Data Sources

ISM PMI Manufacturing

- https://www.ismworld.org/supply-management-news-and-reports/reports/ism-report-on-business/ ISM PMI Services
- https://www.ismworld.org/supply-management-news-and-reports/reports/ism-report-on-business/ ISM PMI Manufacturing Prices
- https://www.ismworld.org/supply-management-news-and-reports/reports/ism-report-on-business/ ISM PMI Services Prices
- https://www.ismworld.org/supply-management-news-and-reports/reports/ism-report-on-business/ UMC Consumer Sentiment
- https://fred.stlouisfed.org/series/UMCSENT FED Funds
- https://fred.stlouisfed.org/series/FEDFUNDS 10 Year Tresury
- https://fred.stlouisfed.org/series/GS10 M2
- https://fred.stlouisfed.org/series/M2NS Capacity Utilization
- https://fred.stlouisfed.org/series/TCU Manufacturing New Orders
- https://fred.stlouisfed.org/series/UMTMNO Nonfarm Employment
- https://fred.stlouisfed.org/series/PAYNSA Unemployment Rate
- https://fred.stlouisfed.org/series/UNRATE Retail Trade
- https://fred.stlouisfed.org/series/RSXFSN CPI Core
- https://fred.stlouisfed.org/series/CPILFENS

Obtaining, cleaning and preparing data

In [12]:

```
import pandas as pd
import pandas_datareader.data as web
import numpy as np
import datetime
```

In [13]:

```
#datetime data range

from_date = datetime.date(1900,1,1)
to_date = datetime.date(2021,11,1)
```

In [19]:

```
#obtaining data from Federal Reserve Economic Data | FRED | St. Louis Fed

fred_data = web.DataReader(['FEDFUNDS','GS10','M2NS','PERMIT','UMCSENT','TCU','UMTMNO',
                            'PAYNSA','UNRATE','RSXFSN','CPILFENS'],
                               data_source='fred',start=from_date, end=to_date)
fred_data.dropna(inplace=True)
```

In [20]:

```
fred_data.head()
```

Out[20]:

	FEDFUNDS	GS10	M2NS	PERMIT	UMCSENT	TCU	UMTMNO	PAYNSA	UNRATE	RSXFSN	CPILFENS
DATE											
1992-02-01	4.06	7.34	3390.1	1146.0	68.8	79.8145	228230.0	106977	7.4	131244.0	145.6

DATE	FEDFUNDS	GS10	M2NS	PERMIT	UMCSENT	TCU	UMTMNO	PAYNSA	UNRATE	RSXFSN	CPILFENS
1992-03-01	3.98	7.54	3404.8	1082.0	76.0	80.3033	245052.0	107495	7.4	142488.0	146.4
1992-04-01	3.73	7.48	3418.9	1054.0	77.2	80.7450	236726.0	108330	7.4	147175.0	146.6
1992-05-01	3.82	7.39	3388.0	1056.0	79.2	80.8311	238178.0	109137	7.6	152420.0	146.7
1992-06-01	3.76	7.26	3388.7	1057.0	80.4	80.6997	254919.0	109626	7.8	151849.0	146.9

In [21]:

```
# changing working directory

import os

cwd = os.getcwd()
os.chdir('D:/Data Science Projects/US_Core_Inflation_Forecast')
print("Current working directory: {0}".format(cwd))

# obtaining data from csv file (Institute for Supply and Management PMI)

ism_man_data = pd.read_csv('ISM Manufacturing.csv')
ism_serv_data = pd.read_csv('ISM Services.csv')
```

```
Current working directory: D:\Data Science Projects\US_Core_Inflation_Forecast\IPYNB Files
```

In [22]:

```
print(ism_man_data.head())
print(ism_serv_data.head())
```

```
        Release Date Observation Date  PMI M Composite  PMI M Prices
0  Jan 01, 1970 (Dec)           Dec-69             52.0          82.2
1  Feb 01, 1970 (Jan)           Jan-70             48.7          80.6
2  Mar 01, 1970 (Feb)           Feb-70             47.4          74.5
3  Apr 01, 1970 (Mar)           Mar-70             46.9          67.8
4  May 01, 1970 (Apr)           Apr-70             45.0          75.1
        Release Date Observation Date  PMI S Composite  PMI S Prices
0  Aug 01, 1997 (Jul)           Jul-97             56.7          50.9
1  Sep 01, 1997 (Aug)           Aug-97             62.0          53.3
2  Oct 01, 1997 (Sep)           Sep-97             56.2          53.1
3  Nov 01, 1997 (Oct)           Oct-97             56.6          53.1
4  Dec 01, 1997 (Nov)           Nov-97             58.5          54.3
```

In [23]:

```
# cleaning, sorting and merging databases

    #ISM databases
ism_data = pd.merge(left=ism_serv_data, right=ism_man_data, how='inner', on='Observation D
ism_data.drop(columns=['Release Date_x','Release Date_y'],inplace=True)
ism_data['Observation Date'] = pd.to_datetime(arg=ism_data['Observation Date'], format='%b
ism_data.set_index('Observation Date', inplace=True)

    #FRED databases
fred_data.columns = ['FED Funds Rate','10 Year Treasury Rate','M2','Building Permits',
                     'Consumer Sentiment','Capacity Utilization','Manufacturing New Orders'
                      'Nonfarm Employment','Unemployment Rate SA','Retail Trade','CPI Core
```

In [24]:

```
# checking data types
```

```
print(fred_data.dtypes)
print(ism_data.dtypes)
```

```
FED Funds Rate              float64
10 Year Treasury Rate       float64
M2                          float64
Building Permits            float64
Consumer Sentiment          float64
Capacity Utilization        float64
Manufacturing New Orders    float64
Nonfarm Employment            int64
Unemployment Rate SA        float64
Retail Trade                float64
CPI Core NSA                float64
dtype: object
PMI S Composite    float64
PMI S Prices       float64
PMI M Composite    float64
PMI M Prices       float64
dtype: object
```

In [25]:

```
# merging ism and fred data

data_all = pd.merge(ism_data,fred_data,how='inner',left_index=True, right_index=True)
data_all.tail()
```

Out[25]:

	PMI S Composite	PMI S Prices	PMI M Composite	PMI M Prices	FED Funds Rate	10 Year Treasury Rate	M2	Building Permits	Consumer Sentiment	Capacity Utilization	Manufactu New Or
2021-07-01	64.1	82.3	59.5	85.7	0.10	1.32	20609.1	1630.0	81.2	76.1550	492(
2021-08-01	61.7	75.4	59.9	79.4	0.09	1.28	20810.7	1721.0	70.3	75.9923	525(
2021-09-01	61.9	77.5	61.1	81.2	0.08	1.37	20995.6	1586.0	72.8	75.2106	529
2021-10-01	66.7	82.9	60.8	85.7	0.08	1.58	21178.6	1653.0	71.7	76.0962	524
2021-11-01	69.1	82.3	61.1	82.4	0.08	1.56	21425.9	1717.0	67.4	76.6150	517

In [26]:

```
# data manipulation

data_all['Released Date'] = data_all.index + pd.DateOffset(months=1) # release date for ea
data_all['PMI Composite Avg'] = np.average(data_all[['PMI S Composite','PMI M Composite']]
data_all['PMI Prices Avg'] = np.average(data_all[['PMI S Prices','PMI M Prices']],axis=1)

data_all = data_all[['Released Date',
                     'PMI M Composite','PMI S Composite','PMI Composite Avg',
                     'PMI M Prices','PMI S Prices','PMI Prices Avg',
                     'Building Permits','Consumer Sentiment',
                     'FED Funds Rate','10 Year Treasury Rate','M2',
                     'Capacity Utilization','Manufacturing New Orders',
                     'Nonfarm Employment','Unemployment Rate SA',
                     'Retail Trade',
                     'CPI Core NSA']]

# percentage change calculation

data_calc = data_all.copy(deep=True)
```

```
data_calc['Building Permits YoY'] = data_calc['Building Permits'].pct_change(periods=12) *
data_calc['Consumer Sentiment YoY'] = data_calc['Consumer Sentiment'].pct_change(periods=1
data_calc['M2 YoY'] = data_calc['M2'].pct_change(periods=12) * 100
data_calc['Capacity Utilization YoY'] = data_calc['Capacity Utilization'].pct_change(peric
data_calc['Manufacturing New Orders YoY'] = data_calc['Manufacturing New Orders'].pct_char
data_calc['Nonfarm Employment YoY'] = data_calc['Nonfarm Employment'].pct_change(periods=1
data_calc['Unemployment Rate SA Adj'] = data_calc['Unemployment Rate SA'] * (-1)
data_calc['Retail Trade YoY'] = data_calc['Retail Trade'].pct_change(periods=12) * 100
data_calc['CPI Core NSA YoY'] = data_calc['CPI Core NSA'].pct_change(periods=12) * 100
```

In [27]:

```
data_calc.head(15)
```

Out[27]:

	Released Date	PMI M Composite	PMI S Composite	PMI Composite Avg	PMI M Prices	PMI S Prices	PMI Prices Avg	Building Permits	Consumer Sentiment	FED Funds Rate	...	CPI Core NSA
1997-07-01	1997-08-01	57.7	56.7	57.20	52.0	50.9	51.45	1440.0	107.1	5.52	...	169.5
1997-08-01	1997-09-01	56.3	62.0	59.15	52.1	53.3	52.70	1449.0	104.4	5.54	...	169.6
1997-09-01	1997-10-01	53.9	56.2	55.05	53.0	53.1	53.05	1494.0	106.0	5.54	...	170.0
1997-10-01	1997-11-01	56.4	56.6	56.50	53.6	53.1	53.35	1499.0	105.6	5.50	...	170.8
1997-11-01	1997-12-01	55.7	58.5	57.10	52.1	54.3	53.20	1469.0	107.2	5.52	...	170.8
1997-12-01	1998-01-01	54.5	55.5	55.00	52.2	54.9	53.55	1456.0	102.1	5.50	...	170.7
1998-01-01	1998-02-01	53.8	57.0	55.40	47.0	52.7	49.85	1555.0	106.6	5.56	...	171.2
1998-02-01	1998-03-01	52.9	56.2	54.55	45.5	51.6	48.55	1647.0	110.4	5.51	...	172.1
1998-03-01	1998-04-01	52.9	54.7	53.80	44.2	47.9	46.05	1605.0	106.5	5.49	...	172.6
1998-04-01	1998-05-01	52.2	54.9	53.55	40.5	46.8	43.65	1547.0	108.7	5.45	...	173.0
1998-05-01	1998-06-01	50.9	56.2	53.55	41.1	47.2	44.15	1554.0	106.5	5.49	...	173.1
1998-06-01	1998-07-01	48.9	55.1	52.00	39.3	45.5	42.40	1551.0	105.6	5.56	...	173.0
1998-07-01	1998-08-01	49.2	55.8	52.50	38.4	47.0	42.70	1610.0	105.2	5.54	...	173.3
1998-08-01	1998-09-01	49.3	53.5	51.40	37.8	47.9	42.85	1654.0	104.4	5.55	...	173.8
1998-09-01	1998-10-01	48.7	55.0	51.85	34.0	46.2	40.10	1577.0	100.9	5.51	...	174.2

15 rows × 27 columns

In [28]:

```
# time shifting and correlation sweet spot
```

```
data_shift_pc = data_calc[12:270] # selecting pre Covid-19 crisis data only
data_shift_ci = data_calc[12:] # selecting all available data (Covid-19 crisis included)

def data_corr_test(data_shift):

    data_shift = data_shift[['PMI M Composite','PMI S Composite','PMI Composite Avg',
                             'PMI M Prices','PMI S Prices','PMI Prices Avg',
                             'Building Permits','Consumer Sentiment',
                             'FED Funds Rate','10 Year Treasury Rate',
                             'Capacity Utilization','Unemployment Rate SA Adj',
                             'Building Permits YoY','Consumer Sentiment YoY','M2 YoY',
                             'Capacity Utilization YoY','Manufacturing New Orders YoY',
                             'Nonfarm Employment YoY','Retail Trade YoY',
                            'CPI Core NSA YoY']]

    time_shift = list(range(0,37))
    columns_x = data_shift.columns[0:19]
    column_y = data_shift.columns[19]
    corr_results = {} # key:columns, values:corr

    #shifting
    for x in columns_x:
        d = data_shift[[x,column_y]]
        corr_results.setdefault(x,[])
        for t in time_shift:
            pearson = d[x].shift(t).corr(d[column_y],method='pearson')
            corr_results[x].append(pearson)

    #summarizing results
    time_shift = {}
    max_corr = {}
    for c in columns_x:
        time_shift[c] = corr_results[c].index(max(corr_results[c]))
        max_corr[c] = max(corr_results[c])

    results = [time_shift, max_corr]
    return results
```

In [29]:

```
# comparing correlation intensity prior to crisis and after the crisis

data_comparison1 = pd.DataFrame(data=data_corr_test(data_shift_pc)[1],index=[0])
data_comparison1 = data_comparison1.transpose()
data_comparison1.columns = ['Pre Crisis Correlation']

data_comparison2 = pd.DataFrame(data=data_corr_test(data_shift_ci)[1],index=[0])
data_comparison2 = data_comparison2.transpose()
data_comparison2.columns = ['With Crisis Correlation']

data_comparison = pd.concat([data_comparison1,data_comparison2],axis=1)
data_comparison['Correlation Difference'] = data_comparison['Pre Crisis Correlation']-data
data_comparison = data_comparison.round(2)
data_comparison.sort_values(by='Correlation Difference')
```

Out[29]:

	Pre Crisis Correlation	With Crisis Correlation	Correlation Difference
M2 YoY	0.34	0.47	-0.13
PMI S Prices	0.33	0.31	0.02
Building Permits YoY	0.38	0.33	0.05
PMI Prices Avg	0.31	0.25	0.06
PMI M Prices	0.30	0.20	0.10

	Pre Crisis Correlation	With Crisis Correlation	Correlation Difference
Building Permits	0.52	0.42	0.10
Consumer Sentiment YoY	0.41	0.28	0.13
Consumer Sentiment	0.65	0.52	0.14
Unemployment Rate SA Adj	0.65	0.51	0.15
Retail Trade YoY	0.68	0.49	0.19
PMI S Composite	0.70	0.46	0.24
Manufacturing New Orders YoY	0.53	0.29	0.24
10 Year Treasury Rate	0.40	0.15	0.25
FED Funds Rate	0.64	0.38	0.26
Capacity Utilization YoY	0.57	0.30	0.26
Nonfarm Employment YoY	0.74	0.47	0.27
PMI Composite Avg	0.65	0.38	0.27
PMI M Composite	0.59	0.33	0.27
Capacity Utilization	0.76	0.40	0.35

In [30]:

```
#selection of variables for further evaluation

_ = pd.DataFrame(data_corr_test(data_shift_pc)).transpose().round(2).sort_values(by=1,asce
_.columns = ['Time shift (Months)','Correlation']
_.drop(index=['PMI Composite Avg','Unemployment Rate SA Adj','PMI M Composite','Capacity U
              'Consumer Sentiment YoY','10 Year Treasury Rate','Building Permits YoY','M2 Y
              'PMI Prices Avg','PMI M Prices'])
```

Out[30]:

	Time shift (Months)	Correlation
Capacity Utilization	15.0	0.76
Nonfarm Employment YoY	15.0	0.74
PMI S Composite	18.0	0.70
Retail Trade YoY	18.0	0.68
Consumer Sentiment	21.0	0.65
FED Funds Rate	8.0	0.64
Manufacturing New Orders YoY	17.0	0.53
Building Permits	18.0	0.52
PMI S Prices	17.0	0.33

Short Summary of the results above

Money Supply (M2) is the only indicator that shows better correlation with data including Covid reccession than data until Covid pandemic (end of 2019.). Huge injections by the FED during the lockdown could explain this phenomenon, meaning that big increase in money supply could be one of the main reasons for the jump in core inflation (excluding food and energy) during the last few months.

Purchasing Managers Index Prices component shows negligible difference in two observed data, including Building Permits.

All other indicators show small to medium difference in two observed data, some of the most notable being manufacturing and interest rate indicators, where difference ranges from 0.25 to 0.35.

Economic slowdown caused by the coronavirus pandemic was very volatile. Due to this event, majority of economic indicators show drop in performance for predicting core inflation. To avoid this volatile effect, next observations and modelling will be performed on the data NOT containing period of coronavirus pandemic (2020. and onwards).

In [31]:

```
# data adjusting

time_shift = data_corr_test(data_shift_pc)[0]
col_adj = {'PMI S Composite':time_shift['PMI S Composite'],'PMI S Prices':time_shift['PMI
           'Building Permits':time_shift['Building Permits'],'Consumer Sentiment':time_shi
           'FED Funds Rate':time_shift['FED Funds Rate'],'Capacity Utilization':time_shift
           'Manufacturing New Orders YoY':time_shift['Manufacturing New Orders YoY'],
           'Nonfarm Employment YoY':time_shift['Nonfarm Employment YoY'],
           'Retail Trade YoY':time_shift['Retail Trade YoY'],'CPI Core NSA YoY':0}
data_adj = data_shift_pc.copy(deep=True)
data_adj = data_adj[col_adj.keys()]

#reseting index for concat
data_adj['Covering Date'] = data_adj.index
data_adj.reset_index(drop=True, inplace=True)

#creating new table for 2 year forward empty datetime space
new_rows = {'Covering Date':pd.date_range(start='2020-01-01',end='2022-01-01',freq='MS'),
            'PMI S Composite':np.nan,'PMI S Prices':np.nan,
            'Building Permits':np.nan,'Consumer Sentiment':np.nan,
           'FED Funds Rate':np.nan,'Capacity Utilization':np.nan,
           'Manufacturing New Orders YoY':np.nan,'Nonfarm Employment YoY':np.nan,'Retail T
           'CPI Core NSA YoY':np.nan}
new_df = pd.DataFrame(new_rows)

#concating tables together
data_final = pd.concat([data_adj,new_df],ignore_index=True)
data_final['Covering Date'] = data_final['Covering Date'].dt.strftime('%m-%Y')

#shifting values
data_final['PMI S Composite'] = data_final['PMI S Composite'].shift(col_adj['PMI S Composi
data_final['PMI S Prices'] = data_final['PMI S Prices'].shift(col_adj['PMI S Prices'])
data_final['Building Permits'] = data_final['Building Permits'].shift(col_adj['Building Pe
data_final['Consumer Sentiment'] = data_final['Consumer Sentiment'].shift(col_adj['Consume
data_final['FED Funds Rate'] = data_final['FED Funds Rate'].shift(col_adj['FED Funds Rate'
data_final['Capacity Utilization'] = data_final['Capacity Utilization'].shift(col_adj['Cap
data_final['Manufacturing New Orders YoY'] = data_final['Manufacturing New Orders YoY'].sh
data_final['Nonfarm Employment YoY'] = data_final['Nonfarm Employment YoY'].shift(col_adj
data_final['Retail Trade YoY'] = data_final['Retail Trade YoY'].shift(col_adj['Retail Trac

#round on 2 decimal places and change columns order
data_final[['Capacity Utilization','Manufacturing New Orders YoY','Nonfarm Employment YoY'
            'Retail Trade YoY','CPI Core NSA YoY']] = data_final[['Capacity Utilization','
                                                    'Nonfarm Employment YoY','Retail Trade
data_final = data_final[['Covering Date','PMI S Composite','PMI S Prices',
                         'Building Permits','Consumer Sentiment','FED Funds Rate','Manufac
                         'Capacity Utilization','Nonfarm Employment YoY','Retail Trade Yo
                         'CPI Core NSA YoY']]

data_final.tail(26)
```

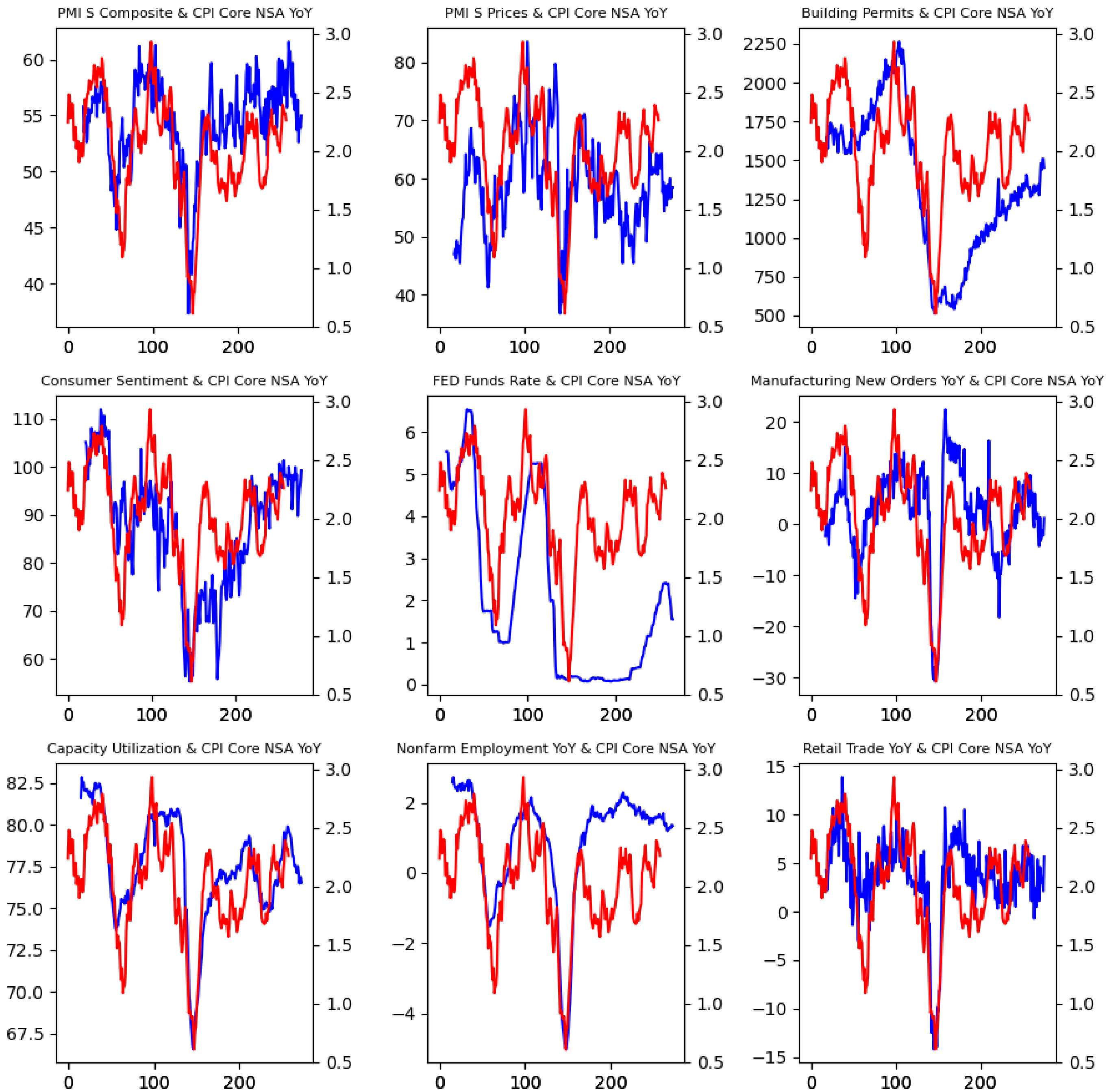
Out[31]:

	Covering Date	PMI S Composite	PMI S Prices	Building Permits	Consumer Sentiment	FED Funds Rate	Manufacturing New Orders YoY	Capacity Utilization	Nonfarm Employment YoY	Retail Trade YoY	C Co NS Yo
257	12-2019	59.1	63.4	1320.0	101.4	2.42	9.57	79.76	1.62	4.86	2.2
258	01-2020	55.7	62.8	1328.0	98.8	2.39	9.47	79.54	1.60	5.96	Na
259	02-2020	58.5	64.2	1264.0	98.0	2.38	4.20	79.37	1.53	5.61	Na
260	03-2020	61.6	61.7	1289.0	98.2	2.40	6.20	79.21	1.56	1.11	Na
261	04-2020	60.3	64.3	1275.0	97.9	2.13	0.49	78.66	1.70	5.76	Na
262	05-2020	60.7	57.6	1318.0	96.2	2.04	-0.53	78.11	1.39	3.90	Na
263	06-2020	57.6	59.4	1338.0	100.1	1.83	6.01	78.09	1.36	-0.70	Na
264	07-2020	56.7	54.4	1295.0	98.6	1.55	1.74	77.52	1.41	2.48	Na
265	08-2020	59.7	58.7	1304.0	97.5	1.55	1.08	77.57	1.23	1.13	Na
266	09-2020	56.1	55.7	1316.0	98.3	NaN	2.16	77.42	1.19	0.49	Na
267	10-2020	55.5	55.4	1337.0	91.2	NaN	-1.84	77.09	1.27	5.40	Na
268	11-2020	56.9	58.9	1337.0	93.8	NaN	-4.25	77.50	1.25	2.55	Na
269	12-2020	55.1	56.5	1276.0	98.4	NaN	1.32	77.16	1.31	1.13	Na
270	01-2021	53.7	58.2	1369.0	97.2	NaN	-3.12	76.47	1.29	4.60	Na
271	02-2021	56.4	60.0	1479.0	100.0	NaN	-2.56	76.83	1.37	3.83	Na
272	03-2021	52.6	56.6	1439.0	98.2	NaN	-1.19	76.53	1.34	2.97	Na
273	04-2021	54.7	58.5	1509.0	98.4	NaN	-2.19	NaN	NaN	3.29	Na
274	05-2021	53.9	58.5	1509.0	89.8	NaN	1.18	NaN	NaN	2.11	Na
275	06-2021	55.0	NaN	1453.0	93.2	NaN	NaN	NaN	NaN	5.66	Na
276	07-2021	NaN	NaN	NaN	95.5	NaN	NaN	NaN	NaN	NaN	Na
277	08-2021	NaN	NaN	NaN	96.8	NaN	NaN	NaN	NaN	NaN	Na
278	09-2021	NaN	NaN	NaN	99.3	NaN	NaN	NaN	NaN	NaN	Na
279	10-2021	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
280	11-2021	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
281	12-2021	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
282	01-2022	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

In [35]:

```
# correlation visualization

import matplotlib.pyplot as plt
%matplotlib notebook

fig = plt.figure(figsize=(9,9))

x_values = data_final.columns[1:10]
y_value = data_final.columns[-1]

row = range(3)
column = range(3)
```

```
x_values_count = 0
subplot_index = 1

for r in row:
    for c in column:
        ax1 = fig.add_subplot(3,3,subplot_index)
        line1 = ax1.plot(data_final.index,data_final[x_values[x_values_count]], 'b-')
        ax1.yaxis.tick_left()
        plt.title(str(x_values[x_values_count])+' & '+str(y_value),fontdict={'fontsize':8}

        ax2 = fig.add_subplot(3,3,subplot_index, sharex=ax1, frameon=False)
        line2 = ax2.plot(data_final.index,data_final[y_value], 'r-')
        ax2.yaxis.tick_right()

        x_values_count += 1
        subplot_index += 1

plt.tight_layout()
```



In [36]:
```
data_ml = data_final.dropna()
```

```python
# dropping columns with high multi-colinearity --> tests performed bellow
data_ml = data_ml.drop(columns=['Capacity Utilization','PMI S Composite',
                                'Consumer Sentiment','Building Permits',
                               'Retail Trade YoY'])
data_ml
```

Out[36]:

	Covering Date	PMI S Prices	FED Funds Rate	Manufacturing New Orders YoY	Nonfarm Employment YoY	CPI Core NSA YoY
21	04-2000	47.3	5.07	-4.05	2.33	2.32
22	05-2000	48.5	5.22	0.53	2.49	2.43
23	06-2000	47.0	5.20	0.97	2.47	2.49
24	07-2000	45.5	5.42	0.07	2.53	2.49
25	08-2000	48.9	5.30	3.08	2.34	2.60
...	...	...	...	...	...	...
253	08-2019	61.5	2.27	6.24	1.59	2.39
254	09-2019	61.8	2.40	8.39	1.60	2.36
255	10-2019	64.3	2.40	9.32	1.57	2.31
256	11-2019	60.7	2.41	3.50	1.67	2.32
257	12-2019	63.4	2.42	9.57	1.62	2.26

237 rows × 6 columns

In [37]:

```python
# multi-collinearity tests

from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
import warnings

def correlation_matrix():
    corr = data_ml[data_ml.columns[1:(len(data_ml.columns)-1)]].corr()
    corr = corr.style.background_gradient(cmap='coolwarm')
    return corr

def vif_with_constant():
    warnings.simplefilter(action='ignore', category=FutureWarning)
    vif_data = data_ml[data_ml.columns[1:(len(data_ml.columns)-1)]]
    X = add_constant(vif_data)
    vif = pd.DataFrame([variance_inflation_factor(X.values,i)
              for i in range(X.shape[1])],
              index=X.columns)
    vif.rename(columns={0:'VIF'},inplace=True)
    vif = vif.style.background_gradient(cmap='coolwarm')
    return vif

def vif_no_constant():
    X = data_ml[data_ml.columns[1:(len(data_ml.columns)-1)]]
    vif_data = pd.DataFrame()
    vif_data["X_variables"] = X.columns
    vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                          for i in range(len(X.columns))]
    vif = vif_data.style.background_gradient(cmap='coolwarm')
    return vif
```

In [38]:
```
correlation_matrix()
```

Out[38]:

	PMI S Prices	FED Funds Rate	Manufacturing New Orders YoY	Nonfarm Employment YoY
PMI S Prices	1.000000	0.256856	0.668921	0.285569
FED Funds Rate	0.256856	1.000000	0.244088	0.390478
Manufacturing New Orders YoY	0.668921	0.244088	1.000000	0.543332
Nonfarm Employment YoY	0.285569	0.390478	0.543332	1.000000

In [39]:
```
vif_with_constant()
```

Out[39]:

	VIF
const	93.487078
PMI S Prices	1.899962
FED Funds Rate	1.221472
Manufacturing New Orders YoY	2.412866
Nonfarm Employment YoY	1.627725

In [40]:
```
vif_no_constant()
```

Out[40]:

	X_variables	VIF
0	PMI S Prices	2.027507
1	FED Funds Rate	2.257043
2	Manufacturing New Orders YoY	1.536350
3	Nonfarm Employment YoY	1.979957

After multi-colinearity tests performed by correlation matrix and variance inflation factor, four independant variables were selected for regression analysis calculation.

Those variables are:

- Purchasing Managers Index with Prices subcomponent, released by Institute for Supply Management
- Federal Funds Effective Rate (Monthly data), released by Board of Governors of the Federal Reserve System (US)
- Manufacturers' New Orders: Total Manufacturing, released by U.S. Census Bureau (calculation: Year-Over-Year change)
- All Employees, Total Nonfarm, released by U.S. Bureau of Labor Statistics (calculation: Year-Over-Year change)

Following independant variables will be used for predicting Consumer Price Index for All Urban Consumers: All Items Less Food and Energy in U.S. City Average on Year-Over-Year change.

Machine learning - Linear Regression

In [41]:

```
#creating training and testing sets

from sklearn.model_selection import train_test_split

X = data_ml[['PMI S Prices',
             'FED Funds Rate',
             'Manufacturing New Orders YoY',
            'Nonfarm Employment YoY']]
y = data_ml['CPI Core NSA YoY']

X_train, X_test, y_train, y_test = train_test_split(X,y,random_state=0,test_size=0.2,trair

print('X_train shape: ',X_train.shape)
print('y_train shape: ',y_train.shape)
print('X_test shape: ', X_test.shape)
print('y_test shape: ', y_test.shape)
```

```
X_train shape:  (189, 4)
y_train shape:  (189,)
X_test shape:  (48, 4)
y_test shape:  (48,)
```

In [42]:

```
# model selection

from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
import statsmodels.api as sm

def train_test_model():

    linreg = LinearRegression().fit(X_train,y_train)
    coef_ = linreg.coef_
    intercept_ = linreg.intercept_

    score_train = linreg.score(X_train, y_train)
    score_test = linreg.score(X_test, y_test)

    y_pred = linreg.predict(X_test)
    residuals = y_test - y_pred
    residuals_sq = residuals**2
    variance = sum(residuals_sq)/(len(residuals)-2)
    standard_error = variance ** 0.5

    print('Train coefficients are {} and train intercept is {:.5f}.'.format(coef_.round(5)
    print('Linear Regression model train score is {:.2f} and test score is {:.2f}.'.format
    print('Standard Deviation of train_test_model is {:.2f}%.'.format(standard_error))

def regression_statistics(X,y):

    N = len(X)
    p = len(X.columns) + 1
    X_with_intercept = np.empty(shape=(N, p), dtype=float)
    X_with_intercept[:, 0] = 1
    X_with_intercept[:, 1:p] = X.values

    ols = sm.OLS(y.values, X_with_intercept)
    ols_result = ols.fit()
    return ols_result.summary(title='Regression Statistics')

def classic_reg_model():

    linreg = LinearRegression().fit(X,y)
```

```
    coef_ = linreg.coef_
    intercept_ = linreg.intercept_

    score_train = linreg.score(X, y)

    y_pred = linreg.predict(X)
    residuals = y - y_pred
    residuals_sq = residuals**2
    variance = sum(residuals_sq)/(len(residuals)-2)
    standard_error = variance ** 0.5

    print('Train coefficients are {} and train intercept is {:.5f}.'.format(coef_.round(5)
    print('Linear Regression model score is {:.2f}.'.format(score_train))
    print('Standard Deviation of classic_reg_model is {:.2f}%.'.format(standard_error))
```

In [43]:

```
train_test_model()
```

```
Train coefficients are [-0.0005   0.09826  0.00723  0.13488] and train intercept is 1.7301
6.
Linear Regression model train score is 0.73 and test score is 0.77.
Standard Deviation of train_test_model is 0.22%.
```

In [44]:

```
classic_reg_model()
```

```
Train coefficients are [-0.00151  0.09854  0.00862  0.13212] and train intercept is 1.7772
0.
Linear Regression model score is 0.74.
Standard Deviation of classic_reg_model is 0.23%.
```

In [45]:

```
#regression statiustics of train_test_model

regression_statistics(X_test,y_test)
```

Out[45]:

Regression Statistics

Dep. Variable:	y	**R-squared:**	0.796
Model:	OLS	**Adj. R-squared:**	0.777
Method:	Least Squares	**F-statistic:**	41.95
Date:	Wed, 19 Jan 2022	**Prob (F-statistic):**	2.60e-14
Time:	01:18:24	**Log-Likelihood:**	9.2154
No. Observations:	48	**AIC:**	-8.431
Df Residuals:	43	**BIC:**	0.9253
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	1.9745	0.283	6.971	0.000	1.403	2.546
x1	-0.0059	0.005	-1.202	0.236	-0.016	0.004
x2	0.1032	0.016	6.350	0.000	0.070	0.136
x3	0.0163	0.006	2.947	0.005	0.005	0.027
x4	0.1156	0.025	4.557	0.000	0.064	0.167

Omnibus:	4.892	**Durbin-Watson:**	1.978
Prob(Omnibus):	0.087	**Jarque-Bera (JB):**	3.711
Skew:	-0.591	**Prob(JB):**	0.156
Kurtosis:	3.678	**Cond. No.**	567.

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

In [46]:

```
#regression statistics of classic model

regression_statistics(X,y)
```

Out[46]:

Regression Statistics

Dep. Variable:	y	**R-squared:**	0.736
Model:	OLS	**Adj. R-squared:**	0.731
Method:	Least Squares	**F-statistic:**	161.7
Date:	Wed, 19 Jan 2022	**Prob (F-statistic):**	6.95e-66
Time:	01:18:26	**Log-Likelihood:**	12.184
No. Observations:	237	**AIC:**	-14.37
Df Residuals:	232	**BIC:**	2.972
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	1.7772	0.146	12.181	0.000	1.490	2.065
x1	-0.0015	0.003	-0.596	0.552	-0.007	0.003
x2	0.0985	0.008	11.741	0.000	0.082	0.115
x3	0.0086	0.002	3.450	0.001	0.004	0.014
x4	0.1321	0.012	11.216	0.000	0.109	0.155

Omnibus:	2.604	**Durbin-Watson:**	0.220
Prob(Omnibus):	0.272	**Jarque-Bera (JB):**	2.002
Skew:	0.055	**Prob(JB):**	0.367
Kurtosis:	2.563	**Cond. No.**	578.

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

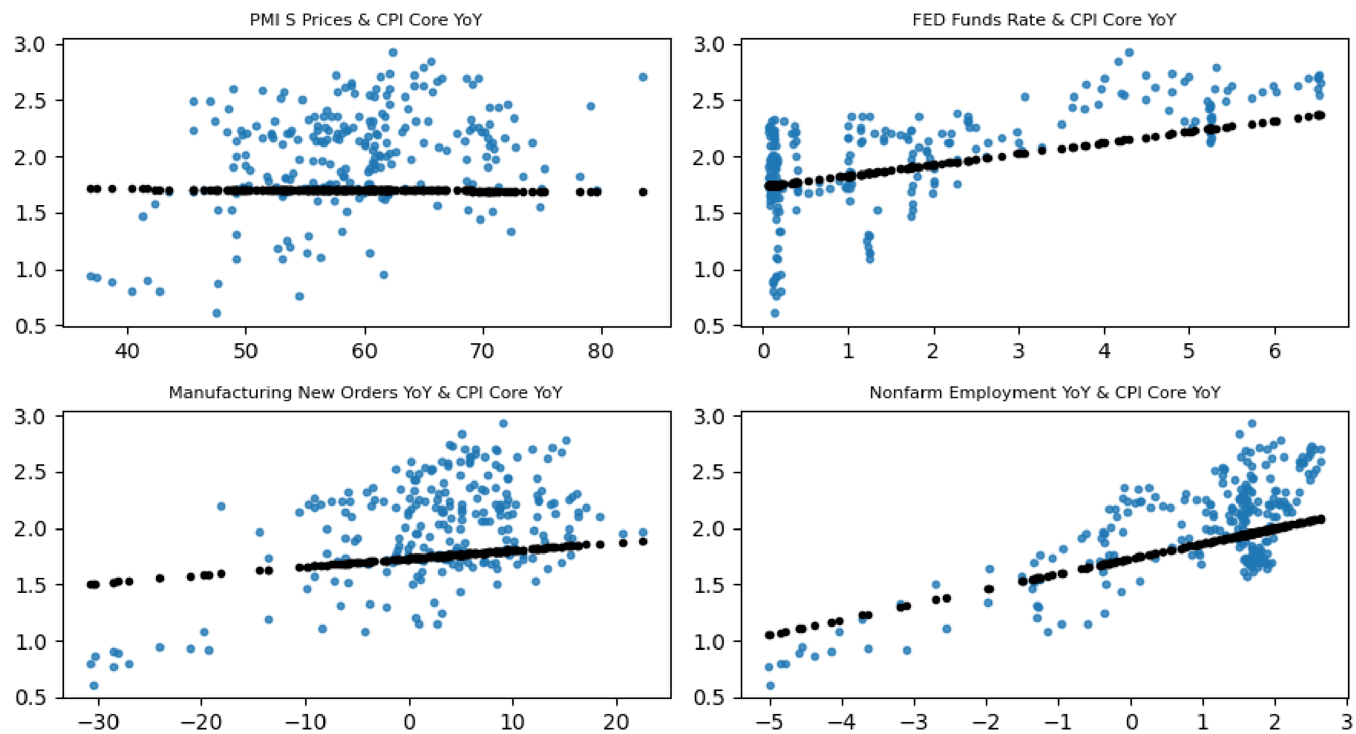
In [47]:

```
# plotting regression model coefficients

def regression_model_subplots():
```

```
    linreg = LinearRegression().fit(X_train,y_train)
    coef_ = linreg.coef_
    intercept_ = linreg.intercept_

    fig = plt.figure(figsize=(9,5))

    row = range(2)
    column = range(2)
    X_count = 0
    subplot_index = 1

    for r in row:
        for c in column:
            ax = fig.add_subplot(2,2,subplot_index)
            line = ax.plot(X[X.columns[X_count]], coef_[X_count] * X[X.columns[X_count]] +
            scatter = plt.scatter(X[X.columns[X_count]], y, marker= 'o', s=10, alpha=0.8)
            title = plt.title(str(X.columns[X_count])+' & '+'CPI Core YoY',fontdict={'font

            X_count += 1
            subplot_index += 1

    plt.tight_layout()
```

In [48]:

```
regression_model_subplots()
```



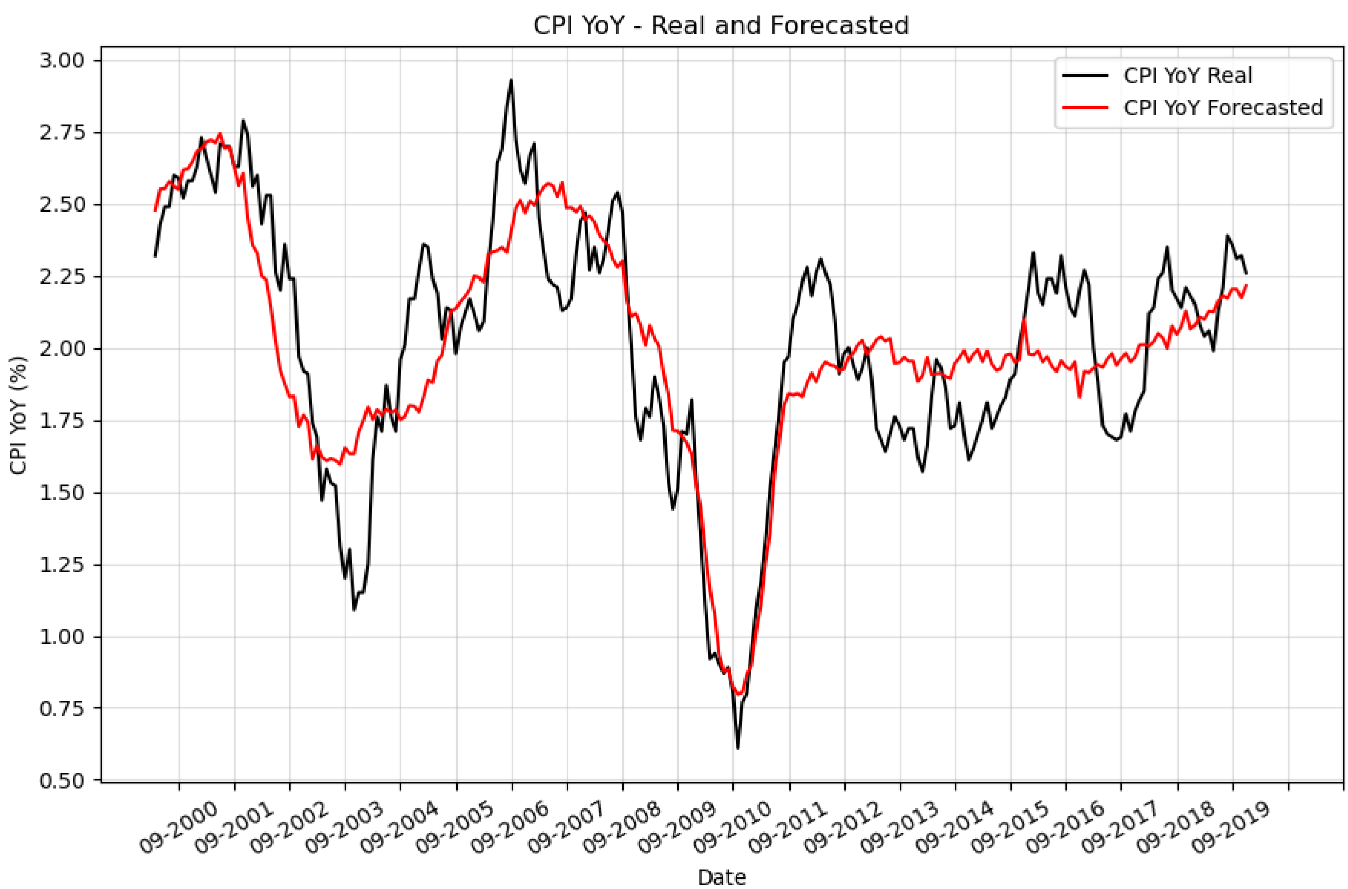
In [49]:

```
# plotting forecasted and real data

from matplotlib.ticker import FixedLocator

def forecast_plot():

    model = LinearRegression().fit(X,y)
    coef_ = model.coef_
    intercept_ = model.intercept_

    df_forecast = pd.concat([X,y],axis=1)
```

```python
    df_forecast.rename(columns={'PMI S Prices':'X1','FED Funds Rate':'X2','Manufacturing N
                               'Nonfarm Employment YoY':'X4','CPI Core NSA YoY':'y'},inpla
    df_forecast['y_pred'] = (coef_[0]*df_forecast['X1'])+(coef_[1]*df_forecast['X2'])+\
                            (coef_[2]*df_forecast['X3'])+(coef_[3]*df_forecast['X4'])+inte
    df_forecast['Date'] = data_ml['Covering Date']

    fig = plt.figure(figsize=(9,6))
    y_real = plt.plot(df_forecast['Date'],df_forecast['y'],c='black',label='CPI YoY Real')
    y_pred = plt.plot(df_forecast['Date'],df_forecast['y_pred'],c='red',label='CPI YoY For
    x_axis = plt.xticks(list(range(5,260,12)))
    y_axis = plt.yticks([0.50,0.75,1.00,1.25,1.50,1.75,2.00,2.25,2.50,2.75,3.00])
    x_ax = plt.gca().xaxis
    for item in x_ax.get_ticklabels():
        item.set_rotation(30)
    x_name = plt.xlabel('Date')
    y_name = plt.ylabel('CPI YoY (%)')
    title = plt.title('CPI YoY - Real and Forecasted')
    legend = plt.legend()
    grid = plt.grid(alpha=0.4)

    tight = plt.tight_layout()
    return y_real
```

In [50]:

```python
forecast_plot()
```



Out[50]: [<matplotlib.lines.Line2D at 0x2b427124e80>]