itcqlap9l

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Compute a test statistic that would show that 1 model does better than the other. LS and WLS

For example, if you picked LS and WLS, you would compute a statistic for each model, and show that one of those test statistics is better than the otherat different scenarios and datasets.

[11]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import statsmodels.formula.api as smf
import statsmodels.stats.api as sms

plt.rcParams["figure.figsize"]=(14,9) #Figure size and width
```

[12]:
```
df = pd.read_csv("M2. module_2_data.csv")
df.head()
```

[12]:
```
        Date       DXY    METALS       OIL    US_STK  INTL_STK    X13W_TB  \
0   1/4/2016  0.002433  0.024283 -0.007559 -0.013980 -0.019802  0.047297
1   1/5/2016  0.005361 -0.004741 -0.021491  0.001691 -0.001263  0.322581
2   1/6/2016 -0.002213  0.013642 -0.055602 -0.012614 -0.015171  0.000000
3   1/7/2016 -0.009679  0.035249 -0.020606 -0.023992 -0.019255 -0.073171
4   1/8/2016  0.003258 -0.028064 -0.003306 -0.010977 -0.010471  0.000000

    X10Y_TBY    EURUSD  YEAR
0  -0.010577 -0.007316  2016
1   0.001336 -0.002436  2016
2  -0.031584 -0.006978  2016
3  -0.011024  0.002512  2016
4  -0.010683  0.013636  2016
```

0.0.1 1. OLS - Ordinary Least Square Method

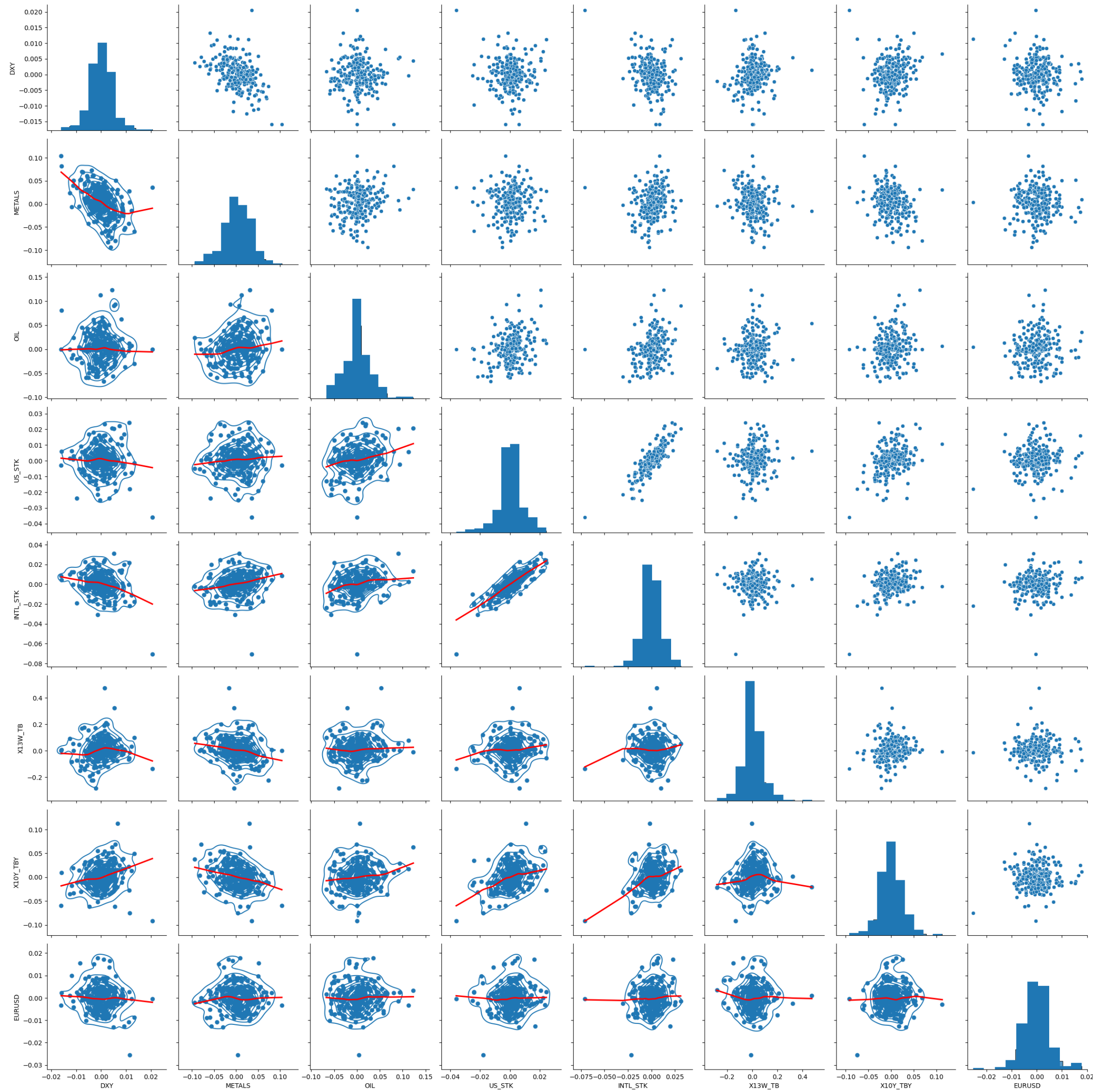
In this data we are assuming: Dependent Value : "DXY" Independent Value : "METALS","OIL","US_STK","INTL_STK","X13W_TB","X10Y_TBY","EURUSD"

[18]:

```
#Scatterplot, Histogram, and Correlation graph matrix for Exogenous Variables␣
↪and Endogeneous Variables
def corr(x,y,**kwargs):
    coef = np.corrcoeff(x,y)[0][1] # Calculate the value
    label = r"$\rho$ ="+ str(rand(coef,2)) # make the label
    # Add the label to the plot
    ax=plt.gca()
    ax.annotate(label,xy=(0.3,0.15),size=20,xycoords=ax.transAxes)
```

```
[19]: # Create a default pairplot
grid = sns.
↪pairplot(df,vars=["DXY","METALS","OIL","US_STK","INTL_STK","X13W_TB","X10Y_TBY","EURUSD"],h
# Map a histogram to the diagonal
grid = grid.map_diag(plt.hist)

# Map a density plot and regression line to the lower triangle
grid = grid.map_lower(sns.kdeplot)
grid = grid.map_lower(sns.regplot, lowess=True, line_kws={"color": "red"})
```



Observations : 1. The upper right triangle of the matrix showcases the correlation values of all two-way correlation value of all two way combinations. 2. The lower left triangle of the matrix showcases the scatterplots for all the two way combinations of all the variables. 3. The graph of the diagonal of the matrix are the histogram of all variables.

[41]:
```
#Linear regression result
model = smf.ols("DXY ~␣
↪METALS+OIL+US_STK+INTL_STK+X13W_TB+X10Y_TBY+EURUSD",data=df).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    DXY   R-squared:                       0.381
```

```
Model:                            OLS   Adj. R-squared:                  0.363
Method:                 Least Squares   F-statistic:                     21.31
Date:                Tue, 26 Aug 2025   Prob (F-statistic):           2.72e-22
Time:                        00:13:49   Log-Likelihood:                 1043.0
No. Observations:                 250   AIC:                            -2070.
Df Residuals:                     242   BIC:                            -2042.
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.0002      0.000      0.747      0.456      -0.000       0.001
METALS        -0.0540      0.009     -6.036      0.000      -0.072      -0.036
OIL            0.0195      0.009      2.224      0.027       0.002       0.037
US_STK         0.3064      0.058      5.327      0.000       0.193       0.420
INTL_STK      -0.3340      0.045     -7.406      0.000      -0.423      -0.245
X13W_TB       -0.0003      0.003     -0.111      0.912      -0.006       0.006
X10Y_TBY       0.0196      0.011      1.731      0.085      -0.003       0.042
EURUSD        -0.0693      0.045     -1.532      0.127      -0.158       0.020
==============================================================================
Omnibus:                        9.767   Durbin-Watson:                   2.185
Prob(Omnibus):                  0.008   Jarque-Bera (JB):               18.012
Skew:                           0.131   Prob(JB):                     0.000123
Kurtosis:                       4.289   Cond. No.                         293.
==============================================================================

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

IN ORDER TO COMPARE THE OLS AND WLS REGRESSION MODEL WE ARE SELECTING ONE INDEPENDENT VARIABLE AS A DEFAULT PARAMETER "X10Y_TBY"

[42]:
```python
#Linear regression result
model_1 = smf.ols("DXY ~ X10Y_TBY",data=df).fit()
print(model_1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    DXY   R-squared:                       0.030
Model:                            OLS   Adj. R-squared:                  0.026
Method:                 Least Squares   F-statistic:                     7.738
Date:                Tue, 26 Aug 2025   Prob (F-statistic):            0.00582
Time:                        00:14:07   Log-Likelihood:                 986.78
No. Observations:                 250   AIC:                            -1970.
Df Residuals:                     248   BIC:                            -1963.
Df Model:                           1
Covariance Type:            nonrobust
```

```
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.0001      0.000      0.474      0.636      -0.000      0.001
X10Y_TBY       0.0336      0.012      2.782      0.006       0.010      0.057
==============================================================================
Omnibus:                       26.741   Durbin-Watson:                   1.909
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               94.918
Skew:                           0.322   Prob(JB):                     2.45e-21
Kurtosis:                       5.949   Cond. No.                         40.7
==============================================================================

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

[43]:
```python
#Parameters with 6 significant digits
model_1.summary2().tables[1]
```

[43]:

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
Intercept	0.000141	0.000297	0.474101	0.635845	-0.000444	0.000725
X10Y_TBY	0.033568	0.012067	2.781725	0.005823	0.009800	0.057336

The estimate from the above variables result showcases that: 1. If the Oil increase by 0.01 or 1% the value for DXY will increase by 0.019497 or (~ 1.95%). 2. Whereas, the (Independent variable) P-values < 0.05, has more significant or impact over the (Dependent Varaible) As a repercussion, the independent variable with p-value greater than the designated parameter can be remove from the model to increase the model efficacy.

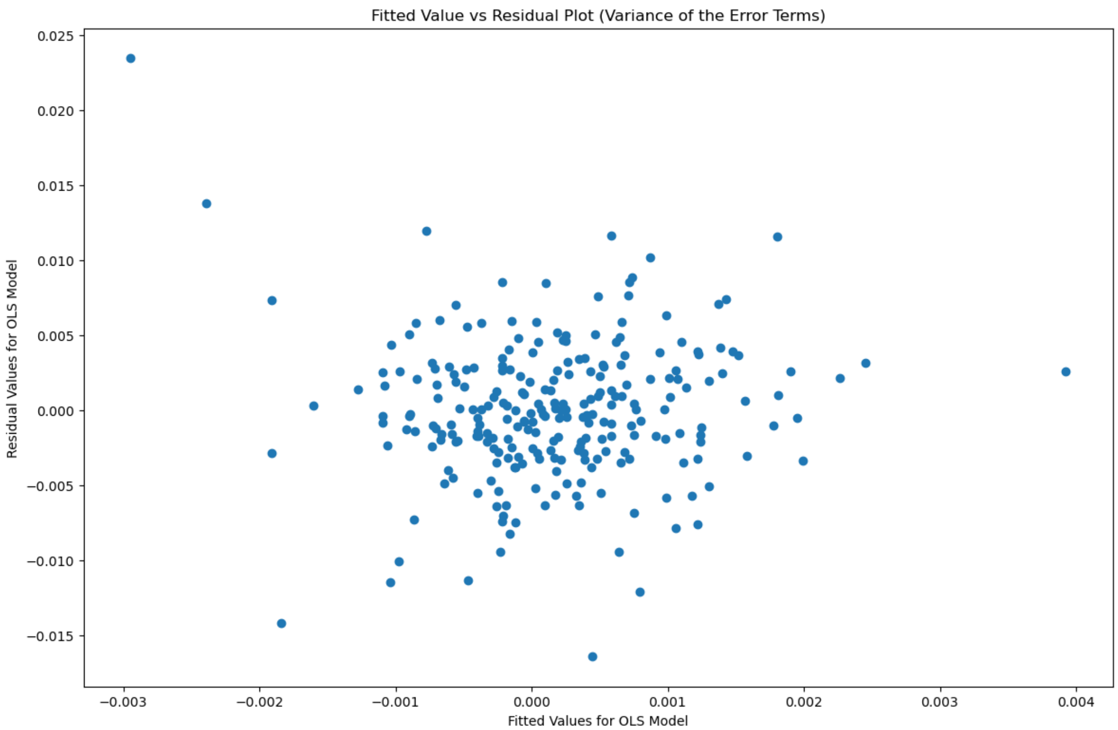
0.0.2 2. WLS - Weighted Least Square Regression

2.1 Scatter Plot for OLS Fitted Values and OLS Residual

[44]:
```python
# Scatter Plot for OLS Fitted Value and OLS Residuals

#Calculate the fitted Value and Residuals
model_1fitted = model_1.fittedvalues
model_1residual = model_1.resid

plt.scatter(x=model_1fitted,y=model_1residual)
plt.title("Fitted Value vs Residual Plot (Variance of the Error Terms)")
plt.xlabel("Fitted Values for OLS Model")
plt.ylabel("Residual Values for OLS Model")
plt.show()
```



The conclusion draw from this sccatter plot about the presense of heteroskedasticity is somewhat ambigous. However, from visual aid it has been clear that there is a clear low concentration of the scatter point when we move from 0 towards positive values. Although, to double confirm we will run Breusch-Pagan test.

2.2 Breusch-Pagan Test

[45]:
```
# Breusch-Pagan Test
name = ["Lagrange multiplier statistic", "p-value", "f-value", "f p-value"]
test = sms.het_breuschpagan(model_1.resid, model_1.model.exog)
pd.DataFrame(test, index=name, columns=[""])
```

[45]:

Lagrange multiplier statistic	13.897238
p-value	0.000193
f-value	14.597521
f p-value	0.000168

It is confirmed that the model_1 consists of the Heteroskedasticity as the p-value is less than 0.005. As a repercussion we can eliminate the Null Hypothesis, that the model consists Homoscedasticity.

2.3 WLS Reggression Result

[47]:
```
# Add absolute Residuals and Fitted Values to dataset columns
df["abs_residuals"]=np.abs(model_1.resid)
```

```python
df["fitted_values"]=model_1.fittedvalues

# Fit OLS model with absolute residuals and fitted values
model_temp = smf.ols("abs_residuals ~ fitted_values",data=df).fit()

#Compute the weights and add it to the dataset columns
weights = model_temp.fittedvalues
weights = weights**-2
df["weights"]=weights

#Fit WLS Model
Y = df["DXY"].tolist()
X = df["X10Y_TBY"].tolist()
X = sm.add_constant(X) # Add the intercept point

model_2 = sm.WLS(Y,X,df["weights"]).fit()
print(model_2.summary())
```

```
                            WLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.100
Model:                            WLS   Adj. R-squared:                  0.096
Method:                 Least Squares   F-statistic:                     27.59
Date:                Tue, 26 Aug 2025   Prob (F-statistic):           3.23e-07
Time:                        00:24:55   Log-Likelihood:                 994.52
No. Observations:                 250   AIC:                            -1985.
Df Residuals:                     248   BIC:                            -1978.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0001      0.000      0.346      0.730      -0.000       0.001
x1             0.0516      0.010      5.253      0.000       0.032       0.071
==============================================================================
Omnibus:                       10.978   Durbin-Watson:                   1.965
Prob(Omnibus):                  0.004   Jarque-Bera (JB):               23.475
Skew:                           0.063   Prob(JB):                     7.99e-06
Kurtosis:                       4.496   Cond. No.                         35.0
==============================================================================

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

Observations : 1. The "X10Y_TBY" stil has a positive coefficient and coefficient is still significant. 2. The R squared value has also improved from 0.3 to 0.10. It implies that the independent variable more accurately explains the movement of dependent variable in the WLS Regression

Model as compared to the OLS Regression Model.

[ ]:
```

```