

Homework #3.2

```
In [ ]: %matplotlib inline
import warnings
warnings.filterwarnings('ignore')
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
from statsmodels.stats.diagnostic import het_white
from arch import arch_model

pd.set_option('display.max_rows', 500)
```

```
In [ ]: # read data
macro = pd.read_excel('data/hw_3_2_data.xlsx', sheet_name='macro')
sp500 = pd.read_excel('data/hw_3_2_data.xlsx', sheet_name="s&p500")
```

1. Assessing the OLS Model

1. OLS Regression CPI and Money

```
In [ ]: X = macro.M2
y = macro.CPI
model = sm.OLS(y, sm.add_constant(X))
results = model.fit()
results.summary()
```

Out[]:

OLS Regression Results

Dep. Variable:	CPI	R-squared:	0.827
Model:	OLS	Adj. R-squared:	0.827
Method:	Least Squares	F-statistic:	3618.
Date:	Sun, 26 Jun 2022	Prob (F-statistic):	8.42e-291
Time:	23:02:24	Log-Likelihood:	-3721.7
No. Observations:	760	AIC:	7447.
Df Residuals:	758	BIC:	7457.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	62.7397	1.645	38.145	0.000	59.511	65.969
M2	0.0145	0.000	60.151	0.000	0.014	0.015
Omnibus:	42.247	Durbin-Watson:	0.001			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	36.033			
Skew:	-0.458	Prob(JB):	1.50e-08			
Kurtosis:	2.454	Cond. No.	9.54e+03			

Notes:

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

[2] The condition number is large, 9.54e+03. This might indicate that there are strong multicollinearity or other numerical problems.

a) $R^2 = 0.827$

b) $\beta = 0.0145$

2- Regression of growth rates

```
In [ ]: inflation = macro.set_index('date')[['CPI', 'M2']].pct_change(12, freq='M').res
X = inflation.M2
y = inflation.CPI
model = sm.OLS(y, sm.add_constant(X)).fit()
model.summary()
```

Out[]:

OLS Regression Results

Dep. Variable:	CPI	R-squared:	0.008
Model:	OLS	Adj. R-squared:	0.007
Method:	Least Squares	F-statistic:	6.370
Date:	Sun, 26 Jun 2022	Prob (F-statistic):	0.0118
Time:	23:02:24	Log-Likelihood:	1610.0
No. Observations:	748	AIC:	-3216.
Df Residuals:	746	BIC:	-3207.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	0.0320	0.002	13.839	0.000	0.027	0.037
M2	0.0729	0.029	2.524	0.012	0.016	0.130
Omnibus:	211.421	Durbin-Watson:	0.020			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	484.782			
Skew:	1.517	Prob(JB):	5.38e-106			
Kurtosis:	5.519	Cond. No.	28.2			

Notes:

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

a) $R^2 = 0.008$

b) $\beta = 0.0729$

3- Discussion

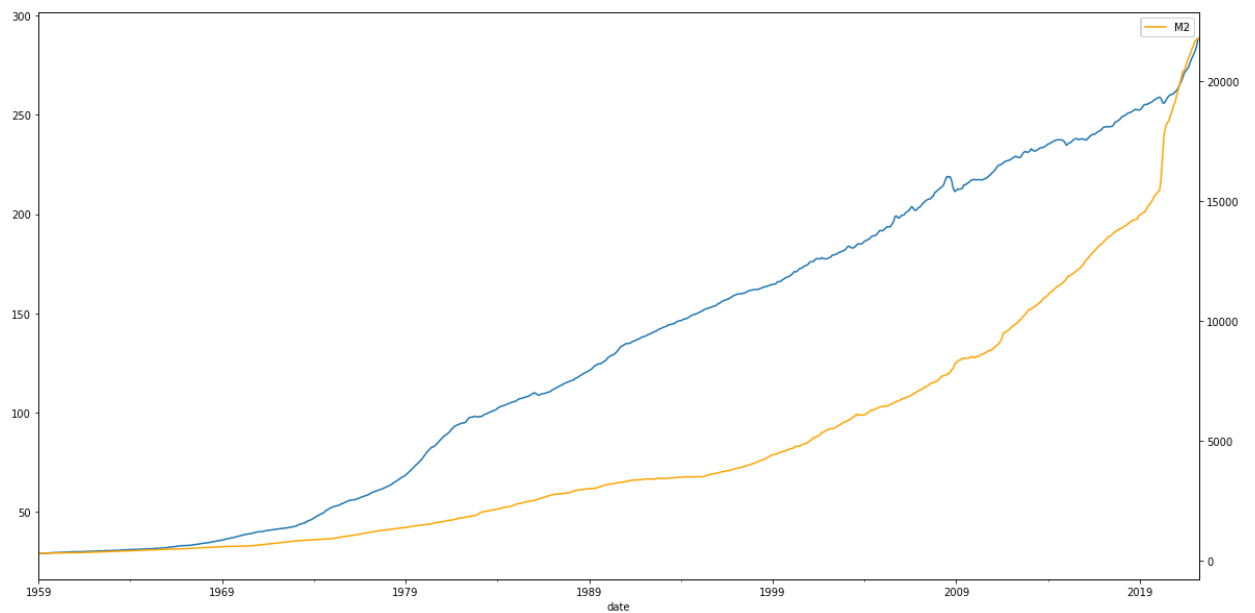
The correlation between CPI and Money seems to be stronger than the correlation between inflation and money growth.

However, CPI is non-stationary and will tend to have a strong correlation with anything that has an upward trend. Which in this case is Money.

Hence, the correlation observed here could be spurious. Regressing CPI on Money doesn't make sense.

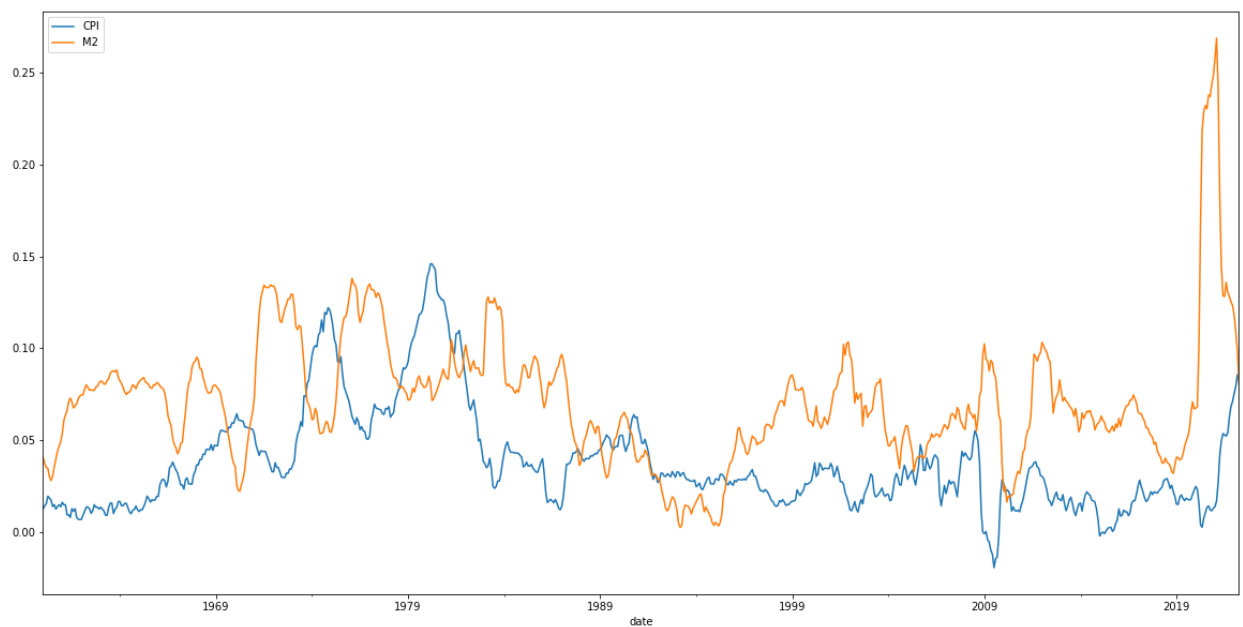
```
In [ ]: fig, ax1 = plt.subplots()
macro.set_index('date')[['CPI']].plot(figsize=(20, 10), ax=ax1)
ax2 = ax1.twinx()
macro.set_index('date')[['M2']].plot(figsize=(20, 10), ax=ax2, c='orange')
```

Out[]: <AxesSubplot:xlabel='date'>



```
In [ ]: inflation.set_index('date')[['CPI', 'M2']].plot(figsize=(20, 10))
```

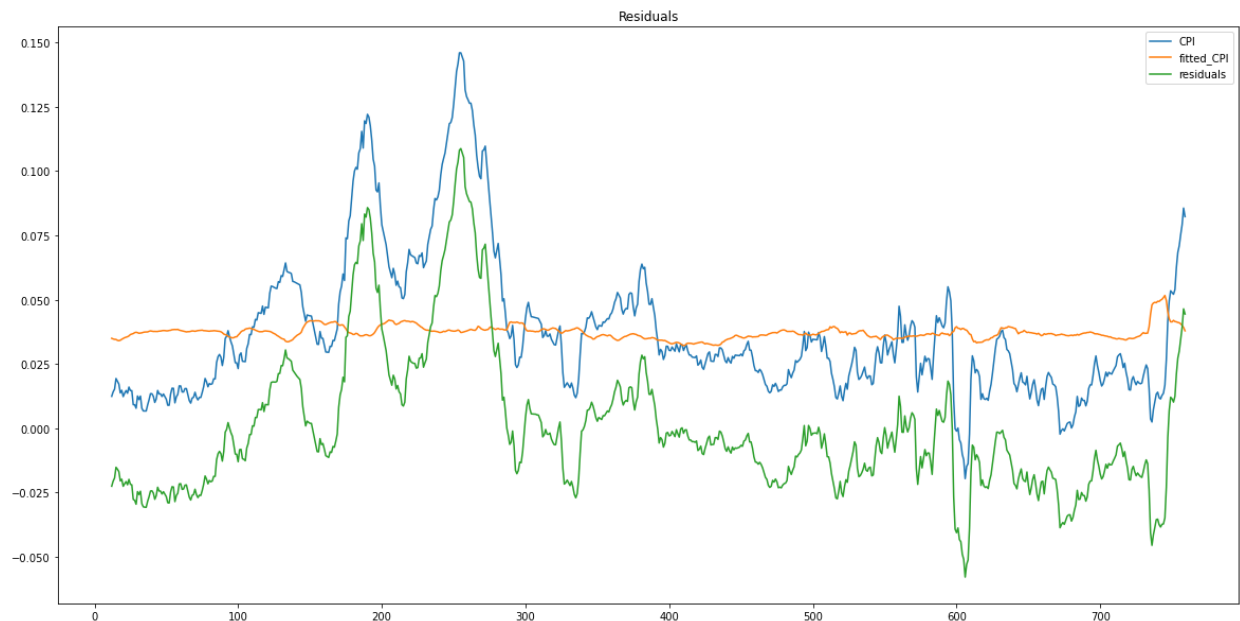
```
Out[ ]: <AxesSubplot:xlabel='date'>
```



4.

```
In [ ]: predicted = pd.concat([y, pd.DataFrame(data=model.predict(sm.add_constant(X)),
predicted['residuals'] = predicted['CPI'] - predicted['fitted_CPI']
predicted.plot(title='Residuals', figsize=(20, 10))
```

```
Out[ ]: <AxesSubplot:title={'center': 'Residuals'}>
```



- a) The residuals don't seem to be drawn from a constant variance.
- b) They do seem to have some serial correlation.

5.

- a) Looking at the reported p-values from 2. α and β estimates seem to be statistically significant.
- b) Yes, given that the homoscedasticity assumption doesn't hold the standard error is misspecified.
- c) The estimated β would be more trustworthy for larger sample sizes.

6.

- a) From 2. the Durbin-Watson value is 0.020 which indicates presence of serial correlation.
- b) Using White test (see below), we have an extremely small $p - value = 9.75 * 10^{-5}$ which means that the errors aren't homoscedastic.

```
In [ ]: white_test = het_white(model.resid, model.model.exog)
labels = ['LM Statistic', 'LM-Test p-value', 'F-Statistic', 'F-Test p-value']
print(dict(zip(labels, white_test)))

{'LM Statistic': 18.469958814741208, 'LM-Test p-value': 9.756620279329117e-05,
'F-Statistic': 9.43081061790568, 'F-Test p-value': 9.020683988503916e-05}
```

2. Forecasting via Regression

```
In [ ]: # build dataset
def build_dataset(h, macro):
    inflation = macro.set_index('date')[['CPI', 'M2']].pct_change(h, freq='M')
    inflation['y'] = inflation.set_index('date')['CPI'].shift(h, freq='M').resid
```

```

    return inflation.dropna()

def fit_model(y, X):
    return sm.OLS(y, sm.add_constant(X)).fit()

```

1. Forecast using lagged infation

```

In [ ]: h_values = [1, 12, 24, 36]
        for h in h_values:
            inflation_lagged = build_dataset(h, macro)
            results = fit_model(inflation_lagged['Y'], inflation_lagged['CPI'])
            print(f'\n\n\t##### Results for h={h} #####')

```

Results for h=1

OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.399
Model:                  OLS    Adj. R-squared:       0.398
Method:                 Least Squares    F-statistic:       501.8
Date:                   Sun, 26 Jun 2022    Prob (F-statistic): 1.22e-85
Time:                   23:02:27    Log-Likelihood:    3482.7
No. Observations:      758    AIC:              -6961.
Df Residuals:          756    BIC:              -6952.
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0011	0.000	9.115	0.000	0.001	0.001
CPI	0.6312	0.028	22.401	0.000	0.576	0.686

```

=====
Omnibus:                92.917    Durbin-Watson:       2.143
Prob(Omnibus):          0.000    Jarque-Bera (JB):     798.226
Skew:                   0.113    Prob(JB):             4.65e-174
Kurtosis:               8.022    Cond. No.             317.
=====

```

Notes:

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

Results for h=12

OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.555
Model:                  OLS    Adj. R-squared:       0.555
Method:                 Least Squares    F-statistic:       917.1
Date:                   Sun, 26 Jun 2022    Prob (F-statistic): 2.40e-131
Time:                   23:02:27    Log-Likelihood:    1877.3
No. Observations:      736    AIC:              -3751.
Df Residuals:          734    BIC:              -3741.
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0101	0.001	8.782	0.000	0.008	0.012
CPI	0.7488	0.025	30.284	0.000	0.700	0.797

```

=====
Omnibus:                79.392    Durbin-Watson:       0.089
Prob(Omnibus):          0.000    Jarque-Bera (JB):     159.073
Skew:                   0.650    Prob(JB):             2.87e-35
Kurtosis:               4.870    Cond. No.             35.5
=====

```

Notes:

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

Results for h=24

```

OLS Regression Results
=====
Dep. Variable:          y      R-squared:          0.405
Model:                  OLS    Adj. R-squared:       0.404
Method:                 Least Squares  F-statistic:       483.2
Date:                  Sun, 26 Jun 2022  Prob (F-statistic): 4.27e-82
Time:                  23:02:27  Log-Likelihood:    1228.1
No. Observations:      712      AIC:               -2452.
Df Residuals:          710      BIC:               -2443.
Df Model:              1
Covariance Type:       nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.0295      0.003     10.783      0.000      0.024      0.035
CPI            0.6309      0.029     21.983      0.000      0.575      0.687
=====
Omnibus:          188.541    Durbin-Watson:       0.021
Prob(Omnibus):    0.000    Jarque-Bera (JB):    464.720
Skew:             1.371    Prob(JB):            1.22e-101
Kurtosis:         5.854    Cond. No.            17.8
=====

```

Notes:

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

```

##### Results for h=36 #####
OLS Regression Results

```

```

=====
Dep. Variable:          y      R-squared:          0.366
Model:                  OLS    Adj. R-squared:       0.365
Method:                 Least Squares  F-statistic:       395.3
Date:                  Sun, 26 Jun 2022  Prob (F-statistic): 8.36e-70
Time:                  23:02:27  Log-Likelihood:    886.38
No. Observations:      688      AIC:               -1769.
Df Residuals:          686      BIC:               -1760.
Df Model:              1
Covariance Type:       nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.0507      0.004     11.476      0.000      0.042      0.059
CPI            0.5952      0.030     19.881      0.000      0.536      0.654
=====
Omnibus:          135.194    Durbin-Watson:       0.009
Prob(Omnibus):    0.000    Jarque-Bera (JB):    269.015
Skew:             1.109    Prob(JB):            3.84e-59
Kurtosis:         5.112    Cond. No.            11.9
=====

```

Notes:

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

2. Forecast using lagged money growth

```
In [ ]: h_values = [1, 12, 24, 36]
```



```
for h in h_values:
    inflation_lagged = build_dataset(h, macro)
    results = fit_model(inflation_lagged['y'], inflation_lagged['M2'])
    print(f'\n\n\t##### Results for h={h} #####')
```

Results for h=1

OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.000
Model:                  OLS    Adj. R-squared:       -0.001
Method:                 Least Squares    F-statistic:      3.930e-07
Date:                  Sun, 26 Jun 2022    Prob (F-statistic): 0.999
Time:                  23:02:28    Log-Likelihood:    3289.8
No. Observations:      758    AIC:              -6576.
Df Residuals:          756    BIC:              -6566.
Df Model:              1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0030	0.000	16.365	0.000	0.003	0.003
M2	-1.596e-05	0.025	-0.001	0.999	-0.050	0.050

```

=====
Omnibus:                89.567    Durbin-Watson:          0.737
Prob(Omnibus):           0.000    Jarque-Bera (JB):        579.300
Skew:                    0.280    Prob(JB):                1.61e-126
Kurtosis:                7.246    Cond. No.:               222.
=====

```

Notes:

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

Results for h=12

OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.087
Model:                  OLS    Adj. R-squared:       0.086
Method:                 Least Squares    F-statistic:       70.36
Date:                  Sun, 26 Jun 2022    Prob (F-statistic): 2.52e-16
Time:                  23:02:28    Log-Likelihood:    1612.6
No. Observations:      736    AIC:              -3221.
Df Residuals:          734    BIC:              -3212.
Df Model:              1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0208	0.002	9.274	0.000	0.016	0.025
M2	0.2373	0.028	8.388	0.000	0.182	0.293

```

=====
Omnibus:                219.388    Durbin-Watson:          0.021
Prob(Omnibus):           0.000    Jarque-Bera (JB):        543.560
Skew:                    1.555    Prob(JB):                9.28e-119
Kurtosis:                5.837    Cond. No.:               28.5
=====

```

Notes:

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

Results for h=24

```

OLS Regression Results
=====
Dep. Variable:          y      R-squared:          0.267
Model:                  OLS    Adj. R-squared:       0.266
Method:                 Least Squares    F-statistic:       258.9
Date:                  Sun, 26 Jun 2022    Prob (F-statistic): 6.65e-50
Time:                  23:02:28    Log-Likelihood:    1154.0
No. Observations:      712    AIC:               -2304.
Df Residuals:          710    BIC:               -2295.
Df Model:              1
Covariance Type:       nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const         -0.0002      0.005     -0.037      0.970     -0.010      0.010
M2             0.5521      0.034     16.092      0.000      0.485      0.619
=====
Omnibus:                 130.247    Durbin-Watson:          0.011
Prob(Omnibus):           0.000    Jarque-Bera (JB):       232.144
Skew:                    1.095    Prob(JB):               3.89e-51
Kurtosis:                4.740    Cond. No.               19.5
=====

```

Notes:

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

```

##### Results for h=36 #####
OLS Regression Results
=====

```

```

Dep. Variable:          y      R-squared:          0.398
Model:                  OLS    Adj. R-squared:       0.397
Method:                 Least Squares    F-statistic:       453.3
Date:                  Sun, 26 Jun 2022    Prob (F-statistic): 1.31e-77
Time:                  23:02:28    Log-Likelihood:    904.36
No. Observations:      688    AIC:               -1805.
Df Residuals:          686    BIC:               -1796.
Df Model:              1
Covariance Type:       nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const         -0.0316      0.008     -4.133      0.000     -0.047     -0.017
M2             0.6930      0.033     21.290      0.000      0.629      0.757
=====
Omnibus:                 26.466    Durbin-Watson:          0.007
Prob(Omnibus):           0.000    Jarque-Bera (JB):       26.889
Skew:                    0.452    Prob(JB):               1.45e-06
Kurtosis:                2.654    Cond. No.               13.8
=====

```

Notes:

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

3. Forecast using lagged inflation and money growth

```
In [ ]: h_values = [1, 12, 24, 36]
```

```
for h in h_values:
    inflation_lagged = build_dataset(h, macro)
    results = fit_model(inflation_lagged['y'], inflation_lagged[['M2', 'CPI']])
    print(f'\n\n\t##### Results for h={h} #####')
```

Results for h=1

OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.401
Model:                  OLS    Adj. R-squared:       0.400
Method:                 Least Squares    F-statistic:       253.2
Date:                   Sun, 26 Jun 2022    Prob (F-statistic): 7.09e-85
Time:                   23:02:28    Log-Likelihood:    3484.3
No. Observations:      758    AIC:              -6963.
Df Residuals:          755    BIC:              -6949.
Df Model:              2
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0009	0.000	5.287	0.000	0.001	0.001
M2	0.0352	0.020	1.781	0.075	-0.004	0.074
CPI	0.6351	0.028	22.504	0.000	0.580	0.691

```

=====
Omnibus:                95.393    Durbin-Watson:       2.163
Prob(Omnibus):          0.000    Jarque-Bera (JB):    877.513
Skew:                   0.075    Prob(JB):            2.82e-191
Kurtosis:               8.269    Cond. No.            319.
=====

```

Notes:

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

Results for h=12

OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.614
Model:                  OLS    Adj. R-squared:       0.612
Method:                 Least Squares    F-statistic:       581.8
Date:                   Sun, 26 Jun 2022    Prob (F-statistic): 4.81e-152
Time:                   23:02:28    Log-Likelihood:    1928.8
No. Observations:      736    AIC:              -3852.
Df Residuals:          733    BIC:              -3838.
Df Model:              2
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0030	0.002	-1.837	0.067	-0.006	0.000
M2	0.1939	0.018	10.494	0.000	0.158	0.230
CPI	0.7307	0.023	31.586	0.000	0.685	0.776

```

=====
Omnibus:                45.483    Durbin-Watson:       0.095
Prob(Omnibus):          0.000    Jarque-Bera (JB):    115.221
Skew:                   0.308    Prob(JB):            9.55e-26
Kurtosis:               4.838    Cond. No.            35.9
=====

```

Notes:

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

Results for h=24

OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.523
Model:                  OLS    Adj. R-squared:       0.522
Method:                  Least Squares    F-statistic:       388.6
Date:                    Sun, 26 Jun 2022    Prob (F-statistic): 1.15e-114
Time:                    23:02:28    Log-Likelihood:    1306.7
No. Observations:       712    AIC:              -2607.
Df Residuals:           709    BIC:              -2594.
Df Model:                2
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0168	0.004	-3.927	0.000	-0.025	-0.008
M2	0.3841	0.029	13.239	0.000	0.327	0.441
CPI	0.5250	0.027	19.493	0.000	0.472	0.578

```

=====
Omnibus:                79.778    Durbin-Watson:          0.022
Prob(Omnibus):           0.000    Jarque-Bera (JB):       140.498
Skew:                    0.715    Prob(JB):               3.10e-31
Kurtosis:                4.640    Cond. No.:              22.4
=====

```

Notes:

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

Results for h=36

OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.540
Model:                  OLS    Adj. R-squared:       0.539
Method:                  Least Squares    F-statistic:       402.2
Date:                    Sun, 26 Jun 2022    Prob (F-statistic): 2.92e-116
Time:                    23:02:28    Log-Likelihood:    997.05
No. Observations:       688    AIC:              -1988.
Df Residuals:           685    BIC:              -1975.
Df Model:                2
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0389	0.007	-5.791	0.000	-0.052	-0.026
M2	0.5043	0.031	16.123	0.000	0.443	0.566
CPI	0.4079	0.028	14.555	0.000	0.353	0.463

```

=====
Omnibus:                11.287    Durbin-Watson:          0.010
Prob(Omnibus):           0.004    Jarque-Bera (JB):       13.418
Skew:                    0.214    Prob(JB):               0.00122
Kurtosis:                3.534    Cond. No.:              17.0
=====

```

Notes:

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

4.

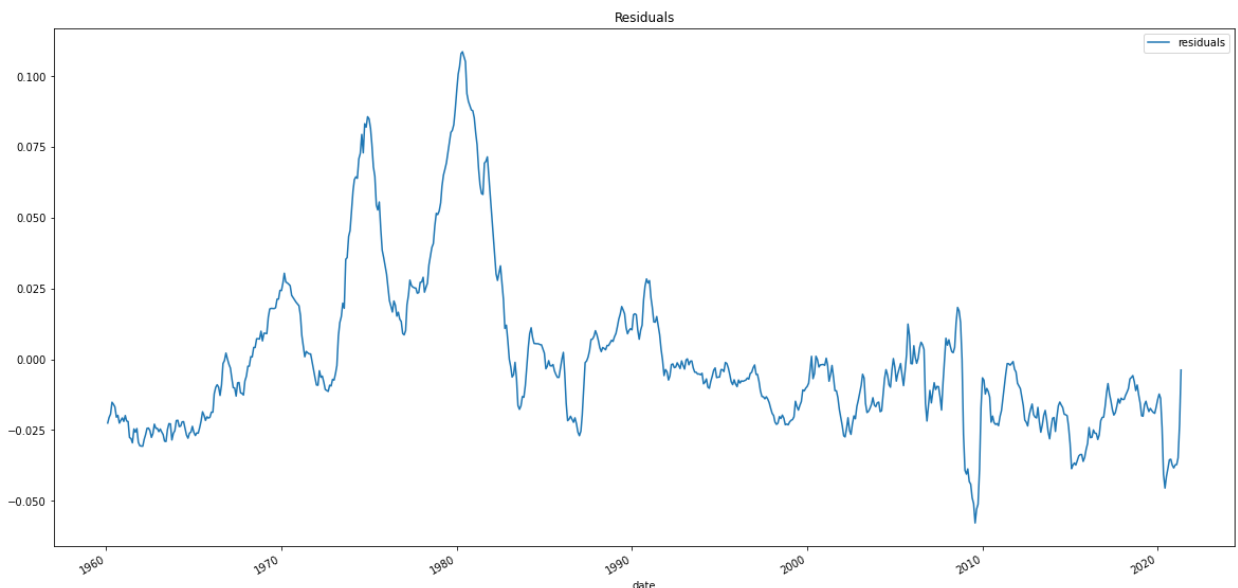
The regression with the combined regressors with $h = 12$ gives the best $R^2 = 0.612$
Combining the regressors seems to improve the forecast

5.

a) Plot residuals for $h = 12$

```
In [ ]: h = 12
inflation_lagged = build_dataset(h, macro)
results = fit_model(inflation_lagged['y'], inflation_lagged[['M2', 'CPI']])
residuals = pd.concat([inflation_lagged['date'], pd.DataFrame(model.resid, columns=['residuals'])])
residuals.set_index('date').plot(title='Residuals', figsize=(20, 10))

Out [ ]: <AxesSubplot:title={'center': 'Residuals'}, xlabel='date'>
```



b) Yes, there seems to have some amount of serial correlation. This is also confirmed by the value of the Durbin-Watson test which is 0.095.

c) The betas as well because with serial correlation the assumption that ϵ and the regressor are uncorrelated is broken.

3. Time-Series Model of Volatility

```
In [ ]: r = sp500
volatility_df = pd.DataFrame(r.Date, columns=['Date']).iloc[61:].set_index('Date')
```

Expanding series

```
In [ ]: column_name = 'expanding_window'
def compute_var(values):
    return (values**2).sum() / len(values)
expanding_series_df = r.copy().set_index('Date').expanding(min_periods=61).apply(compute_var, axis=1, raw=True)
```

```
volatility_df[column_name] = np.sqrt(expanding_series_df.SPY.values)
```

```
vol = volatility_df[:'2008-10-31'].iloc[-1][column_name]; print(f"Volatility on October 2008: {vol}")
vol = volatility_df[:'2020-04-30'].iloc[-1][column_name]; print(f"Volatility on April 2020: {vol}")
vol = volatility_df[:'2022-05-31'].iloc[-1][column_name]; print(f"Volatility on May 2022: {vol}")
```

```
Volatility on October 2008:    0.040591
Volatility on April 2020:     0.042309
Volatility on May 2022:      0.043220
```

Rolling Window

```
In [ ]: column_name = 'rolling_window'
def compute_var(values):
    return (values**2).sum() / len(values)
roling_window_df = r.set_index('Date').rolling(window=61).apply(compute_var).shift(1)
volatility_df[column_name] = np.sqrt(roling_window_df.SPY.values)
```

```
vol = volatility_df[:'2008-10-31'].iloc[-1][column_name]; print(f"Volatility on October 2008: {vol}")
vol = volatility_df[:'2020-04-30'].iloc[-1][column_name]; print(f"Volatility on April 2020: {vol}")
vol = volatility_df[:'2022-05-31'].iloc[-1][column_name]; print(f"Volatility on May 2022: {vol}")
```

```
Volatility on October 2008:    0.029947
Volatility on April 2020:     0.039193
Volatility on May 2022:      0.047886
```

IGARCH

```
In [ ]: column_name = 'IGARCH'
theta = 0.97
sigma = [0.15/np.sqrt(12)]
for i in range(1, len(r)+1):
    sigma += [np.sqrt(theta*sigma[i-1]**2 + (1-theta)*r.iloc[i-1].SPY**2)]

volatility_df[column_name] = sigma[62:]
```

```
vol = volatility_df[:'2008-10-31'].iloc[-1][column_name]; print(f"Volatility on October 2008: {vol}")
vol = volatility_df[:'2020-04-30'].iloc[-1][column_name]; print(f"Volatility on April 2020: {vol}")
vol = volatility_df[:'2022-05-31'].iloc[-1][column_name]; print(f"Volatility on May 2022: {vol}")
```

```
Volatility on October 2008:    0.046590
Volatility on April 2020:     0.048550
Volatility on May 2022:      0.047759
```

GARCH(1,1)

```
In [ ]: column_name = 'GARCH'
am = arch_model(r.SPY)
forecasts = []
for i in range(61, len(r)):
    res = am.fit(first_obs=0, last_obs=i+1, disp="off")
    temp = res.forecast(horizon=1, reindex=False).variance
    fcast = temp.iloc[0]
    forecasts += [fcast.values[0]]

volatility_df[column_name] = np.sqrt(forecasts)
```

```
vol = volatility_df[:'2008-10-31'].iloc[-1][column_name]; print(f"Volatility on October 2008: {vol}")
vol = volatility_df[:'2020-04-30'].iloc[-1][column_name]; print(f"Volatility on April 2020: {vol}")
vol = volatility_df[:'2022-05-31'].iloc[-1][column_name]; print(f"Volatility on May 2022: {vol}")
```


Volatility on October 2008: 0.091378
Volatility on April 2020: 0.084973
Volatility on May 2022: 0.051495

```
In [ ]: volatility_df.plot(title='Volatility', figsize=(20, 10))
```

```
Out[ ]: <AxesSubplot:title={'center':'Volatility'}, xlabel='Date'>
```

