

```
In [109]: ▶ import statsmodels.formula.api as sfm #Biblioteca para estimar modelos est
import pandas as pd #Biblioteca para manipulación de marcos de datos
from pandas.plotting import scatter_matrix #Herramienta de Pandas para dia
import matplotlib.pyplot as plt #Biblioteca para la salida gráfica.
import numpy as np # Biblioteca de funciones matemáticas.
import seaborn as sns
from sklearn.linear_model import LinearRegression
```

```
In [110]: ▶ df = pd.read_excel("datos tesis.xlsx") #Ruta del archivo datos.xlsx
df.head() #Despliegue de las 5 primeras filas del DataFrame
```

Out[110]:

	Date	Close BTC	Inflacion usa	china gdp	inlfacion china	FTSE CHINA	NASDAQ	S&P500	us
0	2015-01-01	217.464005	0.001186	11061.55308	0.015	10622.76	4635.24	1994.99	18206.0
1	2015-02-01	254.263000	0.001186	11061.55308	0.010	10875.82	4963.53	2104.50	18206.0
2	2015-03-01	244.223999	0.001186	11061.55308	0.009	11980.06	4900.88	2067.89	18206.0
3	2015-04-01	236.145004	0.001186	11061.55308	0.013	14158.26	4941.42	2085.51	18206.0
4	2015-05-01	230.190002	0.001186	11061.55308	0.016	13444.67	5070.02	2107.39	18206.0

```
In [4]: df_2 = df.iloc[:,[1,2,3,4,5,6,7,8,9,10,11]] # Dataframe con las variables.
df_2.describe().transpose()
```

Out[4]:

	count	mean	std	min	25%	50%
<b>Close BTC</b>	97.0	13463.331599	16187.666361	217.464005	970.403015	7569.629883
<b>Inflacion usa</b>	97.0	0.027504	0.023794	0.001186	0.012616	0.021301
<b>china gdp</b>	97.0	14154.263725	2463.795110	11061.553080	12310.409371	14279.937501
<b>inlfacion china</b>	97.0	0.019670	0.009742	-0.004000	0.015000	0.018000
<b>FTSE CHINA</b>	97.0	12827.665155	2341.764282	8756.880000	10911.360000	12908.110000
<b>NASDAQ</b>	97.0	8589.786907	3323.980526	4557.950000	5614.790000	7671.790000
<b>S&amp;P500</b>	97.0	2995.346804	815.966805	1920.030000	2278.870000	2816.290000
<b>usa gdp</b>	97.0	21072.527844	2332.562451	18206.020741	19477.336549	21060.473613
<b>ineteres usa</b>	97.0	0.009510	0.009939	0.000000	0.002500	0.005000
<b>intereses china</b>	97.0	0.041995	0.003890	0.036500	0.038500	0.043500
<b>desempleo usa</b>	97.0	0.048845	0.018688	0.034000	0.037000	0.044000



```
In [14]: print(df.columns)
```

```
Index(['Date', 'Close BTC', 'Inflacion usa', 'china gdp', 'inlfacion china',
      'FTSE CHINA ', 'NASDAQ ', 'S&P500 ', 'usa gdp', 'ineteres usa',
      'intereses china', 'desempleo usa'],
      dtype='object')
```

```
In [15]: variables = ['Close BTC', 'Inflacion usa', 'china gdp', 'inlfacion china ',
                    'FTSE CHINA ', 'NASDAQ ', 'S&P500 ', 'usa gdp', 'ineteres usa',
                    'intereses china', 'desempleo usa'] #Variables with correlation
data = df[variables].copy()
data.rename(columns={'Close BTC': 'CBTC',
                    'Inflacion usa': 'IUSA',
                    'china gdp': 'CGDP',
                    'inlfacion china ': 'ICHINA',
                    'FTSE CHINA ': 'FTSE',
                    'NASDAQ ': 'NDAQ',
                    'S&P500 ': 'SP500',
                    'usa gdp': 'UGDP',
                    'ineteres usa': 'inUSA',
                    'intereses china': 'inchi',
                    'desempleo usa': 'dusa'},
            inplace=True)
data.head()
```

Out[15]:

	CBTC	IUSA	CGDP	ICHINA	FTSE	NDAQ	SP500	UGDP	in
0	217.464005	0.001186	11061.55308	0.015	10622.76	4635.24	1994.99	18206.020741	0.0
1	254.263000	0.001186	11061.55308	0.010	10875.82	4963.53	2104.50	18206.020741	0.0
2	244.223999	0.001186	11061.55308	0.009	11980.06	4900.88	2067.89	18206.020741	0.0
3	236.145004	0.001186	11061.55308	0.013	14158.26	4941.42	2085.51	18206.020741	0.0
4	230.190002	0.001186	11061.55308	0.016	13444.67	5070.02	2107.39	18206.020741	0.0

```
In [16]: print(data.columns)
```

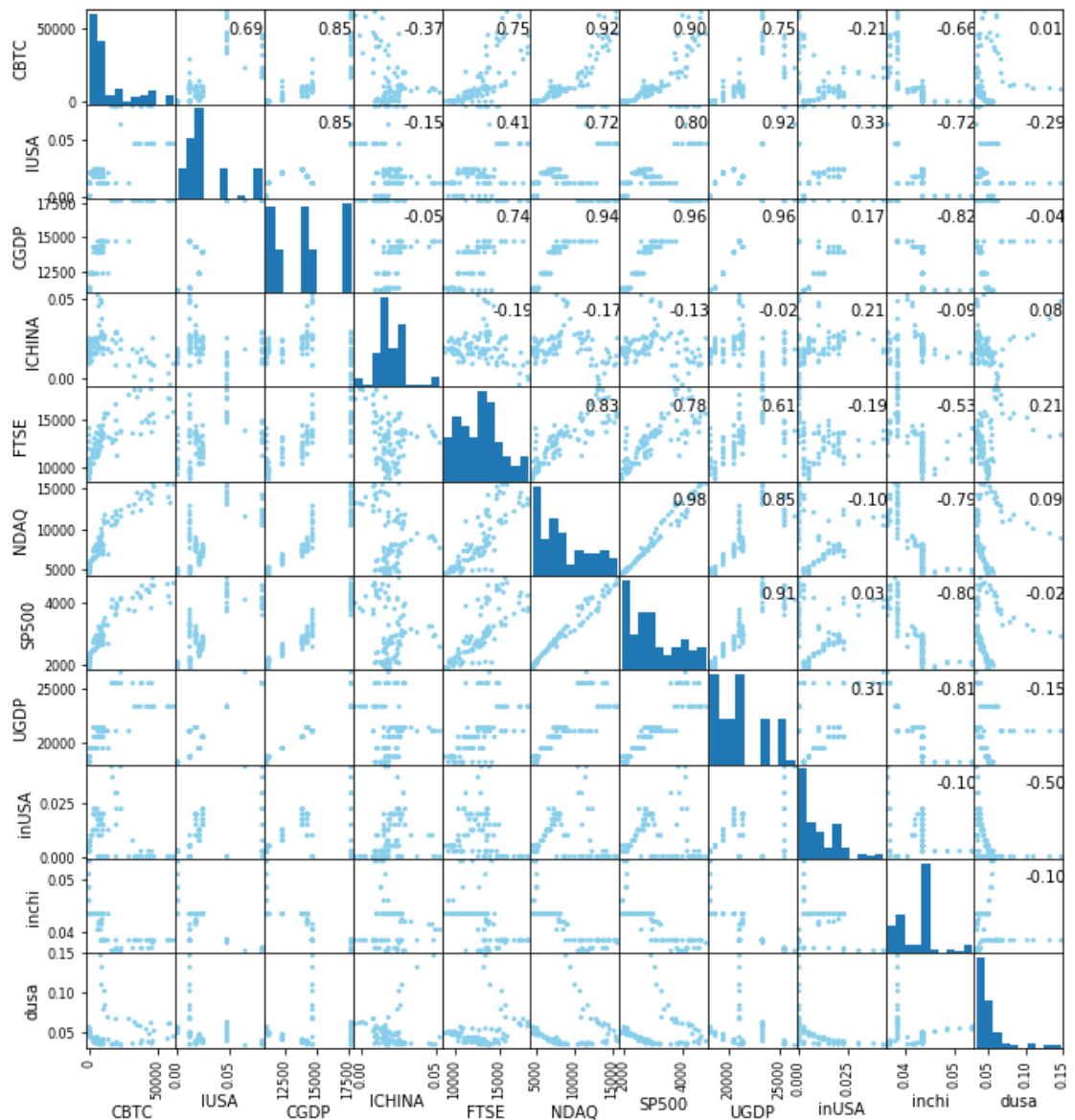
```
Index(['CBTC', 'IUSA', 'CGDP', 'ICHINA', 'FTSE', 'NDAQ', 'SP500', 'UGDP',
      'inUSA', 'inchi', 'dusa'],
      dtype='object')
```

```
In [17]: # Crear La matriz de gráficos de dispersión
axes = scatter_matrix(data, alpha=1, figsize=(11,12), color="skyblue")

# Calcular La matriz de correlación y agregar anotaciones de texto
corr = data.corr().values
for i, j in zip(*np.triu_indices_from(axes, k=1)):
    axes[i, j].annotate("%.2f" %corr[i,j], (0.8, 0.8), xycoords='axes frac

# Guardar La matriz de gráficos de dispersión en una imagen
plt.savefig("matrix_scatter.png", dpi=300)

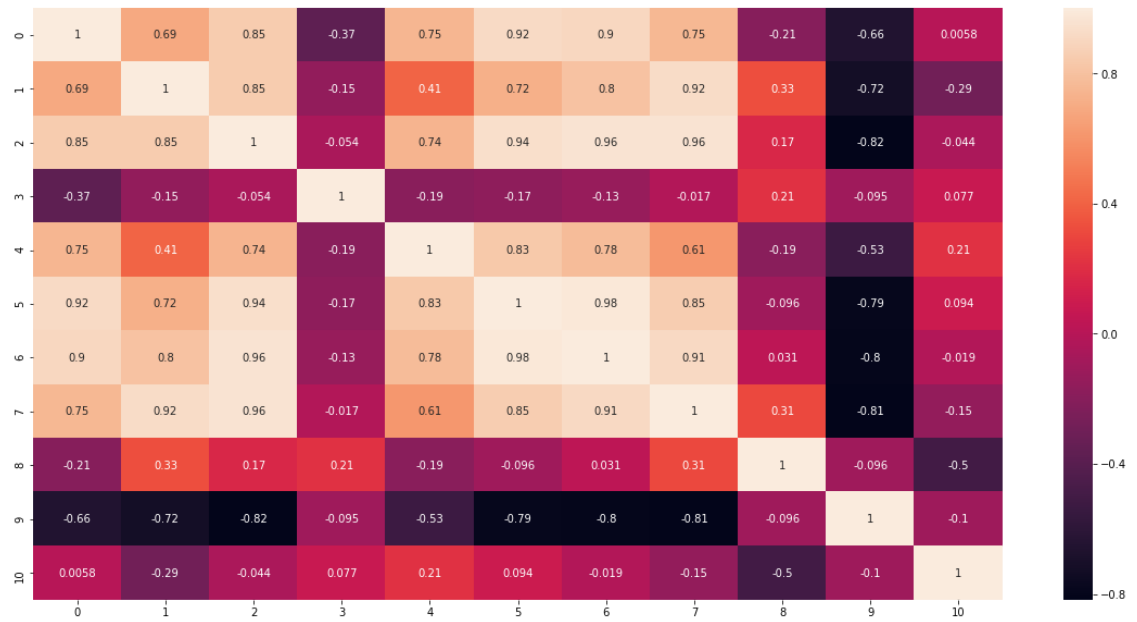
# Mostrar La matriz de gráficos de dispersión en una ventana de visualizac
plt.show()
```



In [133]:



```
plt.figure(figsize = (20, 10))  
sns.heatmap(corr, annot = True)  
plt.show()
```



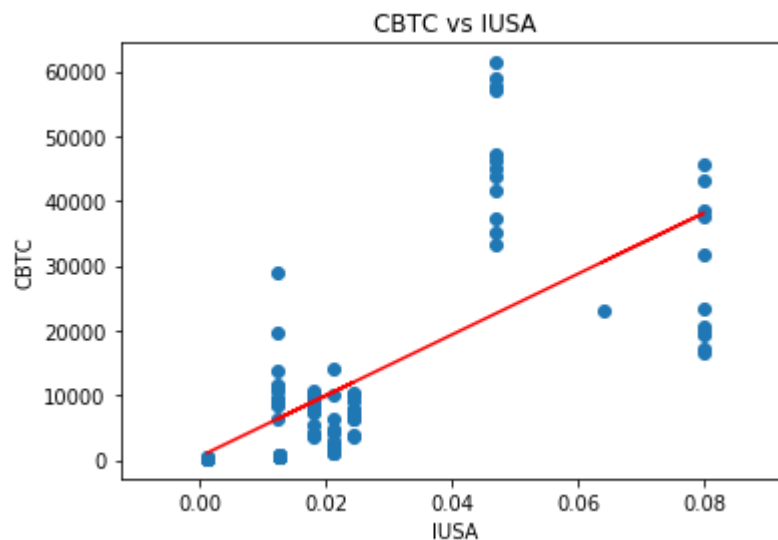
```

In [138]: X = data['IUSA'].values.reshape(-1,1)
Y = data['CBTC'].values.reshape(-1,1)
model = LinearRegression() # create object for the class
model.fit(X, Y) # perform linear regression
r_sq = model.score(X, Y)
r_sq
print(f"coefficient of determination: {r_sq}")
print(f"intercept: {model.intercept_}")
print(f"slope: {model.coef_}")

Y_pred = linear_regressor.predict(X) # make predictions
plt.scatter(X, Y)
plt.plot(X, Y_pred, color='red')
plt.title('CBTC vs IUSA')
plt.xlabel('IUSA')
plt.ylabel('CBTC')
plt.show()

```

coefficient of determination: 0.4757743339923085  
intercept: [556.68900827]  
slope: [[469258.0774742]]



In [112]:

```
# fitting the model

model = smf.ols(formula='CBTC ~ IUSA',data=data).fit()

# model summary
print(model.summary())
```

```

=====
                        OLS Regression Results
=====
=====
Dep. Variable:          CBTC    R-squared:
0.476
Model:                OLS    Adj. R-squared:
0.470
Method:              Least Squares    F-statistic:
86.22
Date:                Fri, 16 Jun 2023    Prob (F-statistic):          5.5
7e-15
Time:                16:11:36    Log-Likelihood:          -1
045.9
No. Observations:          97    AIC:
2096.
Df Residuals:            95    BIC:
2101.
Df Model:                1
Covariance Type:          nonrobust
=====
=====
                        coef      std err          t      P>|t|      [0.025
0.975]
-----
-----
Intercept      556.6890    1833.885      0.304      0.762    -3084.033    419
7.411
IUSA           4.693e+05    5.05e+04     9.285      0.000     3.69e+05     5.
7e+05
=====
=====
Omnibus:          31.042    Durbin-Watson:
0.214
Prob(Omnibus):    0.000    Jarque-Bera (JB):          5
2.077
Skew:            1.368    Prob(JB):          4.9
2e-12
Kurtosis:         5.325    Cond. No.
42.3
=====
=====

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

```
In [116]: model2 = smf.ols(formula='CBTC ~ CGDP',data=data).fit()
```

```
# model summary  
print(model2.summary())
```

```
OLS Regression Results  
=====
```

Dep. Variable:	CBTC	R-squared:	
0.715			
Model:	OLS	Adj. R-squared:	
0.712			
Method:	Least Squares	F-statistic:	
238.7			
Date:	Fri, 16 Jun 2023	Prob (F-statistic):	1.1
7e-27			
Time:	16:13:10	Log-Likelihood:	-1
016.3			
No. Observations:	97	AIC:	
2037.			
Df Residuals:	95	BIC:	
2042.			
Df Model:	1		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
-----						
-----						
Intercept	-6.519e+04	5166.974	-12.616	0.000	-7.54e+04	-5.4
9e+04						
CGDP	5.5567	0.360	15.448	0.000	4.843	
6.271						

```
=====
```

Omnibus:	14.988	Durbin-Watson:	
0.321			
Prob(Omnibus):	0.001	Jarque-Bera (JB):	1
7.852			
Skew:	0.825	Prob(JB):	0.0
00133			
Kurtosis:	4.300	Cond. No.	8.4
2e+04			

```
=====
```

Warnings:

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

[2] The condition number is large, 8.42e+04. This might indicate that there are

strong multicollinearity or other numerical problems.



```
In [117]: model3 = smf.ols(formula='CBTC ~ ICHINA',data=data).fit()
```

```
# model summary  
print(model3.summary())
```

```
OLS Regression Results  
=====
```

Dep. Variable:	CBTC	R-squared:	
0.139			
Model:	OLS	Adj. R-squared:	
0.130			
Method:	Least Squares	F-statistic:	
15.29			
Date:	Fri, 16 Jun 2023	Prob (F-statistic):	0.0
00173			
Time:	16:13:35	Log-Likelihood:	-1
070.0			
No. Observations:	97	AIC:	
2144.			
Df Residuals:	95	BIC:	
2149.			
Df Model:	1		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	2.563e+04	3469.420	7.388	0.000	1.87e+04	3.25e+04
ICHINA	-6.187e+05	1.58e+05	-3.911	0.000	-9.33e+05	-3.05e+05

```
=====
```

Omnibus:	10.807	Durbin-Watson:	
0.087			
Prob(Omnibus):	0.005	Jarque-Bera (JB):	1
1.952			
Skew:	0.859	Prob(JB):	0.
00254			
Kurtosis:	2.939	Cond. No.	
103.			

```
=====
```

Warnings:

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

```
In [118]: model4 = smf.ols(formula='CBTC ~ FTSE',data=data).fit()
```

```
# model summary  
print(model4.summary())
```

```
OLS Regression Results  
=====
```

Dep. Variable:	CBTC	R-squared:	
0.562			
Model:	OLS	Adj. R-squared:	
0.557			
Method:	Least Squares	F-statistic:	
121.8			
Date:	Fri, 16 Jun 2023	Prob (F-statistic):	1.0
3e-18			
Time:	16:13:59	Log-Likelihood:	-1
037.2			
No. Observations:	97	AIC:	
2078.			
Df Residuals:	95	BIC:	
2084.			
Df Model:	1		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
-----						
-----						
Intercept	-5.3e+04	6120.888	-8.659	0.000	-6.52e+04	-4.0
8e+04						
FTSE	5.1812	0.469	11.036	0.000	4.249	
6.113						

```
=====
```

Omnibus:	14.559	Durbin-Watson:	
0.352			
Prob(Omnibus):	0.001	Jarque-Bera (JB):	1
5.979			
Skew:	0.920	Prob(JB):	0.0
00339			
Kurtosis:	3.752	Cond. No.	7.3
0e+04			

```
=====
```

Warnings:

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

[2] The condition number is large, 7.3e+04. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [119]: model5 = smf.ols(formula='CBTC ~ NDAQ',data=data).fit()
```

```
# model summary  
print(model5.summary())
```

```
OLS Regression Results  
=====
```

Dep. Variable:	CBTC	R-squared:	0.847
Model:	OLS	Adj. R-squared:	0.845
Method:	Least Squares	F-statistic:	526.3
Date:	Fri, 16 Jun 2023	Prob (F-statistic):	1.6e-40
Time:	16:14:28	Log-Likelihood:	-986.18
No. Observations:	97	AIC:	1976.
Df Residuals:	95	BIC:	1982.
Df Model:	1		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-2.504e+04	1798.293	-13.923	0.000	-2.86e+04	-2.15e+04
NDAQ	4.4822	0.195	22.942	0.000	4.094	4.870

```
=====
```

Omnibus:	18.337	Durbin-Watson:	0.425
Prob(Omnibus):	0.000	Jarque-Bera (JB):	6.696
Skew:	0.704	Prob(JB):	8e-08
Kurtosis:	5.664	Cond. No.	6e+04

```
=====
```

Warnings:

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

[2] The condition number is large, 2.56e+04. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [120]: model6 = smf.ols(formula='CBTC ~ SP500',data=data).fit()
```

```
# model summary
print(model6.summary())
```

```

OLS Regression Results

=====
=====
Dep. Variable:          CBTC    R-squared:
0.816
Model:                OLS    Adj. R-squared:
0.814
Method:             Least Squares    F-statistic:
421.1
Date:              Fri, 16 Jun 2023    Prob (F-statistic):          1.1
0e-36
Time:              16:14:44    Log-Likelihood:              -9
95.18
No. Observations:          97    AIC:
1994.
Df Residuals:              95    BIC:
2000.
Df Model:                  1
Covariance Type:          nonrobust
=====
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-4.021e+04	2710.145	-14.838	0.000	-4.56e+04	-3.48e+04
SP500	17.9199	0.873	20.520	0.000	16.186	19.654

```

=====
=====
Omnibus:              28.326    Durbin-Watson:
0.386
Prob(Omnibus):          0.000    Jarque-Bera (JB):          5
9.900
Skew:                  1.098    Prob(JB):              9.8
4e-14
Kurtosis:              6.162    Cond. No.              1.1
9e+04
=====
=====

```

Warnings:

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

[2] The condition number is large, 1.19e+04. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [121]: model7 = smf.ols(formula='CBTC ~ UGDP',data=data).fit()
```

```
# model summary  
print(model7.summary())
```

```
OLS Regression Results  
=====
```

Dep. Variable:	CBTC	R-squared:	0.565
Model:	OLS	Adj. R-squared:	0.560
Method:	Least Squares	F-statistic:	123.3
Date:	Fri, 16 Jun 2023	Prob (F-statistic):	7.3e-19
Time:	16:16:44	Log-Likelihood:	-1036.9
No. Observations:	97	AIC:	2078.
Df Residuals:	95	BIC:	2083.
Df Model:	1		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-9.645e+04	9956.901	-9.687	0.000	-1.16e+05	-7.67e+04
UGDP	5.2159	0.470	11.106	0.000	4.284	6.148

```
=====
```

Omnibus:	30.378	Durbin-Watson:	0.219
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3.681
Skew:	1.294	Prob(JB):	0e-12
Kurtosis:	5.566	Cond. No.	1.94e+05

```
=====
```

Warnings:

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

[2] The condition number is large, 1.94e+05. This might indicate that there are

strong multicollinearity or other numerical problems.

```
In [122]: ▶ model8 = smf.ols(formula='CBTC ~ inUSA',data=data).fit()
```

```
# model summary  
print(model8.summary())
```

```
OLS Regression Results  
=====
```

Dep. Variable:	CBTC	R-squared:	
0.043			
Model:	OLS	Adj. R-squared:	
0.033			
Method:	Least Squares	F-statistic:	
4.244			
Date:	Fri, 16 Jun 2023	Prob (F-statistic):	
0.0421			
Time:	16:17:07	Log-Likelihood:	-1
075.1			
No. Observations:	97	AIC:	
2154.			
Df Residuals:	95	BIC:	
2159.			
Df Model:	1		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
-----						
Intercept	1.667e+04	2242.924	7.431	0.000	1.22e+04	2.11e+04
inUSA	-3.368e+05	1.63e+05	-2.060	0.042	-6.61e+05	-1.22e+04

```
=====
```

Omnibus:	17.632	Durbin-Watson:	
0.081			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2
1.360			
Skew:	1.137	Prob(JB):	2.3
0e-05			
Kurtosis:	3.339	Cond. No.	
101.			

```
=====
```

Warnings:

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

```
In [123]: model9 = smf.ols(formula='CBTC ~ inchi',data=data).fit()
```

```
# model summary  
print(model9.summary())
```

```
OLS Regression Results  
=====
```

Dep. Variable:	CBTC	R-squared:	0.434
Model:	OLS	Adj. R-squared:	0.428
Method:	Least Squares	F-statistic:	72.97
Date:	Fri, 16 Jun 2023	Prob (F-statistic):	2.14e-13
Time:	16:17:29	Log-Likelihood:	-1049.6
No. Observations:	97	AIC:	2103.
Df Residuals:	95	BIC:	2108.
Df Model:	1		
Covariance Type:	nonrobust		

```
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	1.286e+05	1.35e+04	9.500	0.000	1.02e+05	1.56e+05
inchi	-2.743e+06	3.21e+05	-8.542	0.000	-3.38e+06	-2.11e+06

```
=====
```

Omnibus:	27.157	Durbin-Watson:	0.161
Prob(Omnibus):	0.000	Jarque-Bera (JB):	7.955
Skew:	1.403	Prob(JB):	3e-09
Kurtosis:	4.231	Cond. No.	259.

```
=====
```

Warnings:

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

In [124]: `model10 = smf.ols(formula='CBTC ~ dusa',data=data).fit()`

```
# model summary
print(model10.summary())
```

```

=====
                        OLS Regression Results
=====
=====
Dep. Variable:          CBTC    R-squared:
0.000
Model:                  OLS    Adj. R-squared:    -
0.010
Method:                 Least Squares    F-statistic:          0.0
03248
Date:                   Fri, 16 Jun 2023    Prob (F-statistic):
0.955
Time:                   16:22:35    Log-Likelihood:          -1
077.3
No. Observations:       97    AIC:
2159.
Df Residuals:           95    BIC:
2164.
Df Model:                1
Covariance Type:        nonrobust
=====
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
-----
-----
Intercept    1.322e+04    4644.565      2.845      0.005    3995.303    2.2
4e+04
dusa         5064.9858    8.89e+04     0.057      0.955   -1.71e+05    1.8
1e+05
=====
=====
Omnibus:          27.268    Durbin-Watson:
0.078
Prob(Omnibus):    0.000    Jarque-Bera (JB):          3
8.190
Skew:             1.449    Prob(JB):              5.1
0e-09
Kurtosis:         4.025    Cond. No.
53.9
=====
=====
```

Warnings:

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

In [ ]:



```
In [132]: ► import statsmodels.api as sm
# fitting the multiple linear regression model
y = df['Close BTC']
x=df[['Inflacion usa', 'china gdp', 'inlfacion china ',
      'FTSE CHINA ', 'NASDAQ ', 'S&P500 ', 'usa gdp', 'ineteres usa',
      'intereses china', 'desempleo usa']]
# with statsmodels
x = sm.add_constant(x) # adding a constant

model = sm.OLS(y, x).fit()
predictions = model.predict(x)

print_model = model.summary()
print(print_model)
```

# OLS Regression Results

```

=====
=====
Dep. Variable:          Close BTC    R-squared:
0.939
Model:                  OLS          Adj. R-squared:
0.932
Method:                 Least Squares    F-statistic:
132.4
Date:                   Fri, 16 Jun 2023    Prob (F-statistic):          8.2
7e-48
Time:                   16:45:03          Log-Likelihood:          -9
41.62
No. Observations:          97          AIC:
1905.
Df Residuals:              86          BIC:
1934.
Df Model:                  10
Covariance Type:          nonrobust
=====
=====

```

	coef	std err	t	P> t	[0.025
0.975]					
-----					
const	-1185.7096	2.08e+04	-0.057	0.955	-4.25e+04
4.01e+04					
Inflacion usa	1.361e+04	8.02e+04	0.170	0.866	-1.46e+05
1.73e+05					
china gdp	7.1408	1.453	4.916	0.000	4.253
10.028					
inlfacion china	-3.926e+05	6.92e+04	-5.672	0.000	-5.3e+05
-2.55e+05					
FTSE CHINA	-0.5141	0.430	-1.196	0.235	-1.368
0.340					
NASDAQ	-3.6165	2.175	-1.663	0.100	-7.941
0.708					
S&P500	24.2140	7.893	3.068	0.003	8.524
39.904					
usa gdp	-4.8302	1.420	-3.401	0.001	-7.653
-2.007					
ineteres usa	-4.705e+05	8.3e+04	-5.668	0.000	-6.35e+05
-3.05e+05					
intereses china	-1.169e+05	2.58e+05	-0.454	0.651	-6.29e+05
3.95e+05					
desempleo usa	-5.689e+04	3.3e+04	-1.725	0.088	-1.22e+05
8675.803					

```

=====
=====
Omnibus:                14.645    Durbin-Watson:
1.123
Prob(Omnibus):          0.001    Jarque-Bera (JB):          1
6.348
Skew:                   0.876    Prob(JB):                  0.0
00282
Kurtosis:               3.987    Cond. No.                  1.8
4e+07

```

```
=====
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```

Warnings:

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

[2] The condition number is large, 1.84e+07. This might indicate that there are strong multicollinearity or other numerical problems.

In [ ]: ▶

In [ ]: ▶

In [43]: ▶

In [ ]: ▶