I will be investigating the impact of SARS-CoV-2, or covid-19, on consumer uncertainty.

- cci - Consumer Confidence Index (CCI) - a monthly survey by The Conference Board that measures how optimistic or pessimistic consumers are regarding financial situations, both current and expected. Administered via survery. Leading indicator reflecting U.S. economic conditions, major purchases, consumer view of economy, business conditions, and labor market currently and over the next six months. Two parts of this index is the current expectations and future expectations
  -1985=100
  -- cci > 100: consumers are optimistic = more spending
  -- cci < 100: consumers are optimistic = less spending
  -- cci < 100: consumers are optimistic = less spending

Released on the last Tuesday of every month.

- cci_cur - CCI Current Expectations component

- cci_exp - CCI Future Expectations component

- umsent - Michigan Consumer Sentiment Index (MCSI) -- a monthly report of consumer confidence levels in the U.S. conducted by the UMICH. Survey results collected via telephone interviews. Also a lead indicator. Differs from CCI in that CCI places more weight on employment and labor market while MCSI focuses primarily on households and future expectations is at 12 months instead of 6 months.
  - same index number scale

Released on the second Friday of each month.

- umsent_cur - MCSI Current Expectations component

- umsent_exp - MCSI Future Expectations component

- ism_man - ISM Manufacturing Index or Manufacturing Purchasing Managers' Index (PMI) -- reflects the demand level of goods by the amount of ordering activity from factories. Index of new orders, production, employment, supplier deliveries, and inventories.
  -- Manufacturing PMI > 50 = expanding manufacturing segment compared to last month
  -- Manufacturing PMI < 50 = contracting " "

This is released on the first business day of each month, so can influence CCI and MCSI.

- ism_non - ISM Non-Manufacturing Index or Non-Manufacturing Purchings Managers' Index (PMI) -- surveys purchasing and supply executives, caputring 15 different (service) industries. Indexes business acitivity, new ordres, employment trends, inventories, and prices.
  -- Finance and Insurance, Agriculture, Retail Trade, Ulilities, Educational Services, etc.

Released on the third business day of the month.

OLS ASSUMTIONS:
[1] The regression model is linear in the coefficients and the error term.
[2] The error term has a population mean of zero.
[3] All independent variables are unncorrelated with the error term.
[4] Observations of the error term are uncorrelated with each other.
[5] The error term has a constant variance (no heteroscedasticity).
[6] No independent variable is a perfect linear function of other explanatory variables.
[7] The error term is normall distributed.

In [2]:
```
# libraries
import numpy as np
import statsmodels.api as sm
import pandas as pd
import statsmodels.formula.api as smf
from statsmodels.tsa.ar_model import AutoReg
from statsmodels.tsa.stattools import adfuller
from statsmodels.compat import lzip
import statsmodels.stats.api as sms
from sklearn.linear_model import LinearRegression
from statsmodels.stats.diagnostic import het_white
from statsmodels.graphics.api import interaction_plot, abline_plot
from statsmodels.stats.anova import anova_lm
from statsmodels.graphics.tsaplots import plot_pacf
from scipy import stats
import statsmodels
import matplotlib.pyplot as plt
from matplotlib import pyplot as plt
import seaborn as sns
```

In [5]:
```
# data
df = pd.read_csv('cur-us_owid_covid_monthly.csv')
pd.set_option('display.max_columns', None)
df = df.dropna()
# df.shape[0]
df.head(5)
```

Out[5]:

	date	total_cases	new_cases	new_cases_smoothed	total_deaths	new_deaths	positive_rate	strir
366	7/1/97	0	0	0.0	0	0	0.0	
367	8/1/97	0	0	0.0	0	0	0.0	
368	9/1/97	0	0	0.0	0	0	0.0	
369	10/1/97	0	0	0.0	0	0	0.0	
370	11/1/97	0	0	0.0	0	0	0.0	

In [4]:
```
df.shape[0]
```

Out[4]: 300

In [124…
```
x_columns = [ 'total_cases', 'cci_lag1', 'umsent']
y = df['cci']
```

In [125…
```
x = df[x_columns]
x = sm.add_constant(x)
```

```
summary = sm.OLS(y,x).fit()
print(summary.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cci   R-squared:                       0.963
Model:                            OLS   Adj. R-squared:                  0.963
Method:                 Least Squares   F-statistic:                     2580.
Date:                Tue, 08 Nov 2022   Prob (F-statistic):          8.59e-212
Time:                        14:29:20   Log-Likelihood:                -925.69
No. Observations:                 300   AIC:                             1859.
Df Residuals:                     296   BIC:                             1874.
Df Model:                           3
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         -26.0172      2.758     -9.433      0.000     -31.445     -20.589
total_cases  2.569e-07   3.33e-08      7.707      0.000    1.91e-07    3.22e-07
cci_lag1        0.7284      0.024     30.365      0.000       0.681       0.776
umsent          0.5963      0.052     11.435      0.000       0.494       0.699
==============================================================================
Omnibus:                        2.881   Durbin-Watson:                   1.863
Prob(Omnibus):                  0.237   Jarque-Bera (JB):                3.144
Skew:                          -0.025   Prob(JB):                        0.208
Kurtosis:                       3.499   Cond. No.                     1.17e+08
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 1.17e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [126…

```
# Breusch-Pagan test
names = ['Lagrange multiplier statistic', 'p-value',
         'f-value', 'f p-value']

# test result
test_result = sms.het_breuschpagan(summary.resid, summary.model.exog)

lzip(names, test_result)
```

Out[126]:

```
[('Lagrange multiplier statistic', 8.25091083213001),
 ('p-value', 0.041101004939359746),
 ('f-value', 2.7903767277975646),
 ('f p-value', 0.04077043426737537)]
```

In [127…

```
x_columns1 = [ 'total_cases', 'cci_lag1', 'ism_man']
y1 = df['cci']

x1 = df[x_columns1]
x1 = sm.add_constant(x1)
summary1 = sm.OLS(y1,x1).fit()
print(summary1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cci   R-squared:                       0.950
Model:                            OLS   Adj. R-squared:                  0.949
Method:                 Least Squares   F-statistic:                     1859.
Date:                Tue, 08 Nov 2022   Prob (F-statistic):          1.19e-191
Time:                        14:29:21   Log-Likelihood:                -972.70
No. Observations:                 300   AIC:                             1953.
Df Residuals:                     296   BIC:                             1968.
Df Model:                           3
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         -12.5427      4.051     -3.096      0.002     -20.515      -4.570
total_cases  -3.12e-08   2.94e-08     -1.062      0.289     -8.9e-08    2.66e-08
cci_lag1        0.9623      0.013     72.542      0.000       0.936       0.988
ism_man         0.3058      0.077      3.992      0.000       0.155       0.457
==============================================================================
Omnibus:                       18.157   Durbin-Watson:                   1.989
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               41.736
Skew:                          -0.247   Prob(JB):                     8.65e-10
Kurtosis:                       4.759   Cond. No.                     1.47e+08
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 1.47e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [128…

```
# Breusch-Pagan test1
names = ['Lagrange multiplier statistic', 'p-value',
         'f-value', 'f p-value']

# test result
test_result1 = sms.het_breuschpagan(summary1.resid, summary1.model.exog)

lzip(names, test_result1)
```

Out[128]:

```
[('Lagrange multiplier statistic', 16.47238972372982),
 ('p-value', 0.0009071604648665212),
 ('f-value', 5.732336912412169),
 ('f p-value', 0.0007977702237826029)]
```

In [129…

```
x_columns2 = [ 'total_cases', 'cci_lag1', 'ism_non']
y2 = df['cci']

x2 = df[x_columns2]
x2 = sm.add_constant(x2)
summary2 = sm.OLS(y2,x2).fit()
print(summary2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cci   R-squared:                       0.951
Model:                            OLS   Adj. R-squared:                  0.951
Method:                 Least Squares   F-statistic:                     1924.
Date:                Tue, 08 Nov 2022   Prob (F-statistic):          1.01e-193
Time:                        14:29:22   Log-Likelihood:                -967.87
No. Observations:                 300   AIC:                             1944.
Df Residuals:                     296   BIC:                             1959.
Df Model:                           3
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const         -22.3721      5.080     -4.404      0.000     -32.370     -12.374
total_cases -4.261e-08   2.91e-08     -1.464      0.144   -9.99e-08    1.47e-08
cci_lag1        0.9383      0.014     65.254      0.000       0.910       0.967
ism_non         0.5173      0.101      5.114      0.000       0.318       0.716
==============================================================================
Omnibus:                       10.619   Durbin-Watson:                   1.999
Prob(Omnibus):                  0.005   Jarque-Bera (JB):               19.513
Skew:                          -0.133   Prob(JB):                     5.79e-05
Kurtosis:                       4.221   Cond. No.                     1.87e+08
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 1.87e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [130…

```python
# Breusch-Pagan test2
names = ['Lagrange multiplier statistic', 'p-value',
         'f-value', 'f p-value']

# test result
test_result2 = sms.het_breuschpagan(summary2.resid, summary2.model.exog)

lzip(names, test_result2)
```

Out[130]:

```
[('Lagrange multiplier statistic', 21.982382621323282),
 ('p-value', 6.578402699373963e-05),
 ('f-value', 7.801406396786069),
 ('f p-value', 4.980828366660121e-05)]
```

In [131…

```python
# Checking for Stationarity, making sure that the mean, variance, and autocorrelation st
# doesn't change over time

df_stationarityTest = adfuller(df['cci'], autolag='AIC')
print('p-value: ', df_stationarityTest[1])
```

```
p-value:  0.27891037351945935
```

for vfi -- multicoliniearity ref

In [132…

```python
# VIF - measuring strength of correlation with between the predictors, checking for mult
# between pedictors
x_columns = df[['total_cases','cci_lag1', 'umsent']]
x = sm.add_constant(x_columns)
y = df['cci']
```

In [133…

```python
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

```python
df4 = pd.DataFrame()

df4['VIF'] = [variance_inflation_factor(x_columns3.values, i)
           for i in range(x_columns3.shape[1])]
df4['feature'] = x_columns3.columns

df4
```

Out[133]:

	VIF	feature
0	1.071352	total_cases
1	13.727316	cci_lag1
2	13.762078	ism_man

In [134…

```python
df2 = df

x_columns3 = df[['total_cases','cci_lag1', 'ism_man']]
x1 = sm.add_constant(x_columns3)
y1 = df['cci']
```

In [135…

```python
from statsmodels.stats.outliers_influence import variance_inflation_factor

df3 = pd.DataFrame()

df3['VIF'] = [variance_inflation_factor(x_columns3.values, i)
           for i in range(x_columns3.shape[1])]
df3['feature'] = x_columns3.columns

df3
```

Out[135]:

	VIF	feature
0	1.071352	total_cases
1	13.727316	cci_lag1
2	13.762078	ism_man

In [136…

```python
df4 = df
x_columns4 = df[['total_cases','cci_lag1', 'ism_man']]
x4 = sm.add_constant(x_columns4)
y4 = df['cci']
```

In [137…

```python
from statsmodels.stats.outliers_influence import variance_inflation_factor

df4 = pd.DataFrame()

df4['VIF'] = [variance_inflation_factor(x_columns4.values, i)
           for i in range(x_columns4.shape[1])]
df4['feature'] = x_columns4.columns

df4
```

Out[137]:

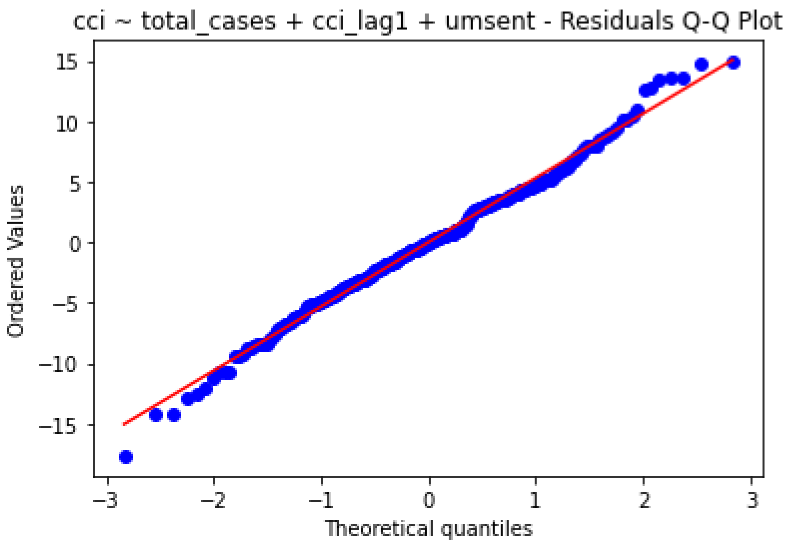
	VIF	feature
0	1.071352	total_cases
1	13.727316	cci_lag1
2	13.762078	ism_man

observered value; resid plot

In [152…

```
# checking the assumption of normality --homoskedasticity
#       data skew and model fit
from scipy import stats

stats.probplot(summary.resid, dist="norm", plot= plt)
plt.title("cci ~ total_cases + cci_lag1 + umsent - Residuals Q-Q Plot")

#Saving plot as a png
#plt.savefig("Model1_Resid_qqplot.png")
```

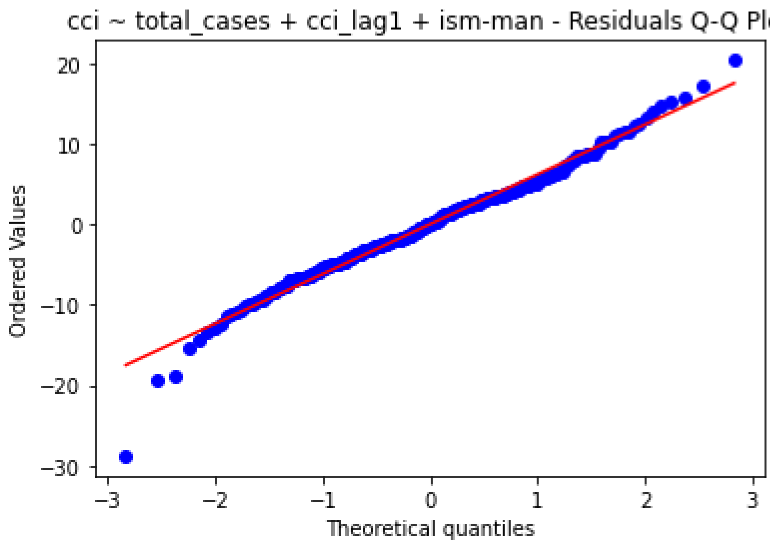
Out[152]: Text(0.5, 1.0, 'cci ~ total_cases + cci_lag1 + umsent - Residuals Q-Q Plot')



In [144…

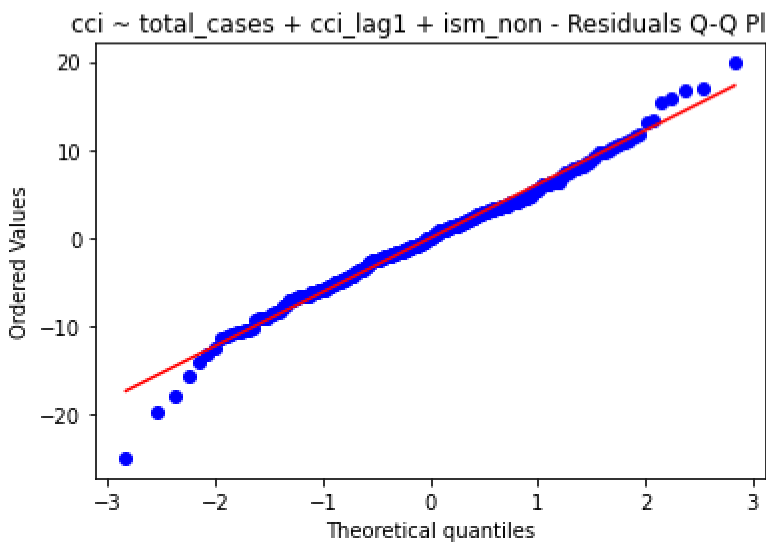
```
from scipy import stats

stats.probplot(summary1.resid, dist="norm", plot= plt)
plt.title("cci ~ total_cases + cci_lag1 + ism-man - Residuals Q-Q Plot")

#Saving plot as a png
#plt.savefig("Model1_Resid_qqplot.png")
```

Out[144]: Text(0.5, 1.0, 'cci ~ total_cases + cci_lag1 + ism-man - Residuals Q-Q Plot')



In [145…
```
from scipy import stats

stats.probplot(summary2.resid, dist="norm", plot= plt)
plt.title("cci ~ total_cases + cci_lag1 + ism_non - Residuals Q-Q Plot")

#Saving plot as a png
#plt.savefig("Model1_Resid_qqplot.png")
```

Out[145]: Text(0.5, 1.0, 'cci ~ total_cases + cci_lag1 + ism_non - Residuals Q-Q Plot')



In [153…
```
table = sm.stats.anova_lm(mo, typ=2)
print(table)
```

```
                  sum_sq     df           F        PR(>F)
total_cases  1687.599639    1.0   59.396999  1.963161e-13
cci_lag1    26196.838522    1.0  922.027691  6.307114e-93
umsent       3715.134343    1.0  130.758402  2.533786e-25
Residual     8410.012276  296.0         NaN           NaN
```

In [147…
```
sy = smf.ols('cci ~ total_cases + cci_lag1 + umsent', df)
mo = sy.fit()
print(mo.summary2())
```

```
                    Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.963
Dependent Variable: cci              AIC:                1859.3818
Date:               2022-11-08 14:33 BIC:                1874.1970
No. Observations:   300              Log-Likelihood:     -925.69
Df Model:           3                F-statistic:        2580.
Df Residuals:       296              Prob (F-statistic): 8.59e-212
R-squared:          0.963            Scale:              28.412
------------------------------------------------------------------
                 Coef.   Std.Err.    t    P>|t|   [0.025   0.975]
------------------------------------------------------------------
Intercept       -26.0172   2.7582 -9.4327 0.0000 -31.4454 -20.5891
total_cases       0.0000   0.0000  7.7069 0.0000   0.0000   0.0000
cci_lag1          0.7284   0.0240 30.3649 0.0000   0.6812   0.7756
umsent            0.5963   0.0521 11.4350 0.0000   0.4937   0.6989
------------------------------------------------------------------
Omnibus:              2.881       Durbin-Watson:         1.863
Prob(Omnibus):        0.237       Jarque-Bera (JB):      3.144
Skew:                 -0.025      Prob(JB):              0.208
Kurtosis:             3.499       Condition No.:         116978028
==================================================================
* The condition number is large (1e+08). This might indicate
strong multicollinearity or other numerical problems.
```

In [148…

```
pg = df.corr()
# pg = pg.to_csv('resid_q-q_plot.csv', encoding='utf-8')
pg
```

Out[148]:

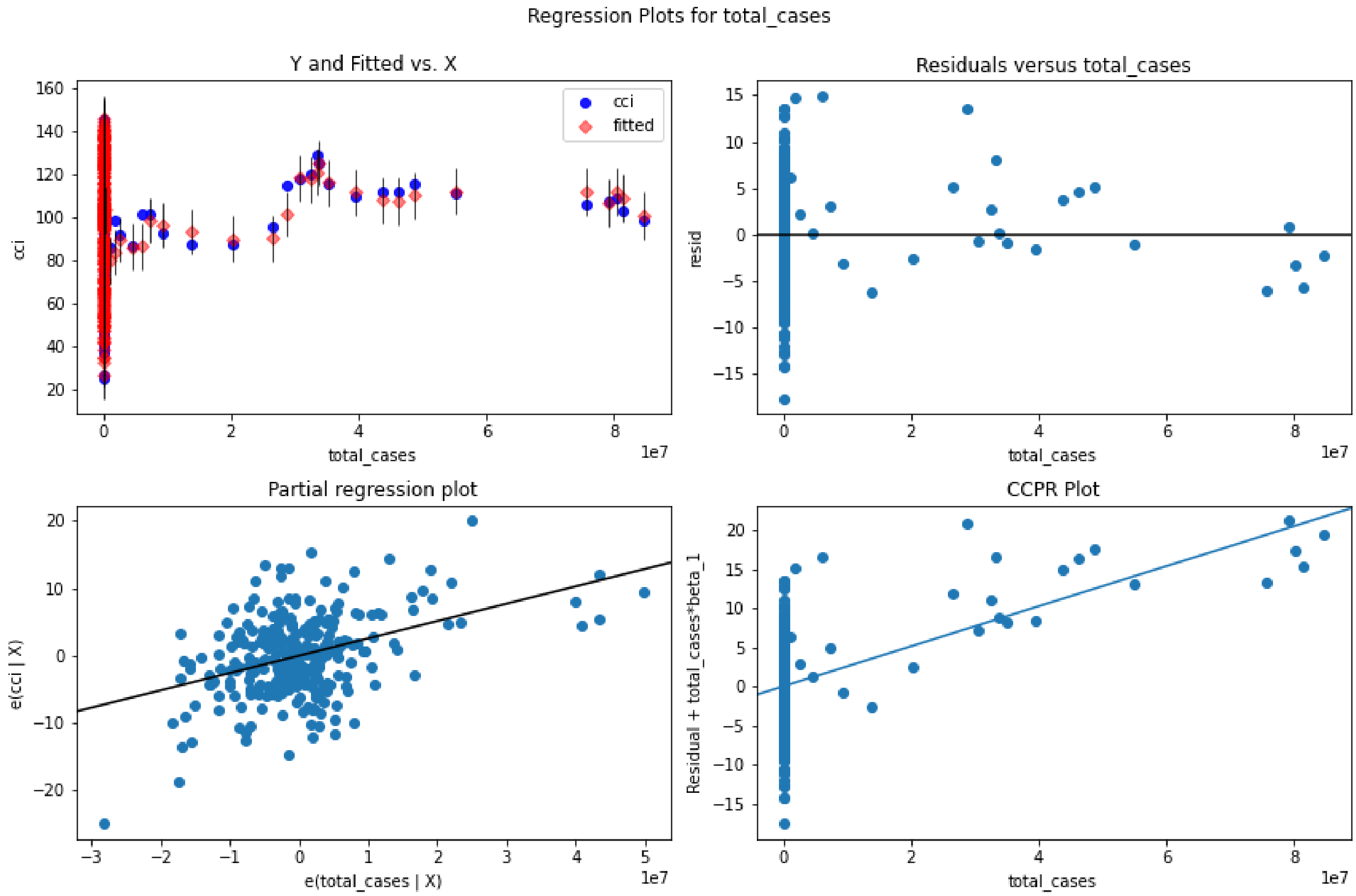
	total_cases	new_cases	new_cases_smoothed	total_deaths	new_deaths	positive_
total_cases	1.000000	0.731918	0.675118	0.983190	0.646423	0.633
new_cases	0.731918	1.000000	0.916267	0.760064	0.857942	0.829
new_cases_smoothed	0.675118	0.916267	1.000000	0.698959	0.748111	0.856
total_deaths	0.983190	0.760064	0.698959	1.000000	0.698337	0.679
new_deaths	0.646423	0.857942	0.748111	0.698337	1.000000	0.780
positive_rate	0.633434	0.829708	0.856726	0.679986	0.780809	1.000
stringency_index	0.595817	0.700117	0.629771	0.699750	0.842179	0.81
cci	0.094413	0.045618	0.045807	0.104197	0.041404	0.02
cci_cur	0.152775	0.074558	0.070557	0.151590	0.042262	0.036
cci_exp	-0.035227	-0.018546	-0.010404	-0.006539	0.031403	0.01
umsent	-0.329655	-0.279644	-0.248900	-0.326883	-0.262999	-0.29
umsent_cur	-0.387146	-0.328161	-0.292073	-0.390106	-0.316011	-0.34
umsent_exp	-0.269706	-0.228921	-0.203722	-0.262853	-0.210001	-0.23
ism_man	0.253471	0.244688	0.229843	0.289170	0.223233	0.15
ism_non	0.280734	0.237940	0.208248	0.325448	0.200169	0.12
cci_lag1	0.098416	0.060226	0.059576	0.104871	0.048653	0.06
cci_lag2	0.100656	0.080145	0.072448	0.104026	0.082889	0.098
cci_lag3	0.099427	0.084317	0.073124	0.102212	0.102229	0.105
cci_lag4	0.098822	0.081383	0.070697	0.102017	0.099910	0.110
cci_lag5	0.099753	0.089600	0.077625	0.103211	0.103438	0.12
total_cases_lag1	0.995610	0.678265	0.613095	0.977683	0.597031	0.59
total_cases_lag2	0.987893	0.667050	0.597711	0.969486	0.559952	0.58
total_deaths_lag1	0.985699	0.742266	0.680348	0.998647	0.668050	0.660
total_deaths_lag2	0.986382	0.736626	0.673357	0.995180	0.648733	0.65

How do I read this?

In [159…

```
#define figure size
fig =plt.figure(figsize=(12,8))

#produce regression plots
fig = sm.graphics.plot_regress_exog(mo, 'total_cases', fig=fig)
```

```
eval_env: 1
```



- 'Y and Fitted vs X' and 'Residuals vs fitted' -- checks linear assumptions of linearity, normality, constant variance (violated-hetero, makes cone shape), and independence.

https://analyse-it.com/docs/user-guide/fit-model/linear/residual-plot

- Partial Regression Plot -- checks inluential points and linearity

- Partial Regression Plot -- checks inluential points, relationship between a regressor and response

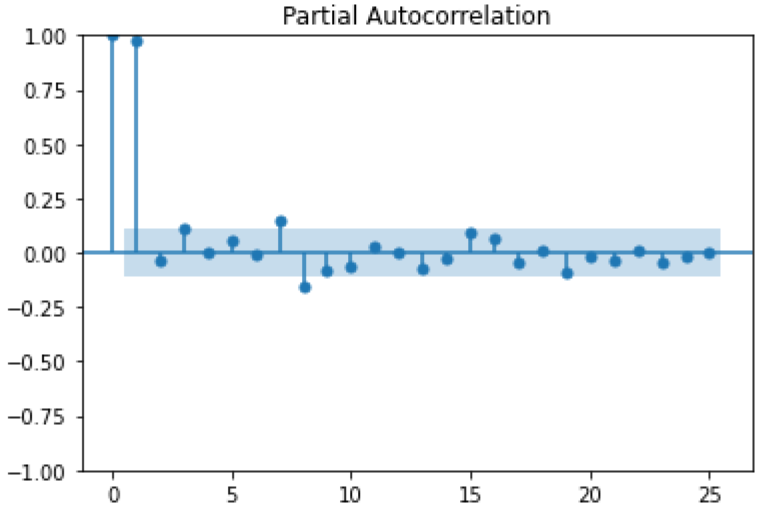
by taking into account the other independent variables. The line is if x was highly correlated with any of the other independent variables.

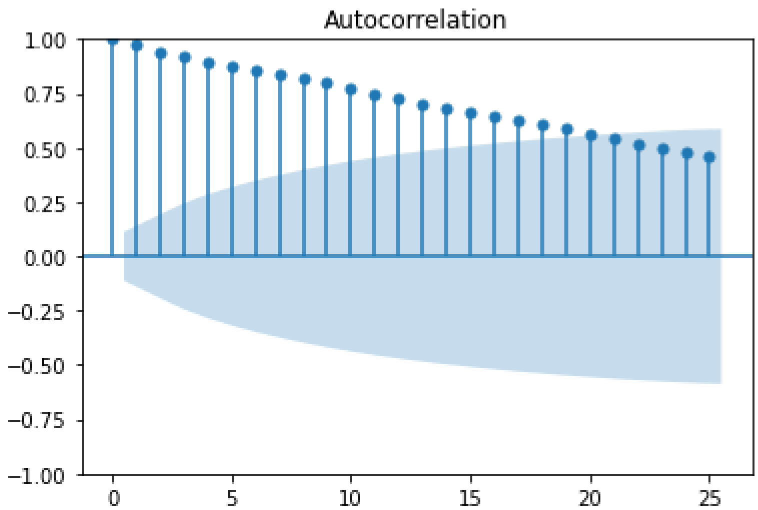
test for heteroskedasticity

In [167…

```
# can determine order of AR model
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.graphics.tsaplots import plot_acf

pacf = plot_pacf(df['cci'], lags=25)
acf = plot_acf(df['cci'], lags=25)
```

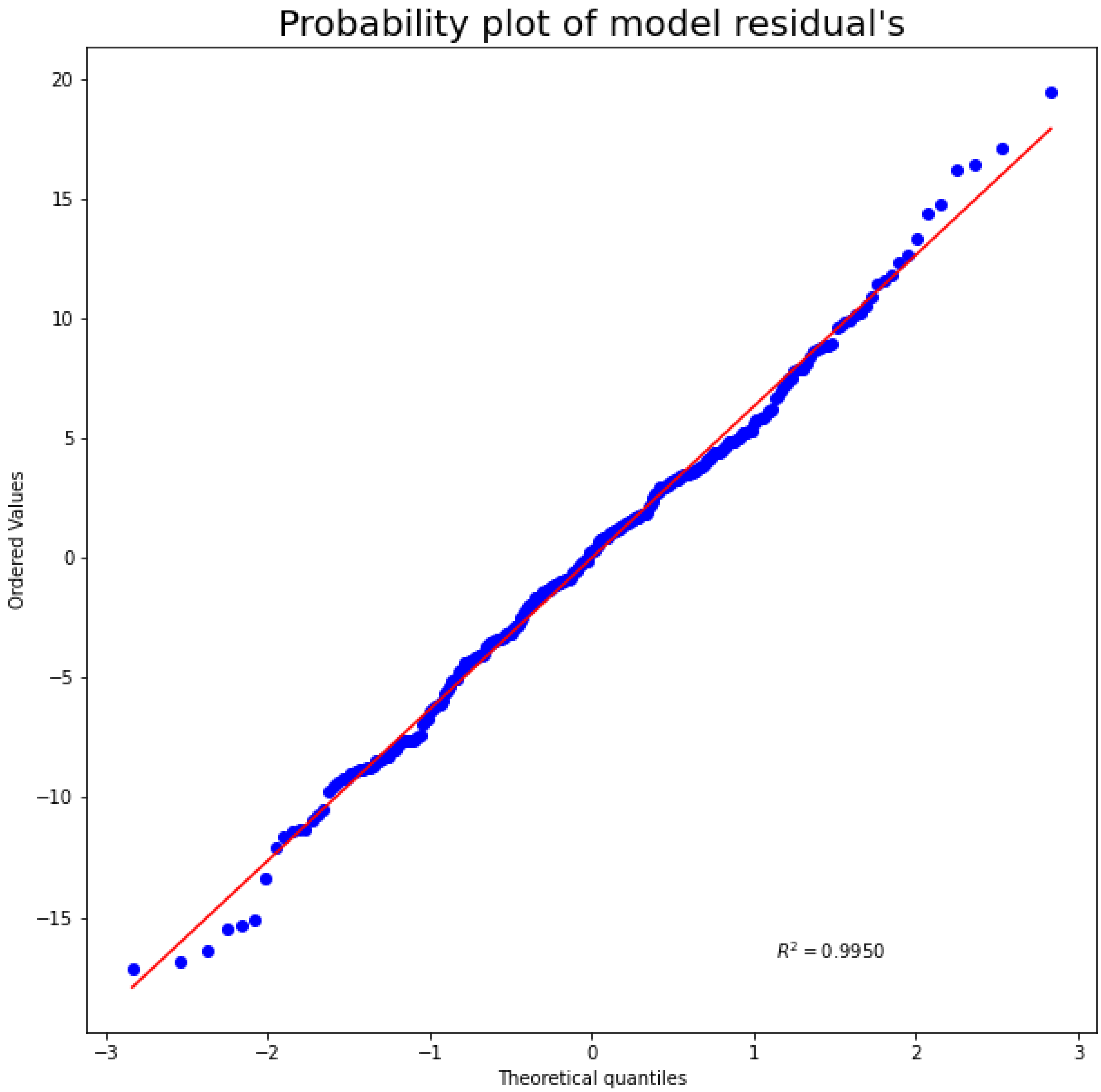
```
/Users/mauricefreese/opt/anaconda3/lib/python3.9/site-packages/statsmodels/graphics/tsap
lots.py:348: FutureWarning: The default method 'yw' can produce PACF values outside of t
he [-1,1] interval. After 0.13, the default will change tounadjusted Yule-Walker ('yw
m'). You can use this method now by setting method='ywm'.
  warnings.warn(
```





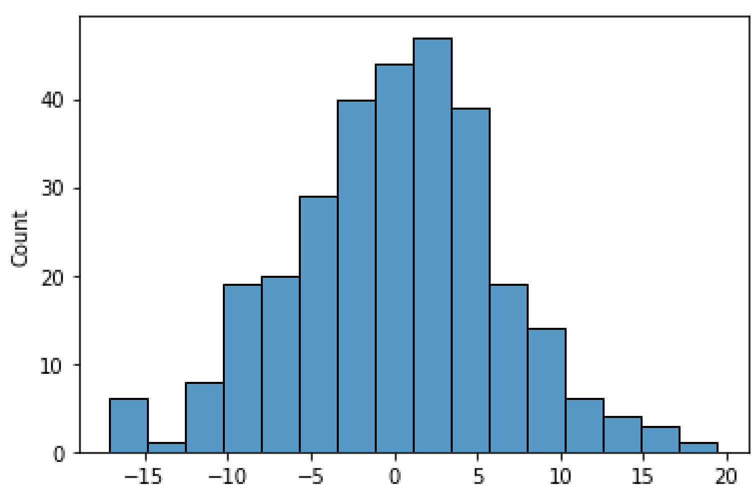
In [101…

```
fig = plt.figure(figsize= (10, 10))
ax = fig.add_subplot(111)

normality_plot, stat = stats.probplot(mo.resid, plot= plt, rvalue= True)
ax.set_title("Probability plot of model residual's", fontsize= 20)
ax.set

plt.show()
```



In [102…

```
import seaborn as sns
sns.histplot(mo.resid);
```



In [103…

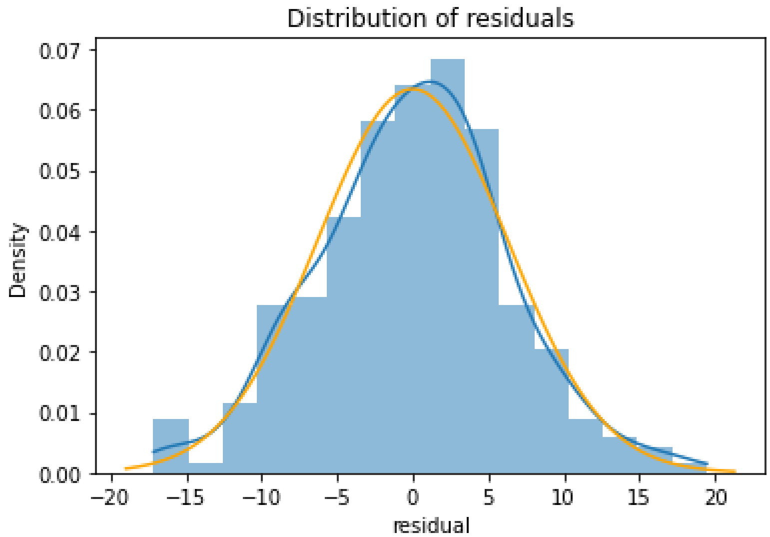
```
mu, std = stats.norm.fit(mo.resid)
mu, std
```

Out[103]: (5.040116472324977 6e-14, 6.290935504613382)

In [105…

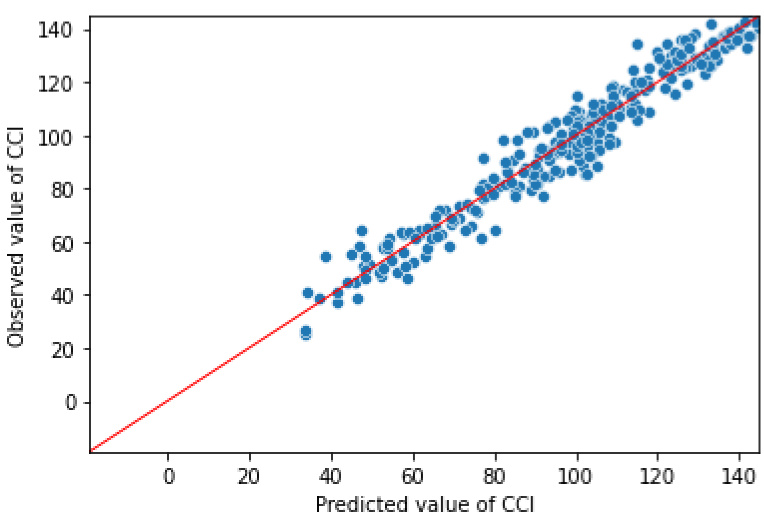
```
fig, ax = plt.subplots()
```

```python
# plot the residuals
sns.histplot(x=mo.resid, ax=ax, stat="density", linewidth=0, kde=True)
ax.set(title="Distribution of residuals", xlabel="residual")

# plot corresponding normal curve
xmin, xmax = plt.xlim() # the maximum x values from the histogram above
x = np.linspace(xmin, xmax, 100) # generate some x values
p = stats.norm.pdf(x, mu, std) # calculate the y values for the normal curve
sns.lineplot(x=x, y=p, color="orange", ax=ax)
plt.show()
```



In [108…

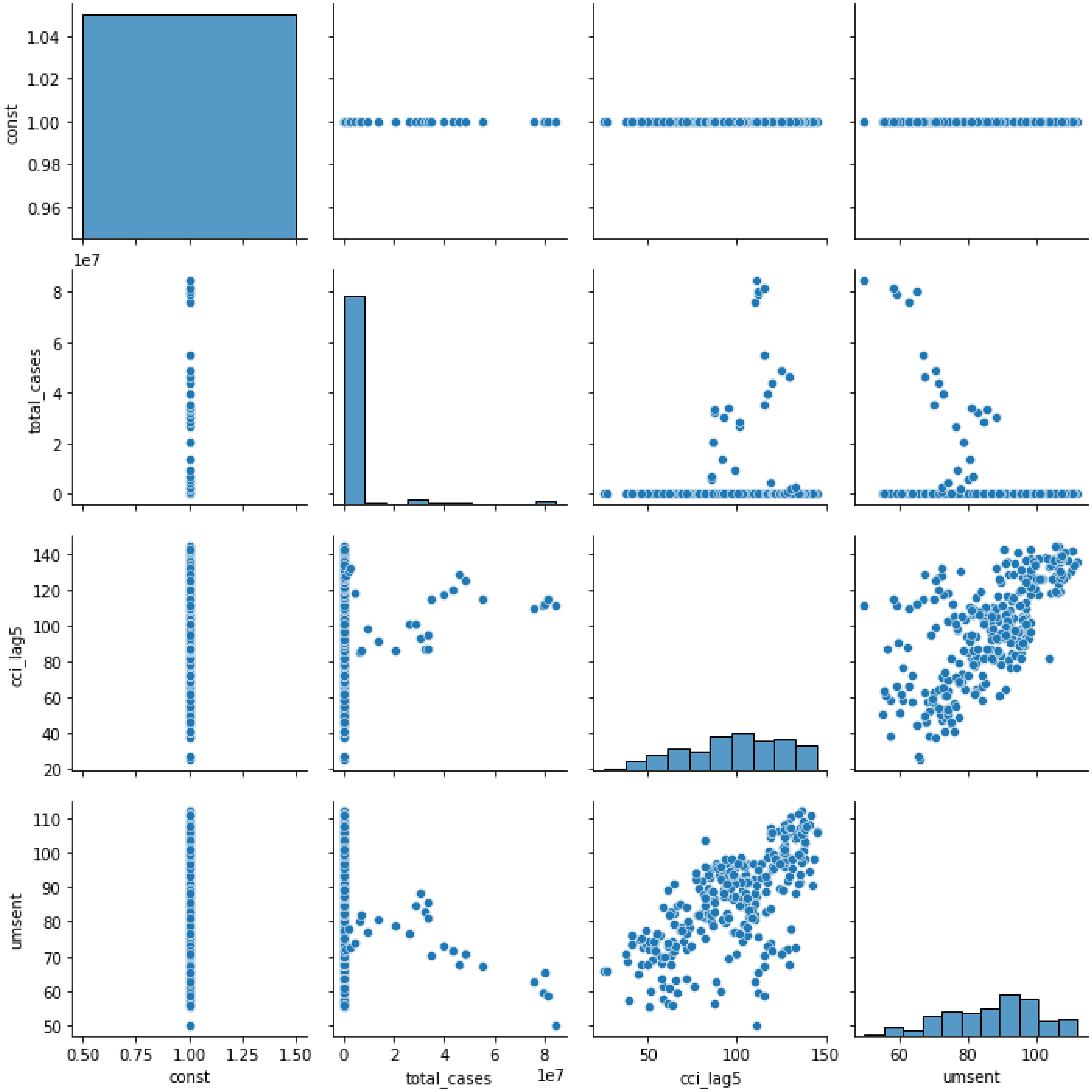
```python
mo.fittedvalues
Y_max = y.max()
Y_min = x.min()

ax = sns.scatterplot(x=mo.fittedvalues, y=y)
ax.set(ylim=(Y_min, Y_max))
ax.set(xlim=(Y_min, Y_max))
ax.set_xlabel("Predicted value of CCI")
ax.set_ylabel("Observed value of CCI")

X_ref = Y_ref = np.linspace(Y_min, Y_max, 100)
plt.plot(X_ref, Y_ref, color='red', linewidth=1)
plt.show()
```



In [117…

```python
sns.pairplot(x)
```

Out[117]: <seaborn.axisgrid.PairGrid at 0x7fa9c3012100>



In [122…

```
# correlation of model
round(x.corr(),3)
```

Out[122]:

	const	total_cases	cci_lag5	umsent
const	NaN	NaN	NaN	NaN
total_cases	NaN	1.00	0.100	-0.330
cci_lag5	NaN	0.10	1.000	0.677
umsent	NaN	-0.33	0.677	1.000

In [128…

```
from sklearn.cross_decomposition import PLSRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import cross_val_predict

# Define PLS object
pls = PLSRegression(n_components=5)
```

```
# Fit
pls.fit(x_columns, y)

# Cross-validation
y_cv = cross_val_predict(pls, x_columns, y, cv=10)

# Calculate scores
score = r2_score(y, y_cv)
mse = mean_squared_error(y, y_cv)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Input In [128], in <cell line: 9>()
      6 pls = PLSRegression(n_components=5)
      8 # Fit
----> 9 pls.fit(x_columns, y)
     11 # Cross-validation
     12 y_cv = cross_val_predict(pls, x_columns, y, cv=10)

File ~/opt/anaconda3/lib/python3.9/site-packages/sklearn/cross_decomposition/_pls.py:211
, in _PLS.fit(self, X, Y)
    192 def fit(self, X, Y):
    193     """Fit model to data.
    194 
    195     Parameters
   (...)
    208         Fitted model.
    209     """
--> 211     check_consistent_length(X, Y)
    212     X = self._validate_data(
    213         X, dtype=np.float64, copy=self.copy, ensure_min_samples=2
    214     )
    215     Y = check_array(Y, dtype=np.float64, copy=self.copy, ensure_2d=False)

File ~/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/validation.py:332, in che
ck_consistent_length(*arrays)
    330 uniques = np.unique(lengths)
    331 if len(uniques) > 1:
--> 332     raise ValueError(
    333         "Found input variables with inconsistent numbers of samples: %r"
    334         % [int(l) for l in lengths]
    335     )

ValueError: Found input variables with inconsistent numbers of samples: [3, 300]
```

In [ ]: