

```
In [43]: import statsmodels.api as sm
import statsmodels.formula.api as smf
import pandas as pd
import numpy as np
```

```
In [44]: civic = pd.read_csv("Civic-142A-Fall24.csv")
```

```
In [45]: train = civic[civic["Year"] < 2020]
test = civic[civic["Year"] >= 2020]
train.head()
```

```
Out[45]:
```

	MonthNumeric	MonthFactor	Year	CivicSales	Unemployment	CivicQueries	CPIAll	C
0	1	January	2014	21824	6.6	66	235.288	
1	2	February	2014	21575	6.7	69	235.547	
2	3	March	2014	27697	6.7	72	236.028	
3	4	April	2014	27611	6.2	69	236.468	
4	5	May	2014	36089	6.3	69	236.918	

```
In [46]: #List of vars to subset
xVars = ["CivicQueries", "CPIAll"]

# filter training and test into independent vars list
Xtrain = train[xVars]
Xtest = test[xVars]

#create target vectors to predict Sales
Ytrain = train[["CivicSales"]]
Ytest = test[["CivicSales"]]

#add Constants
Xtrain = sm.add_constant(Xtrain)
Xtest = sm.add_constant(Xtest)
```

```
In [47]: model = sm.OLS(Ytrain, Xtrain)
```

```
In [48]: results = model.fit()
```

```
In [49]: print(results.summary())
```

OLS Regression Results

=====						
Dep. Variable:	CivicSales	R-squared:	0.395			
Model:	OLS	Adj. R-squared:	0.377			
Method:	Least Squares	F-statistic:	22.51			
Date:	Mon, 27 Jan 2025	Prob (F-statistic):	2.98e-08			
Time:	21:26:57	Log-Likelihood:	-689.88			
No. Observations:	72	AIC:	1386.			
Df Residuals:	69	BIC:	1393.			
Df Model:	2					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	5.713e+04	1.45e+04	3.953	0.000	2.83e+04	8.6e+04
CivicQueries	359.5442	53.958	6.663	0.000	251.901	467.187
CPIAll	-230.2333	64.419	-3.574	0.001	-358.745	-101.722
=====						
Omnibus:	2.257	Durbin-Watson:	1.622			
Prob(Omnibus):	0.323	Jarque-Bera (JB):	1.780			
Skew:	0.224	Prob(JB):	0.411			
Kurtosis:	2.374	Cond. No.	8.77e+03			
=====						

Notes:

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

[2] The condition number is large, 8.77e+03. This might indicate that there are strong multicollinearity or other numerical problems.

In [50]: `test.head(5)`

Out[50]:

	MonthNumeric	MonthFactor	Year	CivicSales	Unemployment	CivicQueries	CPIAll
72	1	January	2020	20054	3.5	74	259.037
73	2	February	2020	25617	3.5	76	259.248
74	3	March	2020	18273	4.4	66	258.124
75	4	April	2020	13410	14.8	57	256.092
76	5	May	2020	27244	13.3	78	255.868

In [51]: `modelMonths = smf.ols("CivicSales ~ CivicQueries + CPIAll + CPIEnergy + Unemployment")`

In [52]: `results2 = modelMonths.fit()`

In [53]: `print(results2.summary())`

OLS Regression Results

```

=====
Dep. Variable:          CivicSales    R-squared:                0.765
Model:                  OLS           Adj. R-squared:           0.697
Method:                 Least Squares F-statistic:              11.19
Date:                   Mon, 27 Jan 2025 Prob (F-statistic):       5.05e-12
Time:                   21:26:57      Log-Likelihood:          -655.83
No. Observations:       72           AIC:                    1346.
Df Residuals:           55           BIC:                    1384.
Df Model:               16
Covariance Type:        nonrobust
=====

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```

=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----
Intercept                    2.597e+04    5.38e+04     0.482    0.631    -8.19e+04
1.34e+05
C(MonthFactor)[T.August]    2810.6266    1501.365     1.872    0.067    -198.177
5819.430
C(MonthFactor)[T.December]  2023.6110    1729.147     1.170    0.247   -1441.678
5488.900
C(MonthFactor)[T.February] -4350.5616    1509.515    -2.882    0.006   -7375.697
-1325.426
C(MonthFactor)[T.January]  -5543.3141    1508.810    -3.674    0.001   -8567.038
-2519.591
C(MonthFactor)[T.July]      796.0087    1510.946     0.527    0.600   -2231.995
3824.012
C(MonthFactor)[T.June]      782.3073    1535.117     0.510    0.612   -2294.135
3858.750
C(MonthFactor)[T.March]     1043.1405    1521.718     0.686    0.496   -2006.451
4092.732
C(MonthFactor)[T.May]       4311.4869    1503.319     2.868    0.006    1298.768
7324.205
C(MonthFactor)[T.November] -1676.6088    1606.548    -1.044    0.301   -4896.202
1542.985
C(MonthFactor)[T.October]  -2192.4334    1513.577    -1.449    0.153   -5225.709
840.842
C(MonthFactor)[T.September] -1153.0328    1517.026    -0.760    0.450   -4193.221
1887.155
CivicQueries                 257.9525     72.508      3.558    0.001     112.642
403.263
CPIAll                      -363.9977     207.430    -1.755    0.085   -779.697
51.702
CPIEnergy                   27.4736      38.325      0.717    0.476    -49.331
104.278
Unemployment                 467.6756    1741.508     0.269    0.789   -3022.385
3957.737
MilesTraveled                0.2420       0.164      1.472    0.147     -0.087
0.571
=====

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```

=====
Omnibus:                    5.209    Durbin-Watson:              1.308
Prob(Omnibus):              0.074    Jarque-Bera (JB):           4.456
Skew:                       0.474    Prob(JB):                   0.108
Kurtosis:                   3.765    Cond. No.                   4.83e+07
=====

```

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Notes:

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

[2] The condition number is large, 4.83e+07. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [54]: model3 = smf.ols("CivicSales ~ CivicQueries + CPIAll + C(MonthFactor)", data = trai
```

```
In [55]: print(model3.summary())
```

OLS Regression Results

```

=====
Dep. Variable:          CivicSales    R-squared:                0.756
Model:                  OLS          Adj. R-squared:           0.701
Method:                 Least Squares F-statistic:              13.79
Date:                   Mon, 27 Jan 2025 Prob (F-statistic):       2.80e-13
Time:                   21:26:57      Log-Likelihood:          -657.24
No. Observations:       72           AIC:                     1342.
Df Residuals:           58           BIC:                     1374.
Df Model:               13
Covariance Type:        nonrobust
=====

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=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----
Intercept                    6.078e+04    1.04e+04     5.838    0.000    3.99e+04
8.16e+04
C(MonthFactor)[T.August]    2297.4909    1441.994     1.593    0.117   -588.974
5183.956
C(MonthFactor)[T.December]  2255.3858    1559.828     1.446    0.154   -866.950
5377.722
C(MonthFactor)[T.February] -4944.7181    1438.721    -3.437    0.001  -7824.632
-2064.804
C(MonthFactor)[T.January]  -5906.4114    1455.679    -4.057    0.000  -8820.269
-2992.554
C(MonthFactor)[T.July]      245.1886    1443.417     0.170    0.866   -2644.125
3134.502
C(MonthFactor)[T.June]      100.0323    1441.306     0.069    0.945   -2785.056
2985.120
C(MonthFactor)[T.March]     374.8885    1437.445     0.261    0.795   -2502.471
3252.248
C(MonthFactor)[T.May]       3743.5754    1437.176     2.605    0.012    866.755
6620.396
C(MonthFactor)[T.November] -2158.3494    1500.261    -1.439    0.156  -5161.449
844.750
C(MonthFactor)[T.October]  -2545.2858    1456.460    -1.748    0.086  -5460.708
370.137
C(MonthFactor)[T.September] -1581.3890    1452.733    -1.089    0.281  -4489.350
1326.572
CivicQueries                 289.3001     48.340     5.985    0.000    192.536
386.064
CPIAll                       -220.2553     49.162    -4.480    0.000   -318.663
-121.848
=====

```

```

=====
Omnibus:                  5.392    Durbin-Watson:              1.293
Prob(Omnibus):            0.067    Jarque-Bera (JB):           4.627
Skew:                     0.493    Prob(JB):                   0.0989
Kurtosis:                 3.755    Cond. No.                   9.12e+03
=====

```

Notes:

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

[2] The condition number is large, $9.12e+03$. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [56]: test.reset_index(drop=True, inplace=True)
         preds = model3.predict(test)
```

```
In [57]: SSR = np.sum((test["CivicSales"] - preds) ** 2)
         y_mean = np.mean(test["CivicSales"])
```

```
In [58]: TSS = np.sum((test["CivicSales"] - y_mean) ** 2)
```

```
In [59]: OSR2 = 1 - (SSR/TSS)
```

```
In [60]: OSR2
```

```
Out[60]: -0.09021353946711175
```

```
In [61]: CCI = pd.read_csv("UMCSENT (1).csv")
```

```
In [70]: civic2 = pd.concat([civic, CCI["UMCSENT"]], axis = 1)
         trainCCI = civic2[civic2["Year"] < 2020]
         testCCI = civic2[civic2["Year"] >= 2020]
         CCI.head()
```

```
Out[70]:
```

	DATE	UMCSENT
0	2014-01-01	81.2
1	2014-02-01	81.6
2	2014-03-01	80.0
3	2014-04-01	84.1
4	2014-05-01	81.9

```
In [63]: model4 = smf.ols("CivicSales ~ UMCSENT + C(MonthFactor) + CivicQueries + CPIAll", d
```

```
In [64]: print(model4.summary())
```

OLS Regression Results

```

=====
Dep. Variable:          CivicSales    R-squared:                0.757
Model:                  OLS          Adj. R-squared:           0.697
Method:                 Least Squares F-statistic:              12.66
Date:                   Mon, 27 Jan 2025 Prob (F-statistic):       9.61e-13
Time:                   21:26:57      Log-Likelihood:          -657.09
No. Observations:       72          AIC:                      1344.
Df Residuals:           57          BIC:                      1378.
Df Model:               14
Covariance Type:        nonrobust
=====

```

```

=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----
Intercept                    6.043e+04    1.05e+04     5.752     0.000     3.94e+04
8.15e+04
C(MonthFactor)[T.August]    2161.0249    1478.960     1.461     0.149    -800.541
5122.590
C(MonthFactor)[T.December]  2405.6354    1600.868     1.503     0.138    -800.048
5611.318
C(MonthFactor)[T.February] -4931.0496    1448.613    -3.404     0.001   -7831.847
-2030.252
C(MonthFactor)[T.January]  -5876.2250    1466.743    -4.006     0.000   -8813.327
-2939.123
C(MonthFactor)[T.July]      158.8047    1464.064     0.108     0.914   -2772.933
3090.543
C(MonthFactor)[T.June]      74.9039    1451.873     0.052     0.959   -2832.422
2982.230
C(MonthFactor)[T.March]     362.0891    1447.295     0.250     0.803   -2536.068
3260.247
C(MonthFactor)[T.May]       3724.6814    1447.310     2.574     0.013     826.492
6622.871
C(MonthFactor)[T.November] -2100.8033    1514.995    -1.387     0.171   -5134.528
932.921
C(MonthFactor)[T.October]  -2562.0591    1466.606    -1.747     0.086   -5498.887
374.769
C(MonthFactor)[T.September] -1640.4358    1467.558    -1.118     0.268   -4579.171
1298.299
UMCSENT                     -36.7838     76.282     -0.482     0.632   -189.537
115.969
CivicQueries                296.8771     51.137     5.805     0.000     194.476
399.278
CPIAll                      -207.1039     56.507    -3.665     0.001   -320.258
-93.950
=====

```

```

=====
Omnibus:                  5.601    Durbin-Watson:              1.287
Prob(Omnibus):            0.061    Jarque-Bera (JB):           4.879
Skew:                     0.499    Prob(JB):                   0.0872
Kurtosis:                 3.793    Cond. No.                   9.73e+03
=====

```

Notes:

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

cified.

[2] The condition number is large, $9.73e+03$. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [65]: preds4 = model4.predict(testCCI)
```

```
In [66]: SSR_model4 = np.sum((testCCI["CivicSales"] - preds4) ** 2)
y_mean_model4 = np.mean(testCCI["CivicSales"])
TSS_model4 = np.sum((testCCI["CivicSales"] - y_mean_model4) ** 2)
```

```
In [67]: RSquared_model4 = 1 - (SSR_model4/TSS_model4)
```

```
In [71]: RSquared_model4
```

```
Out[71]: -0.4579339533332556
```

```
In [ ]:
```