchange_Rate	-83.024604	96.510425	-0.860
0.390			
L1.Exports	-0.078984	2.137771	-0.037
0.971			
L1.Imports	1.616572	1.910778	0.846
0.398			
L1.GDP_Growth	-0.938855	0.474786	-1.977
0.048			
L2.Exchange_Rate	295.932278	108.991571	2.715
0.007			
L2.Exports	-1.104853	2.041836	-0.541
0.588			
L2.Imports	1.292798	1.866669	0.693
0.489			
L2.GDP_Growth	0.239352	0.551353	0.434
0.664			
L3.Exchange_Rate	-29.431516	121.673387	-0.242
0.809			
L3.Exports	2.474300	2.194144	1.128
0.259			
L3.Imports	-2.052210	1.849250	-1.110
0.267			
L3.GDP_Growth	-0.050078	0.495105	-0.101
0.919			
L4.Exchange_Rate	94.979098	108.566295	0.875
0.382			
L4.Exports	-2.933116	2.152168	-1.363
0.173			
L4.Imports	2.408830	1.630006	1.478
0.139			
L4.GDP_Growth	0.409106	0.178550	2.291

0.022

=====
===

Correlation matrix of residuals

	Exchange_Rate	Exports	Imports	GDP_Growth
Exchange_Rate	1.000000	0.285101	0.287664	-0.915981
Exports	0.285101	1.000000	0.798546	-0.146220
Imports	0.287664	0.798546	1.000000	-0.053746
GDP_Growth	-0.915981	-0.146220	-0.053746	1.000000

The VAR model results provide valuable insights into the relationships among macroeconomic variables. The analysis reveals that changes in the exchange rate are influenced by both the lagged exchange rate and GDP growth, while exports are positively affected by the lagged exchange rate and GDP growth. Imports, on the other hand, are influenced by the lagged exchange rate but not significantly impacted by GDP growth. The GDP growth equation shows a negative relationship with the exchange rate, suggesting that an appreciation in the exchange rate may dampen economic growth. The correlation matrix of residuals confirms a negative correlation between the exchange rate and GDP growth, aligning with economic theory. These findings contribute to a deeper understanding of the dynamics and interdependencies among macroeconomic variables, offering valuable insights for policymakers and investors.

2.5 Granger Causality Test

```
[19]: # Performing Granger causality test for each pair of variables
for column1 in df_diff.columns:
    for column2 in df_diff.columns:
        if column1 != column2 and column1 != 'Year' and column2 != 'Year':
            print(f"Granger Causality Test: {column1} --> {column2}")
            test_result = grangercausalitytests(df_diff[[column1, column2]],
            ↪maxlag=maxlag, verbose=False)
            for lag in range(1, maxlag+1):
                p_value = test_result[lag][0]['ssr_ftest'][1]
                print(f"Lag {lag} p-value: {p_value:.4f}")
            print()
```

Granger Causality Test: Exchange_Rate --> Exports

Lag 1 p-value: 0.2402

Lag 2 p-value: 0.5686

Lag 3 p-value: 0.6175

Lag 4 p-value: 0.7716

Granger Causality Test: Exchange_Rate --> Imports

Lag 1 p-value: 0.5197

Lag 2 p-value: 0.7514

Lag 3 p-value: 0.8799
Lag 4 p-value: 0.7477

Granger Causality Test: Exchange_Rate --> GDP_Growth
Lag 1 p-value: 0.1816
Lag 2 p-value: 0.2490
Lag 3 p-value: 0.3760
Lag 4 p-value: 0.0336

Granger Causality Test: Exports --> Exchange_Rate
Lag 1 p-value: 0.0469
Lag 2 p-value: 0.1416
Lag 3 p-value: 0.1097
Lag 4 p-value: 0.2328

Granger Causality Test: Exports --> Imports
Lag 1 p-value: 0.3127
Lag 2 p-value: 0.8027
Lag 3 p-value: 0.6397
Lag 4 p-value: 0.9504

Granger Causality Test: Exports --> GDP_Growth
Lag 1 p-value: 0.3802
Lag 2 p-value: 0.5760
Lag 3 p-value: 0.0708
Lag 4 p-value: 0.3202

Granger Causality Test: Imports --> Exchange_Rate
Lag 1 p-value: 0.2641
Lag 2 p-value: 0.4460
Lag 3 p-value: 0.2187
Lag 4 p-value: 0.4100

Granger Causality Test: Imports --> Exports
Lag 1 p-value: 0.0965
Lag 2 p-value: 0.5399
Lag 3 p-value: 0.7548
Lag 4 p-value: 0.6311

Granger Causality Test: Imports --> GDP_Growth
Lag 1 p-value: 0.6705
Lag 2 p-value: 0.8186
Lag 3 p-value: 0.0407
Lag 4 p-value: 0.2987

Granger Causality Test: GDP_Growth --> Exchange_Rate
Lag 1 p-value: 0.0004
Lag 2 p-value: 0.0001

Lag 3 p-value: 0.0005
Lag 4 p-value: 0.0006

Granger Causality Test: GDP_Growth --> Exports

Lag 1 p-value: 0.0217
Lag 2 p-value: 0.1130
Lag 3 p-value: 0.1201
Lag 4 p-value: 0.3114

Granger Causality Test: GDP_Growth --> Imports

Lag 1 p-value: 0.0671
Lag 2 p-value: 0.2316
Lag 3 p-value: 0.2408
Lag 4 p-value: 0.2967

The results of The Granger causality tests suggest that there are significant causal relationships between some of the variables at certain time lags.

Specifically, the exchange rate is found to be influenced by lagged GDP growth, indicating that changes in economic growth can impact the exchange rate. Additionally, exports are shown to have a causal effect on the exchange rate, suggesting that changes in export levels can influence the exchange rate. On the other hand, imports do not appear to have a significant causal relationship with the exchange rate.

Furthermore, GDP growth is found to have a significant causal relationship with both the exchange rate and exports. This implies that changes in GDP growth can impact the exchange rate and export levels. However, the relationships between GDP growth and imports are not statistically significant.

Overall, these findings highlight the interdependencies among the variables and provide valuable insights into the causal dynamics within the macroeconomic context. Further analysis and consideration of additional factors may be necessary to fully understand the complexities of these relationships and their implications for policy and decision-making.

2.6 Autocorrelation Test

```
[20]: # Autocorrelation
from statsmodels.stats.stattools import durbin_watson

out = durbin_watson(var_model.resid)

df_diff = df_diff[['Exchange_Rate', 'Exports', 'Imports', 'GDP_Growth']]

for col, val in zip(df_diff.columns, out):
    print(col, ': ', round(val, 2))
```

Exchange_Rate : 1.92
Exports : 2.02

Imports : 1.95
GDP_Growth : 1.97

The assumption of independence for residuals in our VAR model holds. there is no autocorrelation