Intermediate Macroeconomics

Data Exercise 2

Name: Salomon Ruiz

NetID: srh450

Country: Italy

Data

For this exercise, all the data series analyzed were obtained from the Fred database. The table below shows the different data series used and their respective units and labels.

Data	Units	Label
Real GDP at Constant National Prices for Italy	Millions of 2017 U.S. Dollars	RGDPNAITA666NRUG
Gross Domestic Product for Italy	Current U.S. Dollars	MKTGDPITA646NWDB
Consumer Price Index of All Items in Italy	Index 2015=100	ITACPIALLMINMEI
Adjusted Unemployment Rate in Italy	Percent	ITAURNAA
M2 for Italy	National Currency	MYAGM2ITM189N
Spot Crude Oil Price: West Texas Intermediate	Dollars per Barrel	WTISPLC

The range of our data goes from 1974 to 2012, except for M2 for Italy since the data was only available up to 1998. For real GDP, nominal GDP and unemployment rate only yearly data was available. For the other series, the average over four quarters was used in the computations of this exercise. In order to calculate the GDP deflator, real GDP was multiplied by 1 million to match the units to those of nominal GDP.

```
import pandas as pd; import numpy as np; import matplotlib as mpl; import matplotlib.pyplot as plt;
import statsmodels.formula.api as smf; import statsmodels.api as sm
%matplotlib inline
```

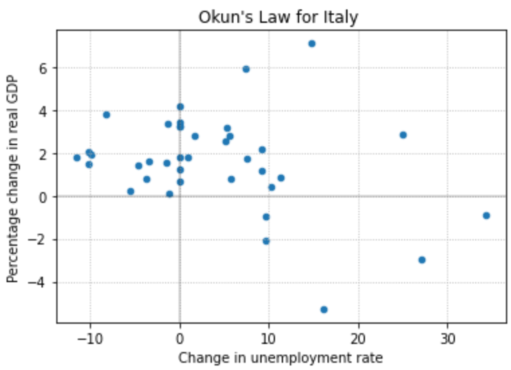
Question 1

```
df = pd.read_csv('data1.csv'); df2 = pd.read_csv('data2.csv')
df = df.rename(columns = {'MKTGDPITA646NWDB':'gdp','RGDPNAITA666NRUG':'real_gdp', 'ITAURNAA':'unrate'}, inplace = False)
df2 = df2.rename(columns = {'MYAGM2ITM189N':'money_supply','ITACPIALLMINMEI':'cpi', 'WTISPLC':'poil'}, inplace = False)
df['DATE'] = pd.to_datetime(df['DATE']); df2['DATE'] = pd.to_datetime(df2['DATE']); df2 = df2.replace('.',np.NaN);
df2['money_supply'] = df2['money_supply'].astype(float); df['cpi'] = df2['cpi'].groupby(df2.index / 4).mean()
df['poil'] = df2['poil'].groupby(df2.index / 4).mean(); df['money_supply'] = df2['money_supply'].groupby(df2.index / 4).mean()
df['pct_change_rgdp'] = df['real_gdp'].pct_change()*100; df['pct_change_unrate'] = df['unrate'].pct_change()*100
df.head()
```

	DATE	gdp	real_gdp	unrate	cpi	poil	money_supply	pct_change_rgdp	pct_change_unrate
0	1974-01-01	1.995640e+11	1302745.750	3.1	7.641165	10.110000	NaN	NaN	NaN
1	1975-01-01	2.276960e+11	1275516.375	3.4	9.364024	11.160000	9.596530e+13	-2.090153	9.677419
2	1976-01-01	2.247170e+11	1366401.750	3.9	10.507548	11.763333	1.206240e+14	7.125379	14.705882
3	1977-01-01	2.575960e+11	1401388.375	4.1	12.635423	13.900000	1.444300e+14	2.560493	5.128205
4	1978-01-01	3.150580e+11	1446795.375	4.1	14.261652	14.850000	1.760650e+14	3.240144	0.000000

```python
ax = df.plot(x ='pct_change_unrate', y='pct_change_rgdp' , kind = 'scatter', title = 'Okun\'s Law for Italy ')
ax.set_ylabel("Percentage change in real GDP"), ax.set_xlabel("Change in unemployment rate"), ax.grid(linestyle=':')
ax.axhline(y=0, color='k', linewidth= 0.3); ax.axvline(x=0, color='k', linewidth= 0.3)
okunslaw = smf.ols('pct_change_rgdp ~ pct_change_unrate', df).fit(); print(okunslaw.summary())
```

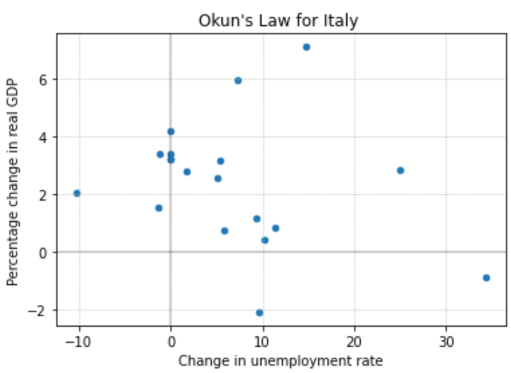
```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:        pct_change_rgdp   R-squared:                       0.094
Model:                            OLS   Adj. R-squared:                  0.069
Method:                 Least Squares   F-statistic:                     3.725
Date:                Thu, 22 Apr 2021   Prob (F-statistic):             0.0615
Time:                        13:40:01   Log-Likelihood:                -82.092
No. Observations:                  38   AIC:                             168.2
Df Residuals:                      36   BIC:                             171.5
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept             1.8898      0.374      5.055      0.000       1.132       2.648
pct_change_unrate    -0.0669      0.035     -1.930      0.062      -0.137       0.003
==============================================================================
Omnibus:                        5.510   Durbin-Watson:                   1.394
Prob(Omnibus):                  0.064   Jarque-Bera (JB):                6.512
Skew:                           0.185   Prob(JB):                       0.0385
Kurtosis:                       4.994   Cond. No.                         11.5
==============================================================================

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



According to our regression, Okun's law for Italy is $\Delta Y/Y = 1.89 - 0.07\Delta$u, which means if there is no change in the unemployment rate, real GDP would increase by 1.89%. However, if the unemployment rate increases by 1%, then real GDP growth would decrease by 0.07%. If we compare these parameter estimates to the US estimates in the textbook, where $\Delta Y/Y = 3 - 2\Delta$u, we can see with the unemployment rate unchanged, there is higher growth in real GDP in the US than in Italy. On the other hand, if the unemployment rate rises by one percentage point, the US real GDP growth is significantly affected since it would fall by 2%, which is a higher decrease than in Italy. A potential reason that explains this difference in the parameter estimates could be the fact unemployment rate in Italy has increased during this time frame to around 10%, while in the US it has fluctuated approximately between 4 and 7%. Therefore, a change in the unemployment rate can have a bigger impact on the US real GDP growth, since they have kept a relatively low unemployment rate.

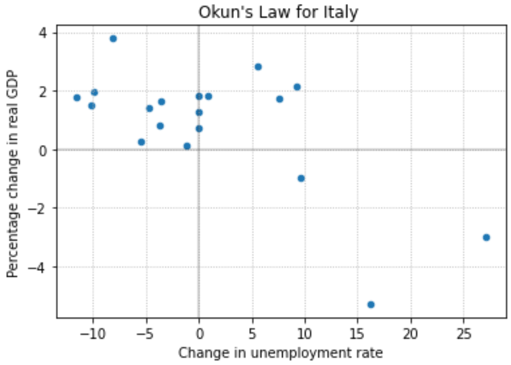
```
sub1 = df.loc[df.index <= 19]; ax = sub1.plot(x ='pct_change_unrate', y='pct_change_rgdp' , kind = 'scatter', title = 'Okun\'s Law for Italy '
)
ax.set_ylabel("Percentage change in real GDP"), ax.set_xlabel("Change in unemployment rate"), ax.grid(linestyle=':')
ax.axhline(y=0, color='k', linewidth= 0.3); ax.axvline(x=0, color='k', linewidth= 0.3)
okunslaw1 = smf.ols('pct_change_rgdp ~ pct_change_unrate', sub1).fit(); print(okunslaw1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        pct_change_rgdp   R-squared:                       0.064
Model:                            OLS   Adj. R-squared:                  0.009
Method:                 Least Squares   F-statistic:                     1.158
Date:                Thu, 22 Apr 2021   Prob (F-statistic):              0.297
Time:                        13:40:02   Log-Likelihood:                -40.571
No. Observations:                  19   AIC:                             85.14
Df Residuals:                      17   BIC:                             87.03
Df Model:                           1
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept             2.7724      0.600      4.620      0.000       1.506       4.039
pct_change_unrate    -0.0544      0.051     -1.076      0.297      -0.161       0.052
==============================================================================
Omnibus:                        3.210   Durbin-Watson:                   1.866
Prob(Omnibus):                  0.201   Jarque-Bera (JB):                1.361
Skew:                           0.514   Prob(JB):                        0.506
Kurtosis:                       3.813   Cond. No.                         14.4
==============================================================================

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



```
sub2 = df.loc[df.index > 19]; ax = sub2.plot(x ='pct_change_unrate', y='pct_change_rgdp' , kind = 'scatter', title = 'Okun\'s Law for Italy ')
ax.set_ylabel("Percentage change in real GDP"), ax.set_xlabel("Change in unemployment rate"), ax.grid(linestyle=':')
ax.axhline(y=0, color='k', linewidth= 0.3); ax.axvline(x=0, color='k', linewidth= 0.3)
okunslaw2 = smf.ols('pct_change_rgdp ~ pct_change_unrate', sub2).fit(); print(okunslaw2.summary())
```

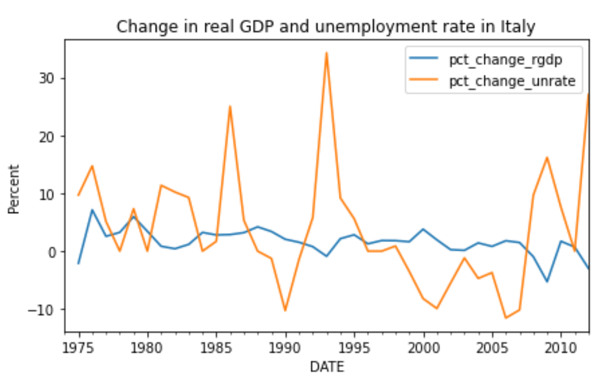
```
                            OLS Regression Results
==============================================================================
Dep. Variable:        pct_change_rgdp   R-squared:                       0.447
Model:                            OLS   Adj. R-squared:                  0.415
Method:                 Least Squares   F-statistic:                     13.75
Date:                Thu, 22 Apr 2021   Prob (F-statistic):            0.00175
Time:                        13:40:02   Log-Likelihood:                -34.612
No. Observations:                  19   AIC:                             73.22
Df Residuals:                      17   BIC:                             75.11
Df Model:                           1
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept             0.9935      0.365      2.725      0.014       0.224       1.763
pct_change_unrate    -0.1411      0.038     -3.707      0.002      -0.221      -0.061
==============================================================================
Omnibus:                        2.794   Durbin-Watson:                   1.525
Prob(Omnibus):                  0.247   Jarque-Bera (JB):                1.063
Skew:                          -0.404   Prob(JB):                        0.588
Kurtosis:                       3.830   Cond. No.                         9.62
==============================================================================

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



After dividing the sample into two subperiods, we notice the change in unemployment rate seems to have a bigger effect on real GDP growth during the second period since it makes it fall by 0.14% compared to 0.05% in the first subperiod. Moreover, the R-square is also considerably higher during the second period with 44.7% compared to only 6.4%, which means our model is better at explaining the second subperiod. We can also see from the scatter plots that the points are less dispersed in the second subperiod and they seem to follow a stronger relationship between the change in real GDP and the change in the unemployment rate. If we plot real GDP growth and the change in the unemployment rate, we realize at the beginning of our sample, during the '70s, there are times in which both the unemployment rate and real GDP growth increase, so this might explain the difference between the two subperiods.

```
ax = df.plot(x ='DATE', y=['pct_change_rgdp', 'pct_change_unrate'], kind = 'line', figsize=(7,4), title = 'Change in real GDP and unemployment
rate in Italy')
ax.set_ylabel("Percent")
```

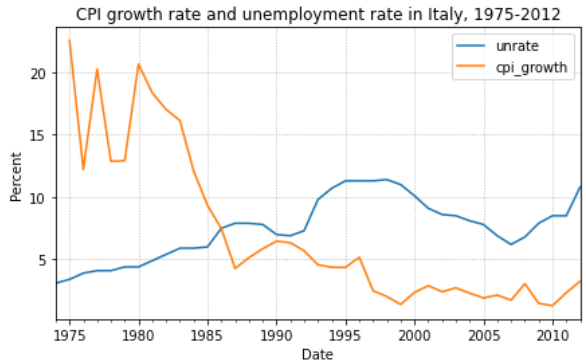
```
Text(0, 0.5, 'Percent')
```

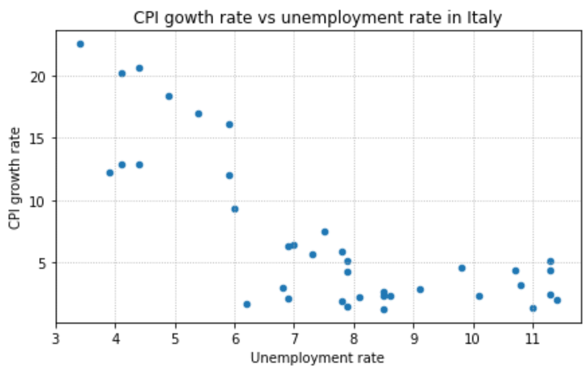


Question 2

```
df['cpi_growth'] =  df['cpi'].pct_change()*100
ax = df.plot(x ='DATE', y=['unrate', 'cpi_growth'], kind = 'line', figsize=(7,4), title= 'CPI growth rate and unemployment rate in Italy, 1975-2012')
ax.set_ylabel("Percent"), ax.set_xlabel("Date"), ax.grid(linestyle=':')
ax = df.plot(x ='unrate', y='cpi_growth' , kind = 'scatter', figsize=(7,4), title='CPI gowth rate vs unemployment rate in Italy' )
ax.set_ylabel("CPI growth rate"), ax.set_xlabel("Unemployment rate"), ax.grid(linestyle=':')
```

```
(Text(0, 0.5, 'CPI growth rate'), Text(0.5, 0, 'Unemployment rate'), None)
```





Question 3

```
phillips = smf.ols('cpi_growth ~ unrate', df).fit()
print(phillips.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             cpi_growth   R-squared:                       0.589
Model:                            OLS   Adj. R-squared:                  0.578
Method:                 Least Squares   F-statistic:                     51.62
Date:                Thu, 22 Apr 2021   Prob (F-statistic):           1.88e-08
Time:                        13:40:03   Log-Likelihood:                -106.21
No. Observations:                  38   AIC:                             216.4
Df Residuals:                      36   BIC:                             219.7
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     22.6368      2.261     10.013      0.000      18.052      27.222
unrate        -2.0405      0.284     -7.185      0.000      -2.617      -1.465
==============================================================================
Omnibus:                        2.132   Durbin-Watson:                   0.656
Prob(Omnibus):                  0.344   Jarque-Bera (JB):                1.297
Skew:                           0.127   Prob(JB):                        0.523
Kurtosis:                       2.132   Cond. No.                         27.7
==============================================================================

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

```
df.corr().loc['cpi_growth', 'unrate']
```

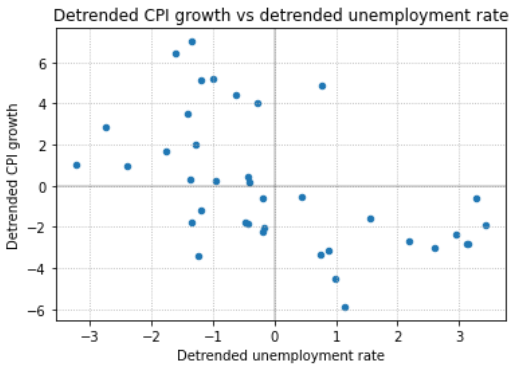
```
-0.7675425716898272
```

The estimated Phillips curve we get is $\Delta CPI = 22.63 - 2.04\Delta$UR, so we can see there is a clear tradeoff between the unemployment rate and inflation. With an unemployment rate equal to zero, inflation would increase by around 22.63%, but as the unemployment rate increases by 1%, inflation falls by 2.04%. Therefore, the estimated $\beta 1$ has the expected sign. By further calculating the correlation coefficient between the two series, we find there is a strong negative correlation between unemployment and inflation since the coefficient is -0.77.

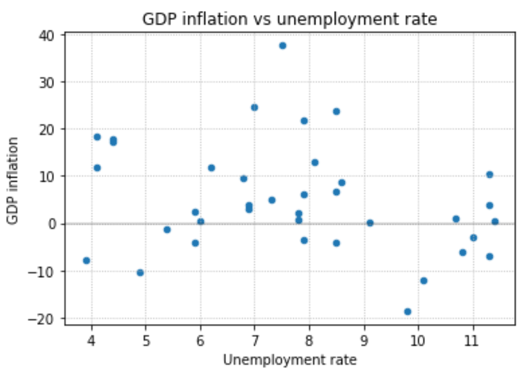
Question 4

```python
df2 = df.iloc[1:]; cycle, trend = sm.tsa.filters.hpfilter(df2['unrate'], 100000); cycle2, trend2 = sm.tsa.filters.hpfilter(df2['cpi_growth'], 100000)
df2["detrended_unemployment_rate"] = cycle; df2["detrended_cpi_growth"] = cycle2
ax = df2.plot(x ='detrended_unemployment_rate', y='detrended_cpi_growth' , kind = 'scatter', title='Detrended CPI growth vs detrended unemployment rate')
ax.set_ylabel("Detrended CPI growth"), ax.set_xlabel("Detrended unemployment rate"), ax.grid(linestyle=':')
ax.axhline(y=0, color='k', linewidth= 0.3); ax.axvline(x=0, color='k', linewidth= 0.3)
```

```
<matplotlib.lines.Line2D at 0x28483be2520>
```

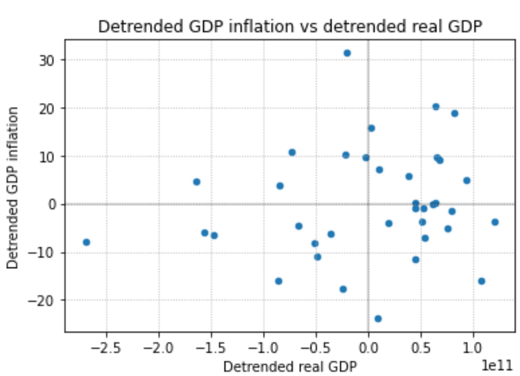



```python
df2['real_gdp'] = df2['real_gdp']*1000000; df2['gdp_deflator'] = (df2['gdp']/df2['real_gdp'])*100
df2['gdp_inflation'] = df2['gdp_deflator'].pct_change()*100; ax = df2.plot(x ='unrate', y='gdp_inflation' , kind = 'scatter', title = 'GDP inflation vs unemployment rate')
ax.set_ylabel("GDP inflation"), ax.set_xlabel("Unemployment rate"), ax.grid(linestyle=':')
ax.axhline(y=0, color='k', linewidth= 0.3);
```




```python
df3 = df2.iloc[1:]; cycle, trend = sm.tsa.filters.hpfilter(df3['real_gdp'], 100000);
cycle2, trend2 = sm.tsa.filters.hpfilter(df3['gdp_inflation'], 100000) ; df3["detrended_real_gdp"] = cycle;  df3["detrended_gdp_inflation"] = cycle2
ax = df3.plot(x ='detrended_real_gdp', y='detrended_gdp_inflation' , kind = 'scatter', title = 'Detrended GDP inflation vs detrended real GDP'
)
ax.set_ylabel("Detrended GDP inflation"), ax.set_xlabel("Detrended real GDP"), ax.grid(linestyle=':')
ax.axhline(y=0, color='k', linewidth= 0.3); ax.axvline(x=0, color='k', linewidth= 0.3)
```

```
<matplotlib.lines.Line2D at 0x28482dd1f70>
```



Out of the three scatter plots above, the first one between the detrended growth of CPI and the detrended unemployment rate suggests a strong relationship between the series.

Question 5

```
sub1 = df.loc[df.index <= 19]; phillips1 = smf.ols('cpi_growth ~ unrate', sub1).fit(); print(phillips1.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:             cpi_growth   R-squared:                       0.720
Model:                            OLS   Adj. R-squared:                  0.703
Method:                 Least Squares   F-statistic:                     43.68
Date:                Thu, 22 Apr 2021   Prob (F-statistic):           4.43e-06
Time:                        13:40:04   Log-Likelihood:                -48.642
No. Observations:                  19   AIC:                             101.3
Df Residuals:                      17   BIC:                             103.2
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     29.2445      2.777     10.530      0.000      23.385      35.104
unrate        -2.9298      0.443     -6.609      0.000      -3.865      -1.995
==============================================================================
Omnibus:                        4.188   Durbin-Watson:                   1.853
Prob(Omnibus):                  0.123   Jarque-Bera (JB):                1.399
Skew:                           0.012   Prob(JB):                        0.497
Kurtosis:                       1.671   Cond. No.                         23.5
==============================================================================

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

```
sub1.corr().loc['cpi_growth', 'unrate']
```

```
-0.8484374097323797
```

```
sub2 = df.loc[df.index > 19]; phillips2 = smf.ols('cpi_growth ~ unrate', sub2).fit(); print(phillips2.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:             cpi_growth   R-squared:                       0.218
Model:                            OLS   Adj. R-squared:                  0.172
Method:                 Least Squares   F-statistic:                     4.745
Date:                Thu, 22 Apr 2021   Prob (F-statistic):             0.0437
Time:                        13:40:04   Log-Likelihood:                -25.130
No. Observations:                  19   AIC:                             54.26
Df Residuals:                      17   BIC:                             56.15
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -0.0110      1.226     -0.009      0.993      -2.597       2.575
unrate         0.2855      0.131      2.178      0.044       0.009       0.562
==============================================================================
Omnibus:                        0.329   Durbin-Watson:                   1.114
Prob(Omnibus):                  0.848   Jarque-Bera (JB):                0.258
Skew:                           0.241   Prob(JB):                        0.879
Kurtosis:                       2.694   Cond. No.                         52.6
==============================================================================

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

```
sub2.corr().loc['cpi_growth', 'unrate']
```

```
0.4671322731893158
```

After splitting our sample into two subsamples, we find a stronger Phillips curve in the first half since $\beta 1$ = -2.92 and R-square is 72%, which is significantly higher than the results obtained in Question 3. Furthermore, the correlation coefficient between the two series in the first half is -0.85, so there is a stronger correlation between unemployment and inflation in the first half of our sample. Surprisingly, our second subsample shows a positive but weaker correlation between the two series, which is the opposite of what the Phillips curve states, but the R-square is only 21.8%.

Question 6

```
df['pct_change_poil'] = df['poil'].pct_change()*100; phillipsoil = smf.ols('cpi_growth ~ unrate + pct_change_poil ', df).fit()
print(phillipsoil.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:             cpi_growth   R-squared:                       0.589
Model:                            OLS   Adj. R-squared:                  0.566
Method:                 Least Squares   F-statistic:                     25.12
Date:                Thu, 22 Apr 2021   Prob (F-statistic):           1.72e-07
Time:                        13:40:04   Log-Likelihood:                -106.19
No. Observations:                  38   AIC:                             218.4
Df Residuals:                      35   BIC:                             223.3
Df Model:                           2                                         
Covariance Type:            nonrobust                                         
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
Intercept          22.5791      2.321      9.729      0.000      17.868      27.291
unrate             -2.0373      0.289     -7.058      0.000      -2.623      -1.451
pct_change_poil     0.0028      0.018      0.158      0.875      -0.033       0.039
==============================================================================
Omnibus:                        2.332   Durbin-Watson:                   0.643
Prob(Omnibus):                  0.312   Jarque-Bera (JB):                1.341
Skew:                           0.113   Prob(JB):                        0.511
Kurtosis:                       2.108   Cond. No.                         138.
==============================================================================

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

After running this regression which includes the change in oil prices, we can see the relationship between unemployment and inflation is still negative and the coefficient is almost the same, which was expected. The coefficient for the change in oil prices is positive but it is small and statistically insignificant (p-value > 0.05 and t-statistic small). Moreover, R-square is basically the same, so there is no increase in explanatory power after including the change in oil prices. The effect of change in oil prices on CPI growth is negligible.

Question 7

```
df['real_gdp'] = df['real_gdp']*1000000
df['gdp_deflator'] = (df['gdp']/df['real_gdp'])*100
df['pct_change_deflator'] = df['gdp_deflator'].pct_change()*100
df['lagged_change_deflator'] = df['pct_change_deflator'].shift(+1)
```

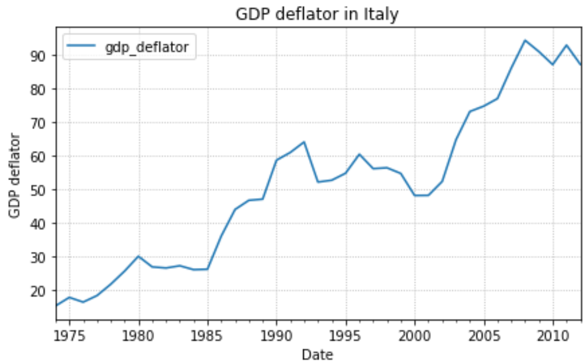
```
deflchange = smf.ols('pct_change_deflator ~ unrate + lagged_change_deflator ', df).fit()
print(deflchange.summary())
```

```
                             OLS Regression Results                            
===============================================================================
Dep. Variable:     pct_change_deflator   R-squared:                       0.093
Model:                             OLS   Adj. R-squared:                  0.039
Method:                  Least Squares   F-statistic:                     1.737
Date:                 Thu, 22 Apr 2021   Prob (F-statistic):              0.191
Time:                         13:40:22   Log-Likelihood:                -140.70
No. Observations:                   37   AIC:                             287.4
Df Residuals:                       34   BIC:                             292.2
Df Model:                            2                                         
Covariance Type:             nonrobust                                         
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
Intercept                 12.8689      7.195      1.789      0.083      -1.753      27.490
unrate                    -1.1330      0.859     -1.319      0.196      -2.878       0.612
lagged_change_deflator     0.1555      0.170      0.917      0.366      -0.189       0.500
==============================================================================
Omnibus:                        4.907   Durbin-Watson:                   1.756
Prob(Omnibus):                  0.086   Jarque-Bera (JB):                3.644
Skew:                           0.523   Prob(JB):                        0.162
Kurtosis:                       4.126   Cond. No.                         51.3
==============================================================================

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

We can see from the regression results that $\beta 1$ is statistically insignificant since it has a small t-stat and a big p-value. Moreover, this model only explains 9.3% of the changes in the GDP deflator, so the hypothesis that the unemployment rate affects not inflation itself, but the change in inflation can be rejected. Additionally, we can see that the lagged change in GDP deflator is also insignificant and $\beta 2$ is different from 1. By plotting the GDP deflator, we can see it has fluctuated a lot during the time period of our data set, so past inflation might not be a good estimator of current inflation for Italy during this time frame.

```
ax = df.plot(x ='DATE', y=['gdp_deflator'], kind = 'line', figsize=(7,4), title = 'GDP deflator in Italy')
ax.set_ylabel("GDP deflator"), ax.set_xlabel("Date"), ax.grid(linestyle=':')
```

```
(Text(0, 0.5, 'GDP deflator'), Text(0.5, 0, 'Date'), None)
```



Question 8

```
df['lagged_unrate'] = df['unrate'].shift(+1)
defllagunr = smf.ols('pct_change_deflator ~ unrate + lagged_unrate ', df).fit()
print(defllagunr.summary())
```

```
                             OLS Regression Results
===============================================================================
Dep. Variable:     pct_change_deflator   R-squared:                       0.113
Model:                             OLS   Adj. R-squared:                  0.062
Method:                  Least Squares   F-statistic:                     2.220
Date:                 Thu, 22 Apr 2021   Prob (F-statistic):              0.124
Time:                         13:58:05   Log-Likelihood:                -144.09
No. Observations:                   38   AIC:                             294.2
Df Residuals:                       35   BIC:                             299.1
Df Model:                            2
Covariance Type:             nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept        16.3337      6.213      2.629      0.013       3.721      28.946
unrate           -3.7414      2.482     -1.507      0.141      -8.780       1.298
lagged_unrate     2.3531      2.431      0.968      0.340      -2.583       7.289
==============================================================================
Omnibus:                        8.501   Durbin-Watson:                   1.641
Prob(Omnibus):                  0.014   Jarque-Bera (JB):                7.710
Skew:                           0.812   Prob(JB):                       0.0212
Kurtosis:                       4.494   Cond. No.                         38.5
==============================================================================

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

According to our results, lagged unemployment rate seems to have a smaller effect on inflation than the current unemployment rate, so including it in our model does not bring a big increase in explanatory power. $\beta 1$ + $\beta 2$ is different from zero, otherwise adding the two variables to our model would have no effect on inflation. A reason why lagged unemployment does not add much explanatory power could be the fact that the unemployment rate affects inflation mostly in the short run.

Question 9

After running all these “experiments”, the subsample that shows the strongest Phillips curve is the first subsample of question 5, which has an R-square of 72%, and where unemployment rate is the only predictor of inflation. During this time period we can see the tradeoff between unemployment and inflation was clear, as inflation was at high levels while the unemployment rate was low. In the second subsample this tradeoff holds but seems less strong.

Question 10

```python
df['change_money'] = df['money_supply'].pct_change()*100
df['lagged_money'] = df['change_money'].shift(+1)
reg = smf.ols('cpi_growth ~ unrate + pct_change_poil+ change_money + lagged_money ', df).fit()
print(reg.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             cpi_growth   R-squared:                       0.803
Model:                            OLS   Adj. R-squared:                  0.777
Method:                 Least Squares   F-statistic:                     31.52
Date:                Thu, 22 Apr 2021   Prob (F-statistic):           1.61e-10
Time:                        14:03:28   Log-Likelihood:                -84.586
No. Observations:                  36   AIC:                             179.2
Df Residuals:                      31   BIC:                             187.1
Df Model:                           4
Covariance Type:            nonrobust
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
Intercept           6.7481      2.878      2.345      0.026       0.879      12.617
unrate             -0.5273      0.302     -1.747      0.090      -1.143       0.088
pct_change_poil     0.0159      0.012      1.330      0.193      -0.008       0.040
change_money        0.2190      0.141      1.559      0.129      -0.068       0.506
lagged_money        0.3591      0.129      2.779      0.009       0.096       0.623
==============================================================================
Omnibus:                        5.920   Durbin-Watson:                   0.931
Prob(Omnibus):                  0.052   Jarque-Bera (JB):                4.707
Skew:                           0.862   Prob(JB):                       0.0951
Kurtosis:                       3.405   Cond. No.                         258.
==============================================================================

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

$\beta 3$ and $\beta 4$ have an expected positive sign as printing more money generate inflation. Money growth does contribute much to explaining inflation and lagged money growth is in fact the variable with the highest t-statistic. Since prices are sticky in the short run, inflation does not increase right away but it takes a while. This is why the lagged money growth is a better estimator to predict inflation. We can see that out of all the previous Phillips curve models, this one has the highest R-square, 80.3%, so it is really good at explaining inflation variations in Italy.

Sources:

[https://fred.stlouisfed.org/ (https://fred.stlouisfed.org/)](https://fred.stlouisfed.org/)

```python
from IPython.core.display import display,HTML
display(HTML('<style>.prompt{width:0px; min-width:0px; visibility: collapse}</style>'))
import warnings
warnings.filterwarnings('ignore')
```