Project: MONETARY AGGREGATES ON MACRO ECONOMIC VAIRABLES

[DATASET INVESTIGATION - CENTRAL BANK OF NIGERIA DATA]

Table of Contents

> Choose a country and calculate between 20-35 years running window correlation between growth rates of money supply (measured by M2 or M3 where available) and: a) real output; b) nominal output; c) money market rates. If possible use quarterly or monthly data.

Introduction

Dataset Description

This project is center on Monetary vairables in developing Economies like Nigeria. Insight, analysis and decricption covers correlation among monetary variables like Money Supply(M2), real and norminal output, money market rates .Reason for choosing developing economies like Nigeria is to validate trends and economies in advanced economies in developing world

Dataset for exploration contain nominal and real GDP, Money And Credit statistics, and money market rates.

Sources of Data

Data and statictis covering monetary variables is assess from Central bank of Nigeria statistical bulettin 'https://www.cbn.gov.ng/documents/Statbulletin.asp'.

Data Analysis Tools

Python 3 with Jupyter notebook is use to explore and analysis the data

Question(s) for Analysis

> - #The following research questions will be a driver to analysis, decription and conclusion.

- Is the correlation decreasing or increasing between money supply and real GDP in recent years?
- Is the correlation decreasing or increasing between money supply and nominal GDP in recent years?
- Is the correlation decreasing or increasing between money supply and money market rate in recent years?
- Can you identify some predicting power of monetary aggregates on studied variables (inflation, real output, nominal output)?

In [1]:
```
# Use this cell to set up import statements for all of the packages that you
#   plan to use.

# load datasets
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Data Wrangling: PUT MY HANDS IN THE DIRTY

> In this section, i will load in the data, embark on cleanliness, and then trim and clean my dataset for analysis to enable me carry out my analysis I only concentrate on vital information that are relevant or that can help us to provide solutions to the research questions that are previously stated above. Step by step cleaning will be perform to finetune the dataset

In [2]:
```
# Load your data and print out a few lines. Perform operations to inspect data
#figure are represented in Billions

m2 = pd.read_csv('MoneyAndCreditStats02092022.csv')
realGDP = pd.read_csv('RealGDP02092022.csv')
norminalGDP = pd.read_csv('NominalGDP02092022.csv')
moneymarketrate = pd.read_csv('MnyMktInd02092022.csv')
```

In [3]:
```
m2.head(5)
```

Out[3]:

	Counts	Year	Month	Narrow Money	Money Supply M3	Net Foreign Assets	Net Domestic Credit	Credit to Government	Credit to Private Sector	Base Money	...	Currency Outside Banks	
0	1	2022	1	18589692.22	45194945.63	8386366.23	50088061.91	14903925.40	35184136.51	13608456.25	...	2779750.75	158
1	2	2022	2	18897327.74	44740264.88	8458893.96	50707660.59	14721135.97	35986524.62	13635912.33	...	2723657.37	161
2	3	2022	3	19610356.83	45664828.96	7563818.91	52787060.85	16319660.37	36467400.48	14301768.29	...	2714074.02	168
3	4	2022	4	19821327.97	47147578.65	7516045.31	54296180.59	16847655.48	37448525.11	14376820.88	...	2833752.73	169
4	5	2022	5	20619559.30	48577983.22	7133673.69	56950238.56	18269043.74	38681194.82	14534947.97	...	2764827.76	178

5 rows × 22 columns

In [4]:
```
#year2022 is remove. Data not complete.(Ongoing)
m2 = m2[m2.Year != 2022]
m2.head(5)
```

Out[4]:

	Counts	Year	Month	Narrow Money	Money Supply M3	Net Foreign Assets	Net Domestic Credit	Credit to Government	Credit to Private Sector	Base Money	...	Currency Outside Banks	
7	8	2021	1	15855542.74	38737379.48	7606156.57	42492010.49	12085727.76	30406282.73	13264907.99	...	2358724.24	13
8	9	2021	2	16484070.12	38796566.64	8403538.47	43091736.20	12586130.06	30505606.14	13395207.29	...	2319993.77	14
9	10	2021	3	16138206.97	38720379.46	6725973.17	43503924.95	12066876.87	31437048.08	13338122.26	...	2305664.20	13
10	11	2021	4	15995932.43	39151453.58	6782878.02	44134011.03	12236471.93	31897539.10	13202697.77	...	2302191.18	13
11	12	2021	5	16256641.72	39856996.98	7356458.68	44669259.81	12552025.37	32117234.44	13064088.63	...	2316426.36	13

5 rows × 22 columns

In [5]:
```
#data before 1999 is drop
m2= m2.drop(m2.index[276:388], inplace=False)
m2.tail(7)
```

Out[5]:

	Counts	Year	Month	Narrow Money	Money Supply M3	Net Foreign Assets	Net Domestic Credit	Credit to Government	Credit to Private Sector	Base Money	...	Currency Outside Banks	Demand Deposits	Qua Mon
276	277	1999	6	364943.84	NaN	608426.92	570168.09	142759.78	427408.32	243082.17	...	146958.47	217985.38	269993
277	278	1999	7	344978.93	NaN	594271.58	547764.57	112297.40	435467.17	239734.40	...	145270.80	199708.13	276362
278	279	1999	8	339881.50	NaN	590640.09	558026.40	109774.54	448251.86	236709.11	...	143211.51	196669.99	290035
279	280	1999	9	353936.80	NaN	623997.05	532292.07	91308.82	440983.25	231158.30	...	149881.30	204055.50	301678
280	281	1999	10	364739.00	NaN	651688.96	531570.32	73666.42	457903.90	252365.98	...	153219.38	211519.62	259360
281	282	1999	11	391954.39	NaN	630080.43	607238.93	143517.41	463721.52	255997.33	...	162063.03	229891.36	316370
282	283	1999	12	393078.80	NaN	666271.20	632010.10	176804.90	455205.20	283421.79	...	186456.00	206622.80	306654

7 rows × 22 columns

In [6]:
```
#resorting
m2 = m2.sort_values(by=['Year','Month'], inplace=False , ascending = [True, True])
m2.head(7)
```

Out[6]:

	Counts	Year	Month	Narrow Money	Money Supply M3	Net Foreign Assets	Net Domestic Credit	Credit to Government	Credit to Private Sector	Base Money	...	Currency Outside Banks	Demand Deposits	Qua Mon
271	272	1999	1	320042.84	NaN	664041.41	275652.47	-115307.50	390959.96	211828.49	...	147460.99	172581.85	215971
272	273	1999	2	326516.93	NaN	655483.88	297281.33	-106877.98	404159.31	207905.98	...	144666.78	181850.15	226501
273	274	1999	3	367568.07	NaN	634905.32	368122.90	-33229.39	401352.29	235075.34	...	150271.94	217296.13	241462
274	275	1999	4	361666.38	NaN	593676.33	441986.83	29115.22	412871.61	222553.00	...	142538.10	219128.28	227335
275	276	1999	5	425458.83	NaN	601553.92	589907.65	154171.78	435735.87	266663.21	...	151823.81	273635.02	260934
276	277	1999	6	364943.84	NaN	608426.92	570168.09	142759.78	427408.32	243082.17	...	146958.47	217985.38	269993
277	278	1999	7	344978.93	NaN	594271.58	547764.57	112297.40	435467.17	239734.40	...	145270.80	199708.13	276362

7 rows × 22 columns

In [7]:
```
#Create new date column
m2['Date'] = pd.date_range(start= '1/1/1999', freq='M', periods=276)
m2.head()
```

Out[7]:

	Counts	Year	Month	Narrow Money	Money Supply M3	Net Foreign Assets	Net Domestic Credit	Credit to Government	Credit to Private Sector	Base Money	...	Demand Deposits	Quasi Money	Domes Ass
271	272	1999	1	320042.84	NaN	664041.41	275652.47	-115307.50	390959.96	211828.49	...	172581.85	215971.0	-128027
272	273	1999	2	326516.93	NaN	655483.88	297281.33	-106877.98	404159.31	207905.98	...	181850.15	226501.2	-102465
273	274	1999	3	367568.07	NaN	634905.32	368122.90	-33229.39	401352.29	235075.34	...	217296.13	241462.0	-25875
274	275	1999	4	361666.38	NaN	593676.33	441986.83	29115.22	412871.61	222553.00	...	219128.28	227335.9	-4674
275	276	1999	5	425458.83	NaN	601553.92	589907.65	154171.78	435735.87	266663.21	...	273635.02	260934.1	84838

5 rows × 23 columns

In [8]:
```
m2.columns
```

Out[8]:
```
Index(['Counts', 'Year', 'Month', 'Narrow Money', 'Money Supply M3',
       'Net Foreign Assets', 'Net Domestic Credit', 'Credit to Government',
       'Credit to Private Sector', 'Base Money', 'Currency in Circulation',
       'Bank Reserves', 'Currency Outside Banks', 'Demand Deposits',
       'Quasi Money', 'Net Domestic Assets', 'Credit To GovernmentFed',
       'Mirror Accounts', 'Other Assets Net', 'Money Supply M2', 'CBN Bills',
       'Special Intervention Reserves', 'Date'],
      dtype='object')
```

In [10]:
```
#groupby the date and Money supply M2 in a quarterly format
money_supplym2 = m2.groupby(m2['Date'].dt.to_period('Q'))['Money Supply M2'].sum()
money_supplym2.head()
```

Out[10]:
```
Date
1999Q1    1698062.04
1999Q2    1910332.65
1999Q3    1906873.53
1999Q4    2032157.69
2000Q1    2166807.97
Freq: Q-DEC, Name: Money Supply M2, dtype: float64
```

Make money_supplym2 a dataframe to use for our analysis

money_supplym2.to_frame().reset_index().round()

In [11]:
```
money_supplym2 = pd.DataFrame(money_supplym2, columns=['Money Supply M2']).reset_index().round()
money_supplym2
```

Out[11]:

	Date	Money Supply M2
0	1999Q1	1698062.0
1	1999Q2	1910333.0
2	1999Q3	1906874.0
3	1999Q4	2032158.0
4	2000Q1	2166808.0
...	...	...
87	2020Q4	110075856.0
88	2021Q1	113932131.0
89	2021Q2	116019002.0
90	2021Q3	120992852.0
91	2021Q4	128517531.0

92 rows × 2 columns

In [13]:
```
money_supplym2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 92 entries, 0 to 91
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Date             92 non-null     period[Q-DEC]
 1   Money Supply M2  92 non-null     float64
dtypes: float64(1), period[Q-DEC](1)
memory usage: 1.6 KB
```

REALGDP

Data on RealGDP csv will be cleaned. What we need in this CSV dataset is the real GDP at market price tag column [GDP at 2010 Constant Market Prices]

Quarterly Data from 1991 to 2020 will be identy from the Master datasheet. It is observed that data from 1999 to 2009 contains annual data and not quartely data. Hence i divide all annual data by 3 and spread it around the four quaterly month

In [12]:
```
realGDP = pd.read_csv('RealGDP02092022.csv')
```

In [13]:
```
realGDP.head()
```

Out[13]:

	Code	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	...	RealEstate	Professi
0	1	1981	Annual	2364.37	1854.76	341.41	77.90	90.30	11753.40	5044.55	...	1063.96	
1	2	1982	Annual	2425.96	1897.08	361.12	73.91	93.86	10189.10	4507.93	...	1074.05	
2	3	1983	Annual	2409.08	1842.70	393.13	75.28	97.96	8255.76	4096.99	...	1086.70	
3	4	1984	Annual	2303.51	1759.12	399.69	76.69	68.01	8392.25	4602.27	...	1086.93	
4	5	1985	Annual	2731.06	2180.91	428.10	78.08	43.97	8768.30	4962.81	...	1091.38	

5 rows × 59 columns

In [14]:
```
#drop rows less than year 1999. Reason because previous year data aren't provided and we want to mainta
in 20 to 21 years
realGDP=realGDP.drop(realGDP.index[0:18], inplace=False)
realGDP.head(13)
```

Out[14]:

	Code	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	...	RealEstate	Profess
18	19	1999	Annual	4703.64	3949.42	541.03	85.07	128.12	10201.81	6572.89	...	1690.33	
19	20	2000	Annual	4840.97	4067.90	553.48	86.35	133.25	10962.84	7302.99	...	1756.08	
20	21	2001	Annual	5024.54	4222.48	570.08	88.07	143.91	11576.32	7685.37	...	1843.82	
21	22	2002	Annual	7817.08	6977.88	597.50	88.69	153.02	11725.42	7247.86	...	1899.13	
22	23	2003	Annual	8364.83	7493.02	622.56	90.02	159.23	13151.23	8975.81	...	1956.11	
23	24	2004	Annual	8888.57	7956.66	663.03	95.87	173.02	13382.86	9275.14	...	2168.33	
24	25	2005	Annual	9516.99	8524.15	707.87	101.55	183.43	13609.76	9323.75	...	2408.82	
25	26	2006	Annual	10222.47	9162.65	756.73	107.66	195.43	13342.47	8907.47	...	2690.07	
26	27	2007	Annual	10958.47	9826.77	809.16	114.25	208.29	13085.27	8508.82	...	3005.42	
27	28	2008	Annual	11645.37	10437.99	864.19	121.22	221.97	12817.79	7989.19	...	3359.76	
28	29	2009	Annual	12330.33	11046.16	920.20	128.31	235.66	13138.95	8030.01	...	3727.34	
29	30	2010	Q1	2594.76	2262.18	237.30	30.42	64.86	3284.29	1952.21	...	888.23	
30	31	2010	Q2	2873.38	2561.46	216.10	34.38	61.43	3314.21	1993.68	...	972.28	

13 rows × 59 columns

About 7years data comes with annual data but will intend to mentain a quarterly data

In [17]:
```
#Quarterly report are missing from 1999 to 2009.

#I identify annual data for 1999-2009 year and divide it 4 places, placing them quaterly.

w= realGDP.iloc[:, [3,4, 5, 6, 7, 8, 9,10, 11,12,13, 14, 15,16, 17, 18, 19, 20,21,22,23,24,25,26,27,28,
29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58]].iloc[0:11].
div(4)
w.head()
```

Out[17]:

	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNaturalGas	CoalMining
18	1175.9100	987.355	135.2575	21.2675	32.0300	2550.4525	1643.2225	1638.1725	0.7025
19	1210.2425	1016.975	138.3700	21.5875	33.3125	2740.7100	1825.7475	1820.4850	0.7475
20	1256.1350	1055.620	142.5200	22.0175	35.9775	2894.0800	1921.3425	1915.7450	0.6825
21	1954.2700	1744.470	149.3750	22.1725	38.2550	2931.3550	1811.9650	1806.4200	0.4275
22	2091.2075	1873.255	155.6400	22.5050	39.8075	3287.8075	2243.9525	2238.1550	0.4275

5 rows × 56 columns

In [18]:
```
#repeat the amount derived and spread it quaterly

w2 = pd.DataFrame(np.repeat(w.values, 4, axis=0))
w2.columns = w.columns
```

In [19]:
```
#Creating new column:  Year and Period columns


#Period
w2['Period'] = ['Q1', 'Q2', 'Q3', 'Q4']* 11

#Year
arr = np.array([1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009])
w2['Year']= (np.repeat(arr, 4))
w2.head()
```

Out[19]:

	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNaturalGas	CoalMining
0	1175.9100	987.355	135.2575	21.2675	32.0300	2550.4525	1643.2225	1638.1725	0.7025
1	1175.9100	987.355	135.2575	21.2675	32.0300	2550.4525	1643.2225	1638.1725	0.7025
2	1175.9100	987.355	135.2575	21.2675	32.0300	2550.4525	1643.2225	1638.1725	0.7025
3	1175.9100	987.355	135.2575	21.2675	32.0300	2550.4525	1643.2225	1638.1725	0.7025
4	1210.2425	1016.975	138.3700	21.5875	33.3125	2740.7100	1825.7475	1820.4850	0.7475

5 rows × 58 columns

In [20]:
```
w2.columns
```

Out[20]:
```
Index(['Agriculture', 'CropProduction', 'Livestock', 'Forestry', 'Fishing',
       'Industry', 'MiningAndQuarrying', 'CrudePetroleumAndNaturalGas',
       'CoalMining', 'MetalOres', 'QuarryingAndOtherMinerals', 'Manufacturing',
       'OilRefining', 'Cement', 'FoodBeverageAndTobacco',
       'TextileApparelAndFootwear', 'WoodAndWoodProducts',
       'PulpPaperAndPaperProducts', 'ChemicalAndPharmaceuticalProducts',
       'NonMetallicProducts', 'PlasticAndRubberProducts',
       'ElectricalAndElectronics', 'BasicMetalIronAndSteel',
       'MotorVehiclesAndAssembly', 'OtherManufacturing',
       'ElectricityGasSteamAndAirCon', 'WaterSupplySewageWaste',
       'Construction', 'Services', 'Trade', 'AccommodationAndFoodServices',
       'TransportationAndStorage', 'RoadTransport',
       'RailTransportAndPipelines', 'WaterTransport', 'AirTransport',
       'TransportServices', 'PostAndCourierServices',
       'InformationAndCommunication', 'Publishing',
       'MotionPicturesSoundRecordingAndMusicProduction', 'Broadcasting',
       'ArtsEntertainmentAndRecreation', 'FinanceAndInsurance',
       'FinancialInstitutions', 'Insurance', 'RealEstate',
       'ProfessionalScientificAndTechnicalServices',
       'AdministrativeAndSupportServicesBusinessServices',
       'PublicAdministration', 'Education', 'HumanHealthAndSocialServices',
       'OtherServices', 'GDP at 2010 Constant Basic Prices',
       'NetTaxesOnProducts', 'GDP at 2010 Constant Market Prices', 'Period',
       'Year'],
      dtype='object')
```

In [22]:
```
#reindex the dataframe columns to look exactly likely the initial data
w2 = w2.reindex(columns=['Year','Period', 'Agriculture', 'CropProduction', 'Livestock', 'Forestry', 'Fi
shing','Industry', 'MiningAndQuarrying', 'CrudePetroleumAndNaturalGas','CoalMining', 'MetalOres', 'Quar
ryingAndOtherMinerals', 'Manufacturing','OilRefining', 'Cement', 'FoodBeverageAndTobacco','TextileAppar
elAndFootwear','WoodAndWoodProducts','PulpPaperAndPaperProducts', 'ChemicalAndPharmaceuticalProducts',
'NonMetallicProducts', 'PlasticAndRubberProducts','ElectricalAndElectronics', 'BasicMetalIronAndSteel',
'MotorVehiclesAndAssembly', 'OtherManufacturing','ElectricityGasSteamAndAirCon', 'WaterSupplySewageWast
e','Construction', 'Services', 'Trade', 'AccommodationAndFoodServices','TransportationAndStorage', 'Roa
dTransport','RailTransportAndPipelines', 'WaterTransport', 'AirTransport','TransportServices', 'PostAnd
CourierServices','InformationAndCommunication', 'Publishing','MotionPicturesSoundRecordingAndMusicProdu
ction', 'Broadcasting','ArtsEntertainmentAndRecreation', 'FinanceAndInsurance','FinancialInstitutions',
 'Insurance', 'RealEstate','ProfessionalScientificAndTechnicalServices','AdministrativeAndSupportServic
esBusinessServices','PublicAdministration', 'Education', 'HumanHealthAndSocialServices','OtherServices'
, 'GDP at 2010 Constant Basic Prices','NetTaxesOnProducts', 'GDP at 2010 Constant Market Prices',])
w2.tail()
```

Out[22]:

	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNaturalGa
39	2008	Q4	2911.3425	2609.4975	216.0475	30.3050	55.4925	3204.4475	1997.2975	1986.930
40	2009	Q1	3082.5825	2761.5400	230.0500	32.0775	58.9150	3284.7375	2007.5025	1995.907
41	2009	Q2	3082.5825	2761.5400	230.0500	32.0775	58.9150	3284.7375	2007.5025	1995.907
42	2009	Q3	3082.5825	2761.5400	230.0500	32.0775	58.9150	3284.7375	2007.5025	1995.907
43	2009	Q4	3082.5825	2761.5400	230.0500	32.0775	58.9150	3284.7375	2007.5025	1995.907

5 rows × 58 columns

In [23]:
```
#drop rows 1999 to 2009 from the Master data for realGDP datasheet
realGDP=realGDP.drop(realGDP.index[0:11], inplace=False)
realGDP.head()
```

Out[23]:

	Code	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	...	RealEstate	Profess
29	30	2010	Q1	2594.76	2262.18	237.30	30.42	64.86	3284.29	1952.21	...	888.23	
30	31	2010	Q2	2873.38	2561.46	216.10	34.38	61.43	3314.21	1993.68	...	972.28	
31	32	2010	Q3	4000.03	3660.10	247.97	33.75	58.21	3422.53	2104.92	...	1062.70	
32	33	2010	Q4	3580.73	3200.16	278.19	37.17	65.21	3805.40	2403.74	...	1204.78	
33	34	2010	Annual	13048.89	11683.90	979.56	135.72	249.71	13826.43	8454.55	...	4127.99	

5 rows × 59 columns

In [24]:
```
#drop code column

#realGDP['Code'].drop()

realGDPdrop = realGDP.drop(columns=['Code'])
```

In [25]:
```
#Merge the two dataframe together
df_all_rows = pd.concat([w2, realGDPdrop])
df_all_rows
```

Out[25]:

	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNatural
0	1999	Q1	1175.9100	987.355	135.2575	21.2675	32.0300	2550.4525	1643.2225	1638.1
1	1999	Q2	1175.9100	987.355	135.2575	21.2675	32.0300	2550.4525	1643.2225	1638.1
2	1999	Q3	1175.9100	987.355	135.2575	21.2675	32.0300	2550.4525	1643.2225	1638.1
3	1999	Q4	1175.9100	987.355	135.2575	21.2675	32.0300	2550.4525	1643.2225	1638.1
4	2000	Q1	1210.2425	1016.975	138.3700	21.5875	33.3125	2740.7100	1825.7475	1820.4
...	...	...	...	...	...	...	...	...	...	
80	2020	Q2	3918.6700	3493.040	289.9600	50.0900	85.5800	3476.0900	1442.8100	1419.0
81	2020	Q3	5484.0600	5063.610	297.8900	46.1300	76.4400	3848.2400	1588.5200	1555.7
82	2020	Q4	5268.2900	4768.370	348.4200	51.3000	100.2000	3670.2200	1191.0500	1147.1
83	2020	Annual	18348.1800	16544.520	1233.1100	190.5100	380.0300	14953.7200	5819.3900	5713.2
84	2021	Q1	3760.8800	3293.950	301.7500	43.5400	121.6400	3996.3200	1562.0600	1556.0

100 rows × 58 columns

In [26]:
```
#remove all rows that contains annual rows since we are using quarterly figure
df_all_rows2 = df_all_rows[df_all_rows.Period != 'Annual']
```

In [27]:
```
realGDPdata = df_all_rows2[['Year', 'Period', 'GDP at 2010 Constant Market Prices']]
realGDPdata
```

Out[27]:

	Year	Period	GDP at 2010 Constant Market Prices
0	1999	Q1	6053.945
1	1999	Q2	6053.945
2	1999	Q3	6053.945
3	1999	Q4	6053.945
4	2000	Q1	6357.605
...	...	...	...
79	2020	Q1	16893.270
80	2020	Q2	16044.510
81	2020	Q3	18109.600
82	2020	Q4	19753.160
84	2021	Q1	16962.510

89 rows × 3 columns

NORMINAL GDP

Data on NormalGDP csv will be cleaned. What we need in this CSV dataset(NominalGDP02092022) is the nominal GDP at market price tag column [GDPatCurrentMarketPrices]

Quarterly Data from 1991 to 2020 will be identify from the Master datasheet. It is observed that data from 1999 to 2009 contains annual data and not quartely data. Hence i divide both annual data by 3 and spread it around the four

In [28]:
```
NGDP = pd.read_csv('NominalGDP02092022.csv')
```

In [30]:
```
NGDP.head(16)
```

Out[30]:

	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNaturalGas
0	1981	Annual	17.05	12.82	2.53	1.16	0.55	54.67	13.12	5.92
1	1982	Annual	20.13	14.32	3.96	1.17	0.67	51.88	9.13	4.93
2	1983	Annual	23.80	16.35	5.19	1.27	0.99	54.16	8.00	4.28
3	1984	Annual	30.37	21.50	6.62	1.38	0.87	50.33	9.89	5.24
4	1985	Annual	34.24	25.07	7.16	1.47	0.54	62.86	14.00	6.59
5	1986	Annual	35.70	25.97	7.39	1.57	0.77	65.05	12.43	5.54
6	1987	Annual	50.29	39.66	8.37	1.59	0.66	80.47	22.29	15.48
7	1988	Annual	73.76	61.85	8.89	1.86	1.17	102.94	22.56	17.30
8	1989	Annual	88.26	71.88	11.79	2.17	2.41	146.83	49.83	44.33
9	1990	Annual	106.63	86.93	14.15	2.35	3.21	175.15	63.69	58.06
10	1991	Annual	123.24	101.65	15.58	2.44	3.58	218.12	76.78	67.50
11	1992	Annual	184.12	153.38	23.03	2.99	4.72	341.66	149.81	142.98
12	1993	Annual	295.32	249.20	36.58	3.97	5.59	417.06	144.69	140.25
13	1994	Annual	445.27	377.31	54.30	5.98	7.68	553.96	132.90	126.92
14	1995	Annual	790.14	670.18	97.20	8.25	14.51	1132.84	448.11	444.02
15	1996	Annual	1070.51	906.89	130.41	10.37	22.84	1530.05	675.58	670.74

16 rows × 58 columns

In [31]:
```
#drop rows less than year 1999
NGDP=NGDP.drop(NGDP.index[0:18], inplace=False)
NGDP.head(13)
```

Out[31]:

	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNaturalGas
18	1999	Annual	1426.97	1204.70	164.37	19.31	38.59	1609.82	600.46	593.44
19	2000	Annual	1508.41	1270.63	172.19	24.49	41.10	2388.83	1274.48	1266.67
20	2001	Annual	2015.42	1699.69	228.56	29.98	57.20	2328.41	975.78	966.79
21	2002	Annual	4251.52	3875.46	271.03	36.23	68.81	2650.03	1051.29	1042.00
22	2003	Annual	4585.93	4161.57	299.22	44.13	81.01	3525.14	1598.74	1588.09
23	2004	Annual	4935.26	4419.06	360.80	56.39	99.00	5145.43	2476.23	2460.55
24	2005	Annual	6032.33	5372.20	463.42	67.45	129.26	6520.74	3301.43	3281.47
25	2006	Annual	7513.30	6723.22	560.25	80.20	149.64	7822.11	4075.35	4044.97
26	2007	Annual	8551.98	7654.22	642.28	91.50	163.99	8441.76	4398.96	4363.63
27	2008	Annual	10100.33	9039.63	758.84	108.10	193.75	9874.38	5310.95	5270.01
28	2009	Annual	11625.44	10419.60	863.40	121.25	221.18	9229.81	4343.06	4297.07
29	2010	Q1	2594.76	2262.18	237.30	30.42	64.86	3284.29	1952.21	1937.63
30	2010	Q2	2873.38	2561.46	216.10	34.38	61.43	3314.21	1993.68	1983.89

13 rows × 58 columns

In [32]:
```
NGDP.columns
```

Out[32]:
```
Index(['Year', 'Period', 'Agriculture', 'CropProduction', 'Livestock',
       'Forestry', 'Fishing', 'Industry', 'MiningAndQuarrying',
       'CrudePetroleumAndNaturalGas', 'CoalMining', 'MetalOres',
       'QuarryingAndOtherMinerals', 'Manufacturing', 'OilRefining', 'Cement',
       'FoodBeverageAndTobacco', 'TextileApparelAndFootwear',
       'WoodAndWoodProducts', 'PulpPaperAndPaperProducts',
       'ChemicalAndPharmaceuticalProducts', 'NonMetallicProducts',
       'PlasticAndRubberProducts', 'ElectricalAndElectronics',
       'BasicMetalIronAndSteel', 'MotorVehiclesAndAssembly',
       'OtherManufacturing', 'ElectricityGasSteamAndAirCon',
       'WaterSupplySewageWaste', 'Construction', 'Services', 'Trade',
       'AccommodationAndFoodServices', 'TransportationAndStorage',
       'RoadTransport', 'RailTransportAndPipelines', 'WaterTransport',
       'AirTransport', 'TransportServices', 'PostAndCourierServices',
       'InformationAndCommunication', 'Publishing',
       'MotionPicturesSoundRecordingAndMusicProduction', 'Broadcasting',
       'ArtsEntertainmentAndRecreation', 'FinanceAndInsurance',
       'FinancialInstitutions', 'Insurance', 'RealEstate',
       'ProfessionalScientificAndTechnicalServices',
       'AdministrativeAndSupportServicesBusinessServices',
       'PublicAdministration', 'Education', 'HumanHealthAndSocialServices',
       'OtherServices', 'GDPatCurrentBasicPrices', 'NetTaxesOnProducts',
       'GDPatCurrentMarketPrices'],
      dtype='object')
```

In [35]:
```
#Quarterly report are missing from 1999 to 2009.

#I identify that annual data for 1999-2009 year and divide it 4 places, placing them quaterly.

Max= NGDP.iloc[:, [2,3, 4, 5, 6, 7, 8, 9,10, 11,12,13, 14, 15,16, 17, 18, 19, 20,21,22,23,24,25,26,27,2
8,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57]].iloc[0:11].d
iv(4)
Max
```

Out[35]:

	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNaturalGas	CoalMining
18	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.1150	148.3600	0.5500
19	377.1025	317.6575	43.0475	6.1225	10.2750	597.2075	318.6200	316.6675	0.6200
20	503.8550	424.9225	57.1400	7.4950	14.3000	582.1025	243.9450	241.6975	0.5600
21	1062.8800	968.8650	67.7575	9.0575	17.2025	662.5075	262.8225	260.5000	0.3625
22	1146.4825	1040.3925	74.8050	11.0325	20.2525	881.2850	399.6850	397.0225	0.3625
23	1233.8150	1104.7650	90.2000	14.0975	24.7500	1286.3575	619.0575	615.1375	0.4200
24	1508.0825	1343.0500	115.8550	16.8625	32.3150	1630.1850	825.3575	820.3675	0.3875
25	1878.3250	1680.8050	140.0625	20.0500	37.4100	1955.5275	1018.8375	1011.2425	0.3550
26	2137.9950	1913.5550	160.5700	22.8750	40.9975	2110.4400	1099.7400	1090.9075	0.4650
27	2525.0825	2259.9075	189.7100	27.0250	48.4375	2468.5950	1327.7375	1317.5025	0.6075
28	2906.3600	2604.9000	215.8500	30.3125	55.2950	2307.4525	1085.7650	1074.2675	0.6950

11 rows × 56 columns

In [38]:
```
#repeat the amount derived and spread it quaterly

norminal = pd.DataFrame(np.repeat(Max.values, 4, axis=0))
norminal.columns = Max.columns
norminal.head()
```

Out[38]:

	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNaturalGas	CoalMining
0	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600	0.55
1	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600	0.55
2	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600	0.55
3	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600	0.55
4	377.1025	317.6575	43.0475	6.1225	10.2750	597.2075	318.620	316.6675	0.62

5 rows × 56 columns

In [39]:
```
#Creating Year and Period columns


#Period
norminal['Period'] = ['Q1', 'Q2', 'Q3', 'Q4']* 11

#Year
arr = np.array([1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009])
norminal['Year']= (np.repeat(arr, 4))
norminal.head()
```

Out[39]:

	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNaturalGas	CoalMining
0	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600	0.55
1	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600	0.55
2	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600	0.55
3	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600	0.55
4	377.1025	317.6575	43.0475	6.1225	10.2750	597.2075	318.620	316.6675	0.62

5 rows × 58 columns

In [35]:
```
norminal.columns
```

Out[35]:
```
Index(['Agriculture', 'CropProduction', 'Livestock', 'Forestry', 'Fishing',
       'Industry', 'MiningAndQuarrying', 'CrudePetroleumAndNaturalGas',
       'CoalMining', 'MetalOres', 'QuarryingAndOtherMinerals', 'Manufacturing',
       'OilRefining', 'Cement', 'FoodBeverageAndTobacco',
       'TextileApparelAndFootwear', 'WoodAndWoodProducts',
       'PulpPaperAndPaperProducts', 'ChemicalAndPharmaceuticalProducts',
       'NonMetallicProducts', 'PlasticAndRubberProducts',
       'ElectricalAndElectronics', 'BasicMetalIronAndSteel',
       'MotorVehiclesAndAssembly', 'OtherManufacturing',
       'ElectricityGasSteamAndAirCon', 'WaterSupplySewageWaste',
       'Construction', 'Services', 'Trade', 'AccommodationAndFoodServices',
       'TransportationAndStorage', 'RoadTransport',
       'RailTransportAndPipelines', 'WaterTransport', 'AirTransport',
       'TransportServices', 'PostAndCourierServices',
       'InformationAndCommunication', 'Publishing',
       'MotionPicturesSoundRecordingAndMusicProduction', 'Broadcasting',
       'ArtsEntertainmentAndRecreation', 'FinanceAndInsurance',
       'FinancialInstitutions', 'Insurance', 'RealEstate',
       'ProfessionalScientificAndTechnicalServices',
       'AdministrativeAndSupportServicesBusinessServices',
       'PublicAdministration', 'Education', 'HumanHealthAndSocialServices',
       'OtherServices', 'GDPatCurrentBasicPrices', 'NetTaxesOnProducts',
       'GDPatCurrentMarketPrices', 'Period', 'Year'],
      dtype='object')
```

In [40]:
```
#reindex the dataframe columns to look exactly likely the initial data
norminal = norminal.reindex(columns=['Year','Period', 'Agriculture', 'CropProduction', 'Livestock', 'Fo
restry', 'Fishing','Industry', 'MiningAndQuarrying', 'CrudePetroleumAndNaturalGas','CoalMining', 'Metal
Ores', 'QuarryingAndOtherMinerals', 'Manufacturing','OilRefining', 'Cement', 'FoodBeverageAndTobacco',
'TextileApparelAndFootwear','WoodAndWoodProducts','PulpPaperAndPaperProducts', 'ChemicalAndPharmaceutic
alProducts','NonMetallicProducts', 'PlasticAndRubberProducts','ElectricalAndElectronics', 'BasicMetalIr
onAndSteel','MotorVehiclesAndAssembly', 'OtherManufacturing','ElectricityGasSteamAndAirCon', 'WaterSupp
lySewageWaste','Construction', 'Services', 'Trade', 'AccommodationAndFoodServices','TransportationAndSt
orage', 'RoadTransport','RailTransportAndPipelines', 'WaterTransport', 'AirTransport','TransportService
s', 'PostAndCourierServices','InformationAndCommunication', 'Publishing','MotionPicturesSoundRecordingA
ndMusicProduction', 'Broadcasting','ArtsEntertainmentAndRecreation', 'FinanceAndInsurance','FinancialIn
stitutions', 'Insurance', 'RealEstate','ProfessionalScientificAndTechnicalServices','AdministrativeAndS
upportServicesBusinessServices','PublicAdministration', 'Education', 'HumanHealthAndSocialServices','Ot
herServices', 'GDPatCurrentBasicPrices','NetTaxesOnProducts', 'GDPatCurrentMarketPrices',])
```

In [41]:
```
norminal.head()
```

Out[41]:

	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNaturalGas
0	1999	Q1	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600
1	1999	Q2	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600
2	1999	Q3	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600
3	1999	Q4	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3600
4	2000	Q1	377.1025	317.6575	43.0475	6.1225	10.2750	597.2075	318.620	316.6675

5 rows × 58 columns

In [42]:
```
#drop rows 1999 to 2009
NGDP=NGDP.drop(NGDP.index[0:11], inplace=False)
NGDP.head()
```

Out[42]:

	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNaturalGas
29	2010	Q1	2594.76	2262.18	237.30	30.42	64.86	3284.29	1952.21	1937.63
30	2010	Q2	2873.38	2561.46	216.10	34.38	61.43	3314.21	1993.68	1983.89
31	2010	Q3	4000.03	3660.10	247.97	33.75	58.21	3422.53	2104.92	2092.03
32	2010	Q4	3580.73	3200.16	278.19	37.17	65.21	3805.40	2403.74	2389.12
33	2010	Annual	13048.89	11683.90	979.56	135.72	249.71	13826.43	8454.55	8402.68

5 rows × 58 columns

In [43]:
```
#Merge the two dataframe together
df_all_norm = pd.concat([norminal, NGDP])
df_all_norm
```

Out[43]:

	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNatur
0	1999	Q1	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148
1	1999	Q2	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148
2	1999	Q3	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148
3	1999	Q4	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148
4	2000	Q1	377.1025	317.6575	43.0475	6.1225	10.2750	597.2075	318.620	316
...	...	...	...	...	...	...	...	...	...	
80	2020	Q2	8139.5200	7198.3500	503.3400	75.5000	362.3400	9402.7800	2641.660	2520
81	2020	Q3	11105.9900	10192.2200	509.9500	69.1600	334.6700	11472.1000	2988.600	2782
82	2020	Q4	10553.4200	9376.3300	598.5400	76.0200	502.5400	12146.7300	2380.480	2066
83	2020	Annual	37241.6100	33177.5400	2121.3700	284.7900	1657.9100	43530.7800	10851.770	10195
84	2021	Q1	8569.3300	7218.3000	613.7200	73.3300	663.9900	13305.5200	2837.380	2822

100 rows × 58 columns

In [44]:
```
#remove all rows that contains annual rows since we are using quarterly figure
df_all_norm2 = df_all_norm[df_all_norm.Period != 'Annual']
df_all_norm2
```

Out[44]:

	Year	Period	Agriculture	CropProduction	Livestock	Forestry	Fishing	Industry	MiningAndQuarrying	CrudePetroleumAndNatural
0	1999	Q1	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3
1	1999	Q2	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3
2	1999	Q3	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3
3	1999	Q4	356.7425	301.1750	41.0925	4.8275	9.6475	402.4550	150.115	148.3
4	2000	Q1	377.1025	317.6575	43.0475	6.1225	10.2750	597.2075	318.620	316.6
...	...	...	...	...	...	...	...	...	...	
79	2020	Q1	7442.6800	6410.6500	509.5500	64.1100	458.3700	10509.1800	2841.040	2827.1
80	2020	Q2	8139.5200	7198.3500	503.3400	75.5000	362.3400	9402.7800	2641.660	2520.0
81	2020	Q3	11105.9900	10192.2200	509.9500	69.1600	334.6700	11472.1000	2988.600	2782.3
82	2020	Q4	10553.4200	9376.3300	598.5400	76.0200	502.5400	12146.7300	2380.480	2066.0
84	2021	Q1	8569.3300	7218.3000	613.7200	73.3300	663.9900	13305.5200	2837.380	2822.4

89 rows × 58 columns

In [45]:
```
NorminalGDP = df_all_norm2[['Year', 'Period', 'GDPatCurrentMarketPrices']]
NorminalGDP
```
Out[45]:

	Year	Period	GDPatCurrentMarketPrices
0	1999	Q1	1370.5875
1	1999	Q2	1370.5875
2	1999	Q3	1370.5875
3	1999	Q4	1370.5875
4	2000	Q1	1765.6875
...	...	...	...
79	2020	Q1	35969.9000
80	2020	Q2	34336.9000
81	2020	Q3	39714.7200
82	2020	Q4	44230.8000
84	2021	Q1	40507.6900

89 rows × 3 columns

In [46]:
```
NorminalGDP.info()
```
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 89 entries, 0 to 84
Data columns (total 3 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Year                      89 non-null     int64  
 1   Period                    89 non-null     object 
 2   GDPatCurrentMarketPrices  89 non-null     float64
dtypes: float64(1), int64(1), object(1)
memory usage: 2.8+ KB
```

Money market rates

In [47]:
```
moneymarket = pd.read_csv('MnyMktInd02092022.csv')
moneymarket.head()
```
Out[47]:

	Code	Year	Month	InterBankCallRate	MRR	MPR	TreasuryBill	SavingsDeposit	OneMonthDeposit	ThreeMonthsDeposit	SixMonthsDep
0	1	2022	1	14.31	NaN	11.5	2.49	1.25	3.79	5.00	
1	2	2022	3	11.33	NaN	11.5	1.75	1.28	3.33	4.41	
2	3	2022	4	8.67	NaN	11.5	1.74	1.28	2.96	4.44	
3	4	2022	5	8.38	NaN	13.0	2.47	1.37	3.57	4.70	
4	5	2022	6	11.10	NaN	13.0	2.41	1.38	3.48	4.55	

In [48]:
```
#year2022 is remove. Data not complete.(Ongoing)
moneymarket = moneymarket[moneymarket.Year != 2022]
moneymarket
```
Out[48]:

	Code	Year	Month	InterBankCallRate	MRR	MPR	TreasuryBill	SavingsDeposit	OneMonthDeposit	ThreeMonthsDeposit	SixMonthsD
6	7	2021	1	4.40	NaN	11.5	0.52	1.86	1.64	2.88	
7	8	2021	2	11.43	NaN	11.5	1.49	1.79	1.82	3.13	
8	9	2021	3	10.10	NaN	11.5	2.00	1.86	2.06	3.05	
9	10	2021	4	30.00	NaN	11.5	2.00	1.86	2.33	3.32	
10	11	2021	5	15.23	NaN	11.5	2.50	1.83	2.84	4.00	
...	...	...	...	...	...	...	...	...	...	...	
192	193	2006	8	3.33	14.0	0.0	8.40	2.91	9.00	9.68	
193	194	2006	9	10.45	14.0	0.0	6.98	2.93	8.98	9.57	
194	195	2006	10	1.40	14.0	0.0	7.94	3.08	10.01	10.23	
195	196	2006	11	9.70	14.0	0.0	7.00	3.10	10.05	10.26	
196	197	2006	12	8.98	NaN	10.0	7.75	3.25	9.99	10.25	

191 rows × 14 columns

In [49]:
```
moneymarket2 = moneymarket[['Year', 'Month', 'MPR']]
moneymarket2
```
Out[49]:

	Year	Month	MPR
6	2021	1	11.5
7	2021	2	11.5
8	2021	3	11.5
9	2021	4	11.5
10	2021	5	11.5
...	...	...	...
192	2006	8	0.0
193	2006	9	0.0
194	2006	10	0.0
195	2006	11	0.0
196	2006	12	10.0

191 rows × 3 columns

In [50]:
```
moneymarket2.index
```
Out[50]:
```
Int64Index([  6,   7,   8,   9,  10,  11,  12,  13,  14,  15,
            ...
            187, 188, 189, 190, 191, 192, 193, 194, 195, 196],
           dtype='int64', length=191)
```

In [51]:
```
#reassigning idex value
moneymarket2.index = np.arange(1, len(moneymarket2) + 1)
```

In [52]:
```
#sorted_df = moneymarket2.sort_values(moneymarket2.last_valid_index(), axis=1,ascending=False)

#moneymarket2.sort_index(axis=1,ascending=False)

#moneymarket3 = moneymarket2.sort_values(by="Year", ascending=1)
#moneymarket3.head(14)

#resorting
moneymarket3 = moneymarket2.sort_values(by=['Year','Month'], inplace=False , ascending = [True, True])
moneymarket3.head(6)
```
Out[52]:

	Year	Month	MPR
180	2006	1	0.0
181	2006	2	0.0
182	2006	3	0.0
183	2006	4	0.0
184	2006	5	0.0
185	2006	6	0.0

In [54]:
```
#reindex the dataset
moneymarket3.index = np.arange(1, len(moneymarket3) + 1)
moneymarket3
```
Out[54]:

	Year	Month	MPR
1	2006	1	0.0
2	2006	2	0.0
3	2006	3	0.0
4	2006	4	0.0
5	2006	5	0.0
...	...	...	...
187	2021	8	11.5
188	2021	9	11.5
189	2021	10	11.5
190	2021	11	11.5
191	2021	12	11.5

191 rows × 3 columns

In [55]:
```
moneymarket3.info()
```
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 191 entries, 1 to 191
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Year    191 non-null    int64  
 1   Month   191 non-null    int64  
 2   MPR     191 non-null    float64
dtypes: float64(1), int64(2)
memory usage: 6.0 KB
```

In [56]:
```
#Create new date column
moneymarket3['Date'] = pd.date_range(start='1/1/2006', freq='M', periods=191)
moneymarket3
```
Out[56]:

	Year	Month	MPR	Date
1	2006	1	0.0	2006-01-31
2	2006	2	0.0	2006-02-28
3	2006	3	0.0	2006-03-31
4	2006	4	0.0	2006-04-30
5	2006	5	0.0	2006-05-31
...	...	...	...	...
187	2021	8	11.5	2021-07-31
188	2021	9	11.5	2021-08-31
189	2021	10	11.5	2021-09-30
190	2021	11	11.5	2021-10-31
191	2021	12	11.5	2021-11-30

191 rows × 4 columns

In [57]:
```
#groupby the date and MPR in a quarterly format
MPRATE = moneymarket3.groupby(moneymarket3['Date'].dt.to_period('Q'))['MPR'].sum()
MPRATE
```
Out[57]:
```
Date
2006Q1     0.0
2006Q2     0.0
2006Q3     0.0
2006Q4    10.0
2007Q1    30.0
          ... 
2020Q4    34.5
2021Q1    34.5
2021Q2    34.5
2021Q3    34.5
2021Q4    23.0
Freq: Q-DEC, Name: MPR, Length: 64, dtype: float64
```

In [58]:
```
#Make MPR a dataframe to use for our analysis
MPRATE = MPRATE.to_frame().reset_index()
MPRATE.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 64 entries, 0 to 63
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype        
---  ------  --------------  -----        
 0   Date    64 non-null     period[Q-DEC]
 1   MPR     64 non-null     float64      
dtypes: float64(1), period[Q-DEC](1)
memory usage: 1.1 KB
```

Exploratory Data Analysis

> Now that i've trimmed and cleaned my data, i'am ready to move on to exploration. **Compute statistics** and **create visualizations** with the goal of addressing the research questions that i posed in the Introduction section. Note that at least two or more kinds of plots will be created as part of the exploration.
>
> - Investigate Look at one variable at a time, and then follow it up by looking at relationships between variables. I will explore at least three variables in relation to the primary question. This will be an exploratory relationship between three variables of interest.

QUESTION 1

In [59]:
```
#relationship between money supply (M2) and real GDP
corr = money_supplym2['Money Supply M2'].corr(realGDPdata['GDP at 2010 Constant Market Prices'])
corr
```
Out[59]: 0.8666902662538728

Rollingwindows Correlation

In [252]:
```
#rolling in 5periods

q1 = money_supplym2['Money Supply M2'].rolling(5).corr(realGDPdata['GDP at 2010 Constant Market Prices'
]).round(5)
q1.head(20)
```
Out[252]:
```
0         NaN
1         NaN
2         NaN
3         NaN
4     0.72161
5     0.84994
6     0.76866
7     0.63960
8     0.79065
9     0.92657
10    0.96271
11    0.92967
12    0.73546
13    0.91871
14    0.83668
15    0.67117
16    0.82804
17    0.91405
18    0.92808
19    0.85915
dtype: float64
```

In [258]:
```
#Convert series into dataframe

smart = pd.DataFrame(q1, columns=['corr']).reset_index().round(5)

#smart =testing.to_frame().reset_index(inplace= False)
smart.head()
```
Out[258]:

	index	corr
0	0	NaN
1	1	NaN
2	2	NaN
3	3	NaN
4	4	0.72161

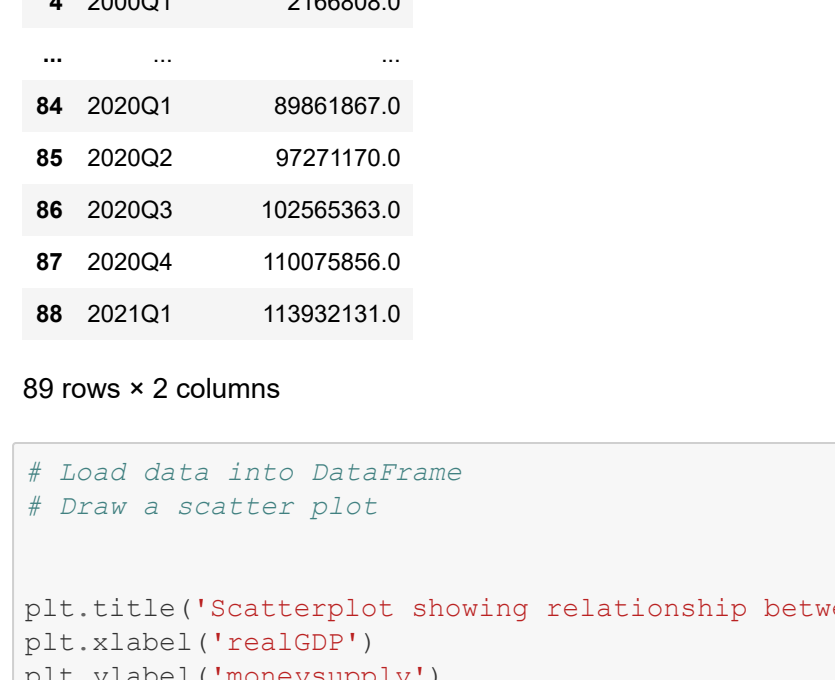
In [254]:
```
#drop index

smart = smart.drop('index', axis=1)
```

In [255]:
```
smart.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 104 entries, 0 to 103
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   corr    56 non-null     float64
dtypes: float64(1)
memory usage: 960.0 bytes
```

In [306]:
```
#smart=smart.dropna()
#plt.figure(figsize=(6, 6))
plt.xlabel('Quarters between 1999-2021 Years')
plt.ylabel('Correlation between M2 and realGDP')

plt.plot( smart['corr'])
```
Out[306]: [<matplotlib.lines.Line2D at 0x2369e674f08>]



We can see that the correclation is increasing in recent year

In [ ]:

SCATTERPLOT VISUALIZATION

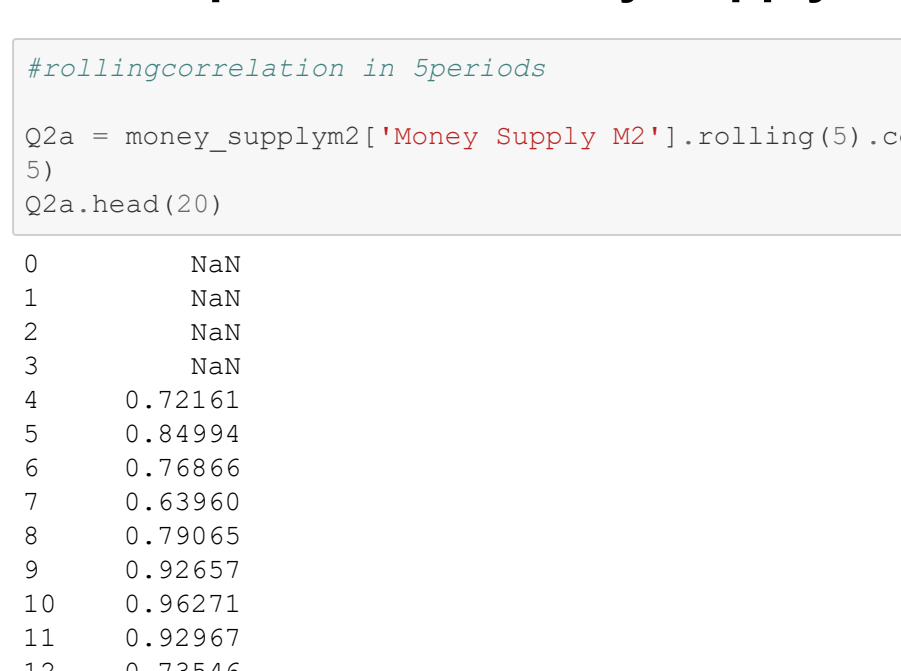
In [154]:
```
#year2022 is remove. to make both data tally to depict a scatterplot graph
ABC = money_supplym2.drop(money_supplym2.index[89:92], inplace=False)
ABC
```
Out[154]:

	Date	Money Supply M2
0	1999Q1	1698062.0
1	1999Q2	1910333.0
2	1999Q3	1906874.0
3	1999Q4	2032158.0
4	2000Q1	2166808.0
...	...	...
84	2020Q1	89861867.0
85	2020Q2	97271170.0
86	2020Q3	102565363.0
87	2020Q4	110075856.0
88	2021Q1	113932131.0

89 rows × 2 columns

In [157]:
```
# Load data into DataFrame
# Draw a scatter plot


plt.title('Scatterplot showing relationship between real GDP and Money Supply')
plt.xlabel('realGDP')
plt.ylabel('moneysupply')
plt.scatter(x=realGDPdata['GDP at 2010 Constant Market Prices'],y=ABC['Money Supply M2'],color= 'Blue',
 s=100,alpha=1)
```
Out[157]: <Figure size 864x72 with 0 Axes>



<Figure size 864x72 with 0 Axes>

QUESTION 2

Is the correlation decreasing or increasing between money supply and nominal GDP in recent years?

In [158]:
```
#Correclation between moneysuply and GDP at current Marketprices
corrNorm = money_supplym2['Money Supply M2'].corr(NorminalGDP['GDPatCurrentMarketPrices'])

corrNorm
```
Out[158]: 0.973404118646151

It is discover that there exist a strong correlation between GDP at current prices and Money Supply

In [264]:
```
#rollingcorrelation in 5periods

Q2a = money_supplym2['Money Supply M2'].rolling(5).corr(NorminalGDP['GDPatCurrentMarketPrices']).round(
5)
Q2a.head(20)
```
Out[264]:
```
0         NaN
1         NaN
2         NaN
3         NaN
4     0.72161
5     0.84994
6     0.76866
7     0.63960
8     0.79065
9     0.92657
10    0.96271
11    0.92967
12    0.73546
13    0.91871
14    0.83668
15    0.67117
16    0.82804
17    0.91405
18    0.92808
19    0.85915
dtype: float64
```

In [281]:
```
#Convert series into dataframe

Q2update = pd.DataFrame(Q2a, columns=['corr2']).reset_index().round(5)

#smart =testing.to_frame().reset_index(inplace= False)
Q2update.head()
```
Out[281]:

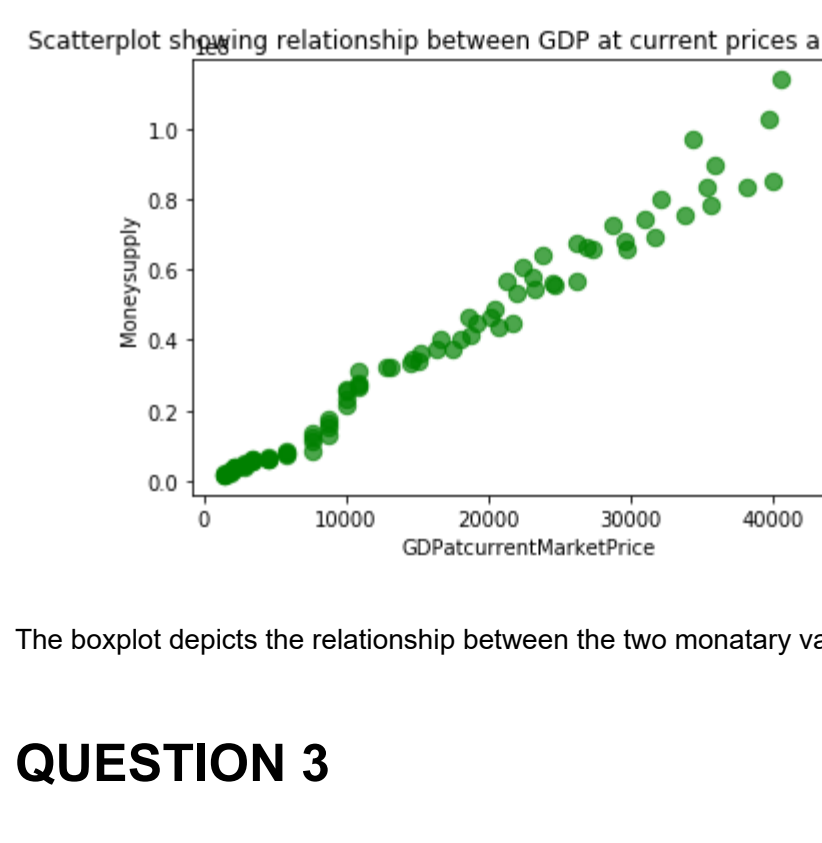
	index	corr2
0	0	NaN
1	1	NaN
2	2	NaN
3	3	NaN
4	4	0.72161

In [282]:
```
#drop index

Q2update = Q2update.drop('index', axis=1)
```

In [305]:
```
#smart=smart.dropna()
#plt.figure(figsize=(6, 6))
plt.xlabel('Quarters between 1999-2021 Years')
plt.ylabel('Correlation between M2 and nominalGDP')

plt.plot( Q2update['corr2'])
```
Out[305]: [<matplotlib.lines.Line2D at 0x2369e609708>]

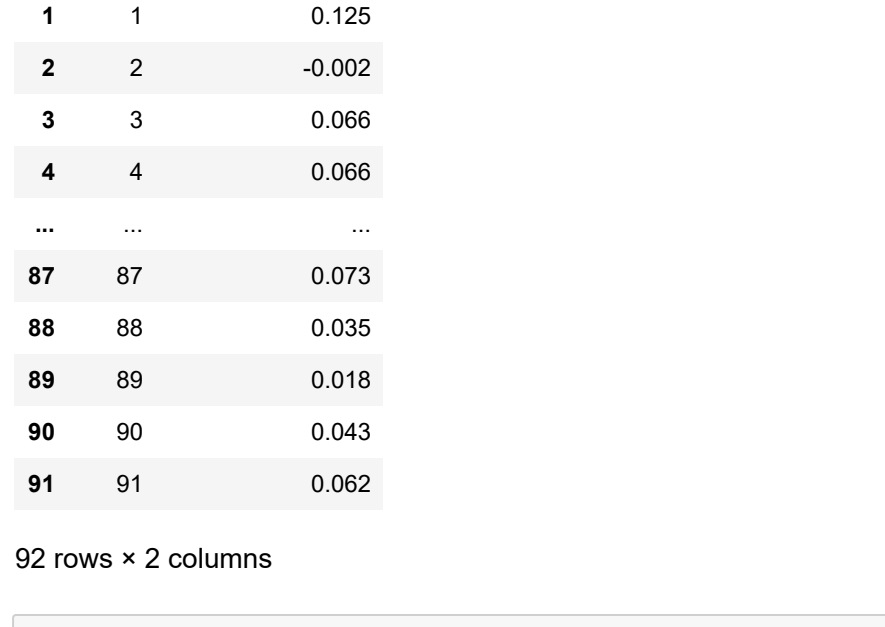


We can see that the correclation is increasing in recent year

SCATTERPLOT VISUALIZATION

In [284]:
```
plt.title('Scatterplot showing relationship between GDP at current prices and Money Supply')
plt.xlabel('GDPatcurrentMarketPrice')
plt.ylabel('Moneysupply')
plt.scatter(x=NorminalGDP['GDPatCurrentMarketPrices'], y=ABC['Money Supply M2'],color= 'Green', s=70,al
pha= 0.7)

#plt.rcParams["figure.figsize"] = (20,30)
```
Out[284]: <matplotlib.collections.PathCollection at 0x2369d423648>



The boxplot depicts the relationship between the two monatary variables listed in the graph

QUESTION 3

Is the correlation decreasing or increasing between money supply and money market rate in recent years?

In [79]:
```
#Quaterly perchange is looked into

M2supplypercent = money_supplym2['Money Supply M2'].pct_change().round(3)

M2percent =M2supplypercent.to_frame().reset_index()
M2percent
```
Out[79]:

	index	Money Supply M2
0	0	NaN
1	1	0.125
2	2	-0.002
3	3	0.066
4	4	0.066
...	...	...
87	87	0.073
88	88	0.035
89	89	0.018
90	90	0.043
91	91	0.062

92 rows × 2 columns

In [136]:
```
M2percent.info()

M2percent['Money Supply M2']
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 92 entries, 0 to 91
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   index            92 non-null     int64  
 1   Money Supply M2  91 non-null     float64
dtypes: float64(1), int64(1)
memory usage: 1.6 KB
```

In [82]:
```
#Correclation between moneysuply and money market rate
corrNormRate = M2percent['Money Supply M2'].corr(MPRATE['MPR'])
corrNormRate
```
Out[82]: -0.040426794756551

Findings show that one percent increase in Money market rate leads to 4 percent decrease in Money supply rate

In [301]:
```
#rollingcorrelation in 5periods

corrNormRate2 = money_supplym2['Money Supply M2'].rolling(7).corr(MPRATE['MPR']).round(5)
corrNormRate2.head(20)
```
Out[301]:
```
0         NaN
1         NaN
2         NaN
3         NaN
4         NaN
5         NaN
6     0.78061
7     0.74241
8     0.64874
9     0.54781
10    0.31047
11    0.70831
12    0.85476
13   -0.21436
14   -0.84215
15   -0.96340
16   -0.89745
17   -0.80550
18   -0.72201
19   -0.53497
dtype: float64
```

In [302]:
```
#Convert series into dataframe

corrNormRate3 = pd.DataFrame(corrNormRate2, columns=['corr3']).reset_index().round(5)

corrNormRate3.head(7)
```
Out[302]:

	index	corr3
0	0	NaN
1	1	NaN
2	2	NaN
3	3	NaN
4	4	NaN
5	5	NaN
6	6	0.78061

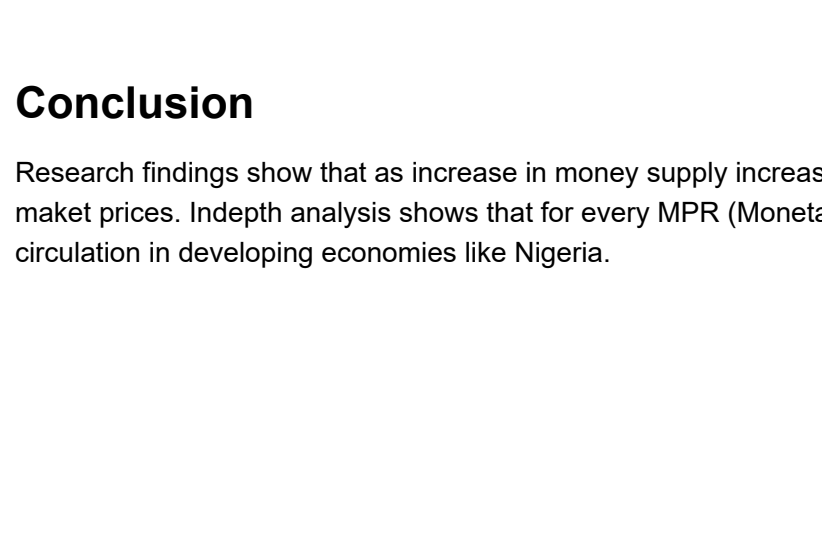
In [303]:
```
#drop index

NormRate3 =corrNormRate3.drop('index', axis=1)
```

In [304]:
```
#moving windows correlation


plt.xlabel('Quarters in Years')
plt.ylabel('Correlation between M2 and moneymarket rate')

plt.plot(NormRate3['corr3'])
```
Out[304]: [<matplotlib.lines.Line2D at 0x2369e59e548>]



In [ ]:
```
#We can see that the correclation is decreasing in recent years
```

QUESTION 4

In [ ]:
```
Can you identify some predicting power of monetary aggregates on studied variables (inflation, real out
put, nominal output)
```

From the above analysis , Monetary aggreagtes like money supply M2 or M3 have a strong predictive power on variable like: real and nomimal output. With M2 money supply, an increase in M2 leads to 0.93% corresponding increase in nominal output and 0.86% corresponding out in real output

Limitation

.Some data does not provide quartely report as we base the analysis on quaterly trends.

.There exist empty data (NAN) in some of the datasheet

.The statistical dataset contains objects and floating values which requires cleaning

Conclusion

Research findings show that as increase in money supply increase both real and norminal GDP but a stronger increase on GDP at current maket prices. Indepth analysis shows that for every MPR (Monetary policy rate) there is a four percent decresase in money supply in circulation in developing economies like Nigeria.