2) Time series

August 8, 2023

1 1) Preparación previa

Carga de librerías

[1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns
%matplotlib inline

import statsmodels.api as sm
import statsmodels.formula.api as smf
import statsmodels.tsa.api as smt

from scipy import stats
from statistics import mode

from sklearn.model_selection import train_test_split

from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_predict
from statsmodels.tsa.holtwinters import SimpleExpSmoothing
from sklearn.model_selection import TimeSeriesSplit
from sklearn.metrics import mean_squared_error

# Se debe instalar pmdarima
from pmdarima import auto_arima #!pip install pmdarima

import warnings
warnings.filterwarnings('ignore')
```

Lectura del dataset

[2]:
```python
df = pd.read_csv('https://raw.githubusercontent.com/Agustin-Bulzomi/Projects/
↪main/Programming/Digital%20House%20(Python)/Support%20Files/Final%20Project/
↪coin_Bitcoin.csv', delimiter=',')
```

Se realizan las modificaciones del dataset pertinentes para el análisis de series de tiempo

[3]:
```python
df['Date'] = pd.to_datetime(df['Date'])
df.index = pd.PeriodIndex(df.Date, freq='D')
df.head()
```

[3]:
```
            SNo     Name Symbol       Date        High         Low  \
Date
2013-04-29    1  Bitcoin    BTC 2013-04-29  147.488007  134.000000
2013-04-30    2  Bitcoin    BTC 2013-04-30  146.929993  134.050003
2013-05-01    3  Bitcoin    BTC 2013-05-01  139.889999  107.720001
2013-05-02    4  Bitcoin    BTC 2013-05-02  125.599998   92.281898
2013-05-03    5  Bitcoin    BTC 2013-05-03  108.127998   79.099998

                  Open       Close  Volume     Marketcap
Date
2013-04-29  134.444000  144.539993     0.0  1.603769e+09
2013-04-30  144.000000  139.000000     0.0  1.542813e+09
2013-05-01  139.000000  116.989998     0.0  1.298955e+09
2013-05-02  116.379997  105.209999     0.0  1.168517e+09
2013-05-03  106.250000   97.750000     0.0  1.085995e+09
```

Dummies

[4]:
```python
df["timeIndex"] = pd.Series(np.arange(len(df['Close'])), index=df.index)

df.head()
```

[4]:
```
            SNo     Name Symbol       Date        High         Low  \
Date
2013-04-29    1  Bitcoin    BTC 2013-04-29  147.488007  134.000000
2013-04-30    2  Bitcoin    BTC 2013-04-30  146.929993  134.050003
2013-05-01    3  Bitcoin    BTC 2013-05-01  139.889999  107.720001
2013-05-02    4  Bitcoin    BTC 2013-05-02  125.599998   92.281898
2013-05-03    5  Bitcoin    BTC 2013-05-03  108.127998   79.099998

                  Open       Close  Volume     Marketcap  timeIndex
Date
2013-04-29  134.444000  144.539993     0.0  1.603769e+09          0
2013-04-30  144.000000  139.000000     0.0  1.542813e+09          1
2013-05-01  139.000000  116.989998     0.0  1.298955e+09          2
2013-05-02  116.379997  105.209999     0.0  1.168517e+09          3
2013-05-03  106.250000   97.750000     0.0  1.085995e+09          4
```

[5]:
```python
df.tail()
```

[5]:
```
                 SNo     Name Symbol       Date         High          Low  \
Date
2021-02-23  2858  Bitcoin    BTC 2021-02-23  54204.92976  45290.59027
2021-02-24  2859  Bitcoin    BTC 2021-02-24  51290.13669  47213.49816
2021-02-25  2860  Bitcoin    BTC 2021-02-25  51948.96698  47093.85302
2021-02-26  2861  Bitcoin    BTC 2021-02-26  48370.78526  44454.84211
2021-02-27  2862  Bitcoin    BTC 2021-02-27  48253.27010  45269.02577

                   Open        Close        Volume     Marketcap  timeIndex
Date
2021-02-23  54204.92976  48824.42687  1.061020e+11  9.099260e+11       2857
2021-02-24  48835.08766  49705.33332  6.369552e+10  9.263930e+11       2858
2021-02-25  49709.08242  47093.85302  5.450657e+10  8.777660e+11       2859
2021-02-26  47180.46405  46339.76008  3.509680e+11  8.637520e+11       2860
2021-02-27  46344.77224  46188.45128  4.591095e+10  8.609780e+11       2861
```

Se agregan las columnas necesarias

[6]:
```python
df['Month'] = df['Date'].dt.month
df['Year'] = df['Date'].dt.year
```

Se crean las dummies

[7]:
```python
dummies_mes = pd.get_dummies(df['Month'], drop_first=True, prefix='Month')
df = df.join(dummies_mes)
df.sample(10)
```

[7]:
```
                 SNo     Name Symbol       Date          High           Low  \
Date
2019-08-12  2297  Bitcoin    BTC 2019-08-12  11528.189370  11320.951500
2015-05-27   759  Bitcoin    BTC 2015-05-27    238.636002    236.695007
2020-02-23  2492  Bitcoin    BTC 2020-02-23   9937.404106   9657.791145
2015-12-14   960  Bitcoin    BTC 2015-12-14    447.141998    430.455994
2014-08-05   464  Bitcoin    BTC 2014-08-05    589.864990    584.101990
2018-07-16  1905  Bitcoin    BTC 2018-07-16   6741.750000   6357.009766
2018-10-19  2000  Bitcoin    BTC 2018-10-19   6493.680000   6445.310000
2019-02-22  2126  Bitcoin    BTC 2019-02-22   4006.538387   3950.816427
2019-04-16  2179  Bitcoin    BTC 2019-04-16   5238.945238   5055.194961
2018-10-28  2009  Bitcoin    BTC 2018-10-28   6502.280000   6447.910000

                    Open         Close        Volume     Marketcap  …  \
Date                                                                 …
2019-08-12  11528.189370  11382.615960  1.364720e+10  2.034410e+11  …
2015-05-27    237.065002    237.283005  1.883700e+07  3.371258e+09  …
2020-02-23   9663.318642   9924.515228  4.118519e+10  1.809630e+11  …
2015-12-14    433.272003    444.182007  1.304960e+08  6.645396e+09  …
2014-08-05    589.010986    585.435974  1.079080e+07  7.671275e+09  …
2018-07-16   6357.009766   6741.750000  4.725800e+09  1.156380e+11  …
```

```
2018-10-19   6478.070000   6465.410000  3.578870e+09  1.120530e+11  …
2019-02-22   3952.406374   4005.526604  7.826525e+09  7.030856e+10  …
2019-04-16   5066.577601   5235.559419  1.161866e+10  9.240461e+10  …
2018-10-28   6482.660000   6486.390000  3.445190e+09  1.125180e+11  …

            Month_3  Month_4  Month_5  Month_6  Month_7  Month_8  Month_9  \
Date
2019-08-12        0        0        0        0        0        1        0
2015-05-27        0        0        1        0        0        0        0
2020-02-23        0        0        0        0        0        0        0
2015-12-14        0        0        0        0        0        0        0
2014-08-05        0        0        0        0        0        1        0
2018-07-16        0        0        0        0        1        0        0
2018-10-19        0        0        0        0        0        0        0
2019-02-22        0        0        0        0        0        0        0
2019-04-16        0        1        0        0        0        0        0
2018-10-28        0        0        0        0        0        0        0

            Month_10  Month_11  Month_12
Date
2019-08-12         0         0         0
2015-05-27         0         0         0
2020-02-23         0         0         0
2015-12-14         0         0         1
2014-08-05         0         0         0
2018-07-16         0         0         0
2018-10-19         1         0         0
2019-02-22         0         0         0
2019-04-16         0         0         0
2018-10-28         1         0         0

[10 rows x 24 columns]
```

Se divide el dataset en Train y Test, usando rangos personalizados

[8]:
```python
# Se utiliza este método para manejar el shape que se aplicará a los demás␣
↪modelos
end_date = '2021-01-27'
mask1 = (df['Date'] <= end_date)
mask2 = (df['Date'] > end_date)
```

[9]:
```python
# Se pasan las máscaras para obtener train y test:
df_train = df.loc[mask1]
df_test = df.loc[mask2]
print("train shape",df_train.shape)
print("test shape",df_test.shape)
```

```
train shape (2831, 24)
```

```
test shape (31, 24)
```

Chequeo de que la primer fecha de test sea la siguiente al final de train:

[10]:
```
df_train.tail()
```

[10]:
```
             SNo     Name Symbol        Date         High          Low  \
Date
2021-01-23  2827  Bitcoin    BTC 2021-01-23  33360.97819  31493.15967
2021-01-24  2828  Bitcoin    BTC 2021-01-24  32944.00894  31106.68577
2021-01-25  2829  Bitcoin    BTC 2021-01-25  34802.74298  32087.78797
2021-01-26  2830  Bitcoin    BTC 2021-01-26  32794.54959  31030.26597
2021-01-27  2831  Bitcoin    BTC 2021-01-27  32564.03024  29367.13922

                   Open        Close        Volume     Marketcap  …  \
Date                                                               …
2021-01-23  32985.75691  32067.64288  4.835474e+10  5.967330e+11  …
2021-01-24  32064.37632  32289.37809  4.864383e+10  6.008890e+11  …
2021-01-25  32285.79891  32366.39305  5.989705e+10  6.023500e+11  …
2021-01-26  32358.61317  32569.84956  6.025542e+10  6.061690e+11  …
2021-01-27  32564.03024  30432.54708  6.257676e+10  5.664170e+11  …

            Month_3  Month_4  Month_5  Month_6  Month_7  Month_8  Month_9  \
Date
2021-01-23        0        0        0        0        0        0        0
2021-01-24        0        0        0        0        0        0        0
2021-01-25        0        0        0        0        0        0        0
2021-01-26        0        0        0        0        0        0        0
2021-01-27        0        0        0        0        0        0        0

            Month_10  Month_11  Month_12
Date
2021-01-23         0         0         0
2021-01-24         0         0         0
2021-01-25         0         0         0
2021-01-26         0         0         0
2021-01-27         0         0         0

[5 rows x 24 columns]
```

[11]:
```
df_test.head()
```

[11]:
```
             SNo     Name Symbol        Date         High          Low  \
Date
2021-01-28  2832  Bitcoin    BTC 2021-01-28  33858.31099  30023.20683
2021-01-29  2833  Bitcoin    BTC 2021-01-29  38406.26096  32064.81419
2021-01-30  2834  Bitcoin    BTC 2021-01-30  34834.70830  32940.18691
2021-01-31  2835  Bitcoin    BTC 2021-01-31  34288.33148  32270.17602
```

```
2021-02-01  2836  Bitcoin    BTC 2021-02-01  34638.21349  32384.22811

                   Open         Close        Volume     Marketcap  …  \
Date                                                                …
2021-01-28  30441.04182  33466.09636  7.651716e+10  6.229100e+11  …
2021-01-29  34318.67169  34316.38765  1.178950e+11  6.387690e+11  …
2021-01-30  34295.93504  34269.52154  6.514183e+10  6.379250e+11  …
2021-01-31  34270.87759  33114.35775  5.275454e+10  6.164530e+11  …
2021-02-01  33114.57724  33537.17682  6.140040e+10  6.243490e+11  …

            Month_3  Month_4  Month_5  Month_6  Month_7  Month_8  Month_9  \
Date
2021-01-28        0        0        0        0        0        0        0
2021-01-29        0        0        0        0        0        0        0
2021-01-30        0        0        0        0        0        0        0
2021-01-31        0        0        0        0        0        0        0
2021-02-01        0        0        0        0        0        0        0

            Month_10  Month_11  Month_12
Date
2021-01-28         0         0         0
2021-01-29         0         0         0
2021-01-30         0         0         0
2021-01-31         0         0         0
2021-02-01         0         0         0

[5 rows x 24 columns]
```

Ploteo de los dos datasets obtenidos:

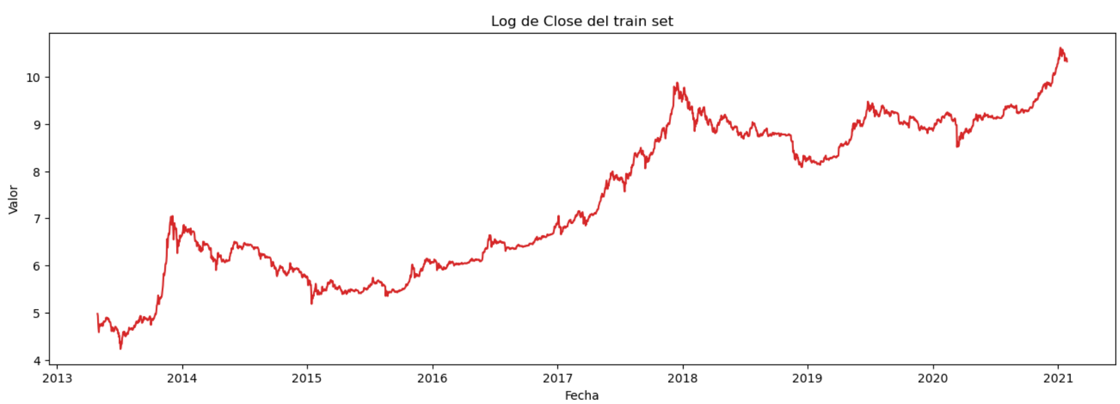
[12]:
```
pd.plotting.register_matplotlib_converters()
f, ax = plt.subplots(figsize=(14,5))
df_train.plot(kind='line', x='Date', y='Close', color='blue', label='Train', ax␣
  ↪= ax)
df_test.plot(kind='line', x='Date', y='Close', color='red', label='Test', ax =␣
  ↪ax)
ax.legend(loc= "upper left")
plt.title('Rango para Train y para Test')
plt.show()
```

Ploteo del Target en escala logarítmica:

[13]:
```
df_train['log_value'] = np.log(df_train['Close'])
df_test['log_value'] = np.log(df_test['Close'])
```

[14]:
```
def plot_df(df, x, y, title = "/", xlabel='Fecha', ylabel='Valor', dpi=100):
    plt.figure(figsize=(16,5), dpi=dpi),
    plt.plot(x, y, color='tab:red'),
    plt.gca().set(title=title, xlabel=xlabel, ylabel=ylabel),
    plt.show()
```

[15]:
```
plot_df(df_train, x=df_train.Date, y=df_train['log_value'],\
    title='Log de Close del train set')
```



Entrenaiento del modelo para analizar el Summary:

[16]:
```
model_log = smf.ols('log_value ~ timeIndex',\
                          data = df_train).fit()
```

[17]:
```
model_log.summary()
```

[17]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_value   R-squared:                       0.835
Model:                            OLS   Adj. R-squared:                  0.835
Method:                 Least Squares   F-statistic:                 1.434e+04
Date:                Tue, 08 Aug 2023   Prob (F-statistic):               0.00
Time:                        21:29:25   Log-Likelihood:                -2770.3
No. Observations:                2831   AIC:                             5545.
Df Residuals:                    2829   BIC:                             5556.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      4.8828      0.024    201.754      0.000       4.835       4.930
timeIndex      0.0018   1.48e-05    119.736      0.000       0.002       0.002
==============================================================================
Omnibus:                      222.150   Durbin-Watson:                   0.004
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              270.407
Skew:                           0.746   Prob(JB):                     1.91e-59
Kurtosis:                       2.747   Cond. No.                     3.27e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.27e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

2 2) Modelos

Se utilizará una plétora de herramientas y recursos para analizar las series de tiempo y sus implicancias. En cada paso se irá visualizando los resultados y almacenando su información para, al final de la notebook, compararlos

2.1 a) Mean

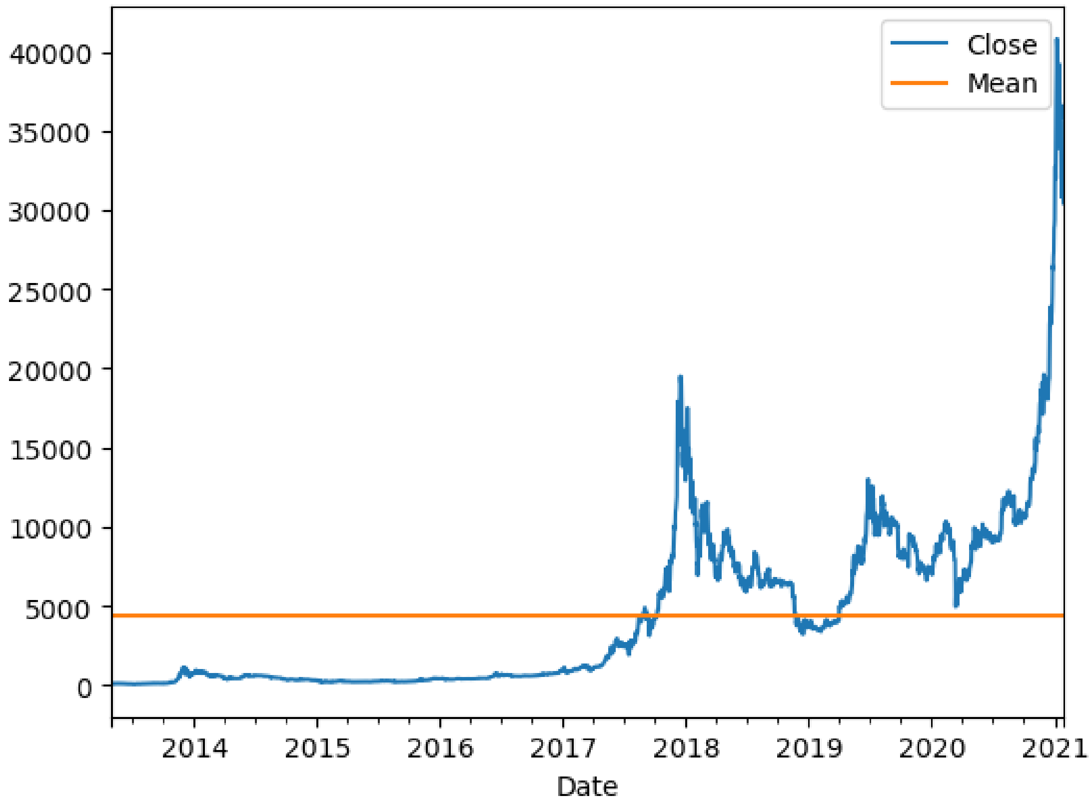
Se aplica el modelo de media constante a train y test:

[18]:
```
# Se calcula el promedio:
model_mean_pred = df_train['Close'].mean()

# La predicción es fija y es la misma para el set de testeo y de entrenamiento:
```

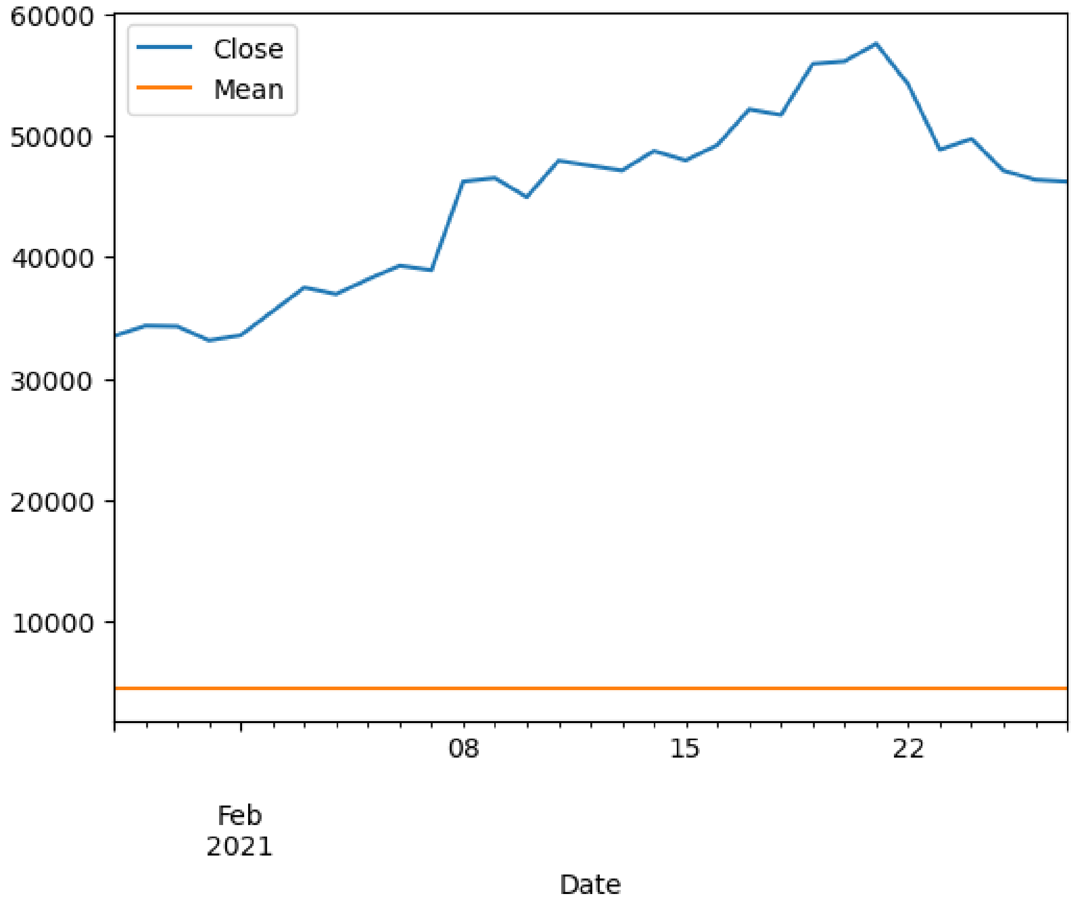
```
df_train["Mean"] = model_mean_pred
df_test["Mean"] = model_mean_pred
```

Ploteo de las predicciones vs las series reales, en train y test:

[19]:
```
df_train.plot(kind="line", y = ["Close", "Mean"]);
```



[20]:
```
df_test.plot(kind="line", y = ["Close", "Mean"]);
```



Se define una función para calcular el RMSE:

[21]:
```
def RMSE(predicted, actual):
    mse = (predicted - actual) ** 2
    rmse = np.sqrt(mse.sum() / mse.count())
    return rmse
```

Se define una función para calcular el MAPE:

[22]:
```
def mean_absolute_percentage_error(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
```

[23]:
```
# Aplicación del MAPE en Mean
model_MAPE = mean_absolute_percentage_error(df_test.Close , df_test.Mean)
print("El MAPE es ", model_MAPE)
```

```
El MAPE es  89.84516144847098
```

[24]:
```python
# Aplicación del RMSE en Mean
print("El RMSE es ", RMSE(df_test.Mean, df_test.Close))
```

```
El RMSE es  40968.433969121186
```

Se guardan los resultados en un DataFrame: El mismo será reutilizado para almacenar los resultados de los distintos modelos a utilizar

[25]:
```python
df_Results = pd.DataFrame(columns = ["Model", "RMSE","MAPE"])
df_Results.loc[0, "Model"] = "Mean"
df_Results.loc[0, "RMSE"] = RMSE(df_test.Mean, df_test.Close)
df_Results.loc[0, "MAPE"] = model_MAPE
df_Results.head()
```

[25]:
```
  Model          RMSE       MAPE
0  Mean  40968.433969  89.845161
```

2.2 b) RandomWalk

Se crea el shift de target en train:

[26]:
```python
df_train["CloseShift"] = df_train.Close.shift()
# La primera observación va a quedar en nan, por lo que se reemplaza por el␣
↪valor siguiente:
df_train["CloseShift"].fillna(method='bfill', inplace=True)
df_train.head()
```

[26]:
```
            SNo     Name Symbol       Date        High         Low  \
Date
2013-04-29    1  Bitcoin    BTC 2013-04-29  147.488007  134.000000
2013-04-30    2  Bitcoin    BTC 2013-04-30  146.929993  134.050003
2013-05-01    3  Bitcoin    BTC 2013-05-01  139.889999  107.720001
2013-05-02    4  Bitcoin    BTC 2013-05-02  125.599998   92.281898
2013-05-03    5  Bitcoin    BTC 2013-05-03  108.127998   79.099998

                  Open       Close  Volume     Marketcap  …  Month_6  \
Date                                                      …
2013-04-29  134.444000  144.539993     0.0  1.603769e+09  …        0
2013-04-30  144.000000  139.000000     0.0  1.542813e+09  …        0
2013-05-01  139.000000  116.989998     0.0  1.298955e+09  …        0
2013-05-02  116.379997  105.209999     0.0  1.168517e+09  …        0
2013-05-03  106.250000   97.750000     0.0  1.085995e+09  …        0

            Month_7  Month_8  Month_9  Month_10  Month_11  Month_12  \
Date
2013-04-29        0        0        0         0         0         0
2013-04-30        0        0        0         0         0         0
2013-05-01        0        0        0         0         0         0
```

```
2013-05-02         0         0         0         0         0         0
2013-05-03         0         0         0         0         0         0

            log_value         Mean   CloseShift
Date
2013-04-29   4.973556  4415.425613   144.539993
2013-04-30   4.934474  4415.425613   144.539993
2013-05-01   4.762088  4415.425613   139.000000
2013-05-02   4.655958  4415.425613   116.989998
2013-05-03   4.582413  4415.425613   105.209999

[5 rows x 27 columns]
```

Se crea el shift de target en test:

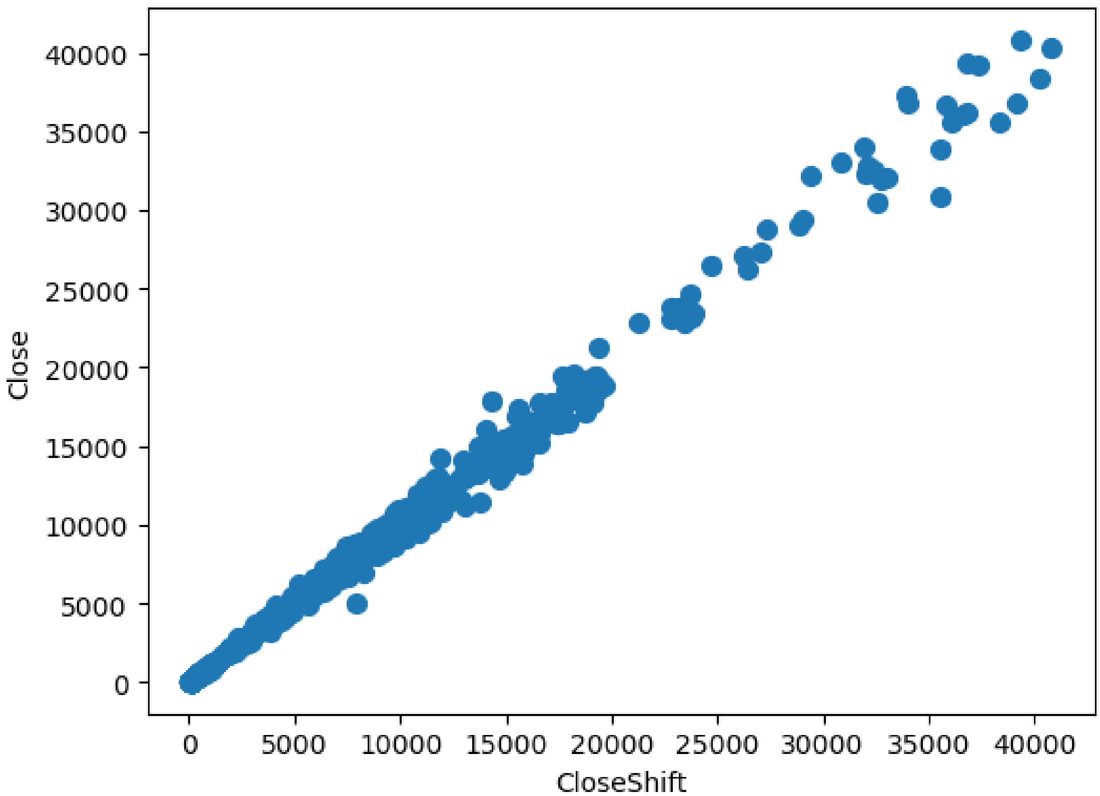
[27]:
```python
df_test["CloseShift"] = df_test.Close.shift()
# Se puede reemplazar el primer nan con el último valor del set de␣
↪entrenamiento:
df_test.iloc[0,26] = df_train.iloc[-1,0]
df_test.head()
```

[27]:
```
            SNo     Name Symbol        Date         High          Low  \
Date
2021-01-28  2832  Bitcoin    BTC 2021-01-28  33858.31099  30023.20683
2021-01-29  2833  Bitcoin    BTC 2021-01-29  38406.26096  32064.81419
2021-01-30  2834  Bitcoin    BTC 2021-01-30  34834.70830  32940.18691
2021-01-31  2835  Bitcoin    BTC 2021-01-31  34288.33148  32270.17602
2021-02-01  2836  Bitcoin    BTC 2021-02-01  34638.21349  32384.22811

                  Open        Close        Volume     Marketcap  …  \
Date                                                             …
2021-01-28  30441.04182  33466.09636  7.651716e+10  6.229100e+11  …
2021-01-29  34318.67169  34316.38765  1.178950e+11  6.387690e+11  …
2021-01-30  34295.93504  34269.52154  6.514183e+10  6.379250e+11  …
2021-01-31  34270.87759  33114.35775  5.275454e+10  6.164530e+11  …
2021-02-01  33114.57724  33537.17682  6.140040e+10  6.243490e+11  …

            Month_6  Month_7  Month_8  Month_9  Month_10  Month_11  Month_12  \
Date
2021-01-28        0        0        0        0         0         0         0
2021-01-29        0        0        0        0         0         0         0
2021-01-30        0        0        0        0         0         0         0
2021-01-31        0        0        0        0         0         0         0
2021-02-01        0        0        0        0         0         0         0

            log_value         Mean   CloseShift
Date
2021-01-28  10.418288  4415.425613   2831.00000
```

```
2021-01-29  10.443378  4415.425613  33466.09636
2021-01-30  10.442012  4415.425613  34316.38765
2021-01-31  10.407722  4415.425613  34269.52154
2021-02-01  10.420410  4415.425613  33114.35775

[5 rows x 27 columns]
```

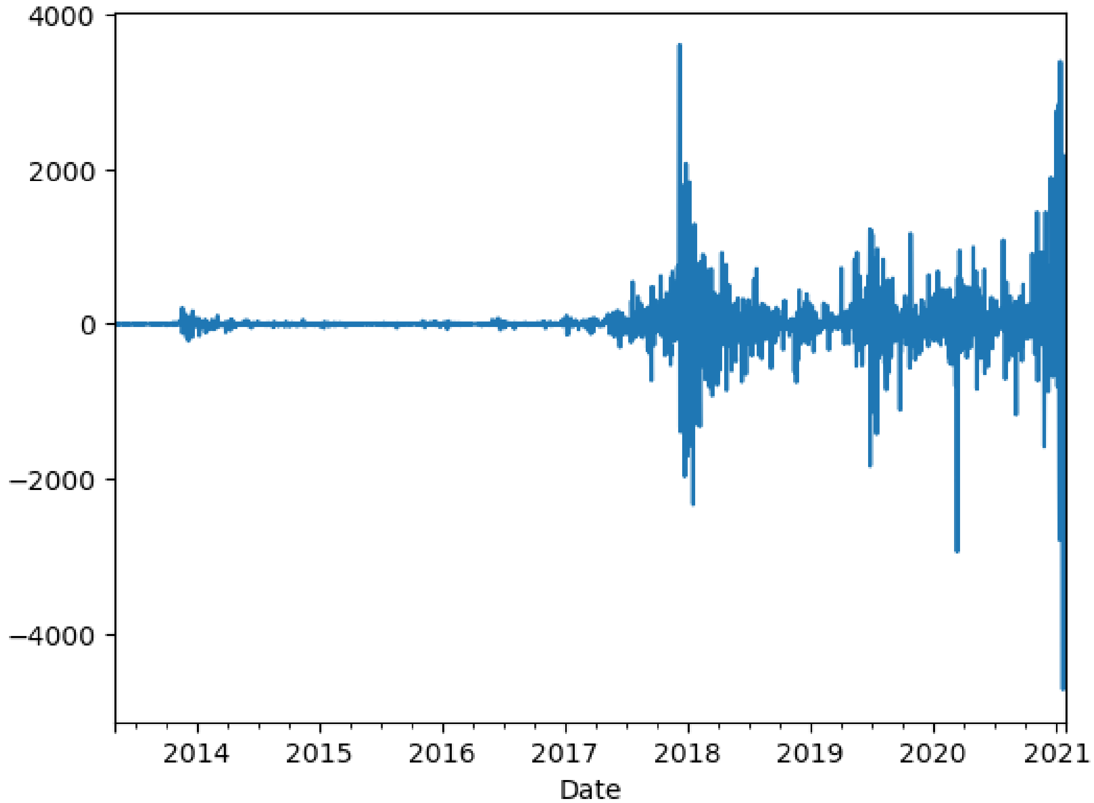
Lag de un período:

[28]:
```python
df_train.plot(kind= "scatter", y = "Close", x = "CloseShift", s = 50);
```



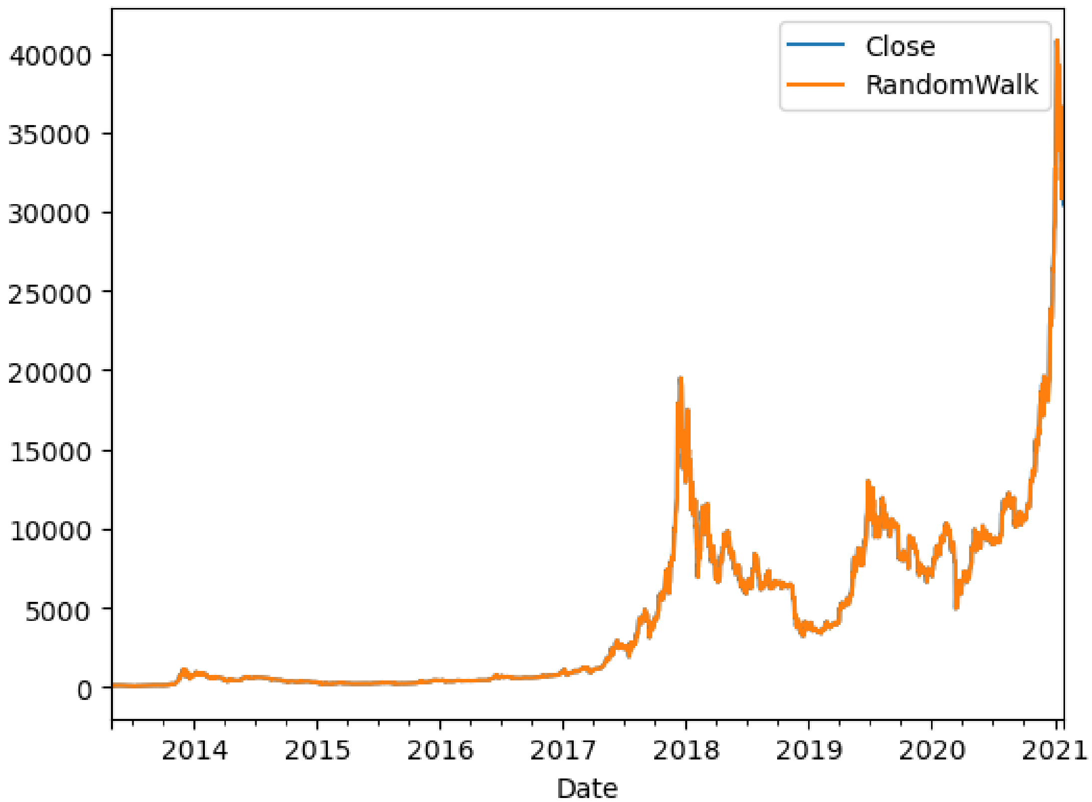
Diferencias entre Target y el lag:

[29]:
```python
df_train["Closediff"] = df_train.Close - df_train.CloseShift
df_train.Closediff.plot();
```



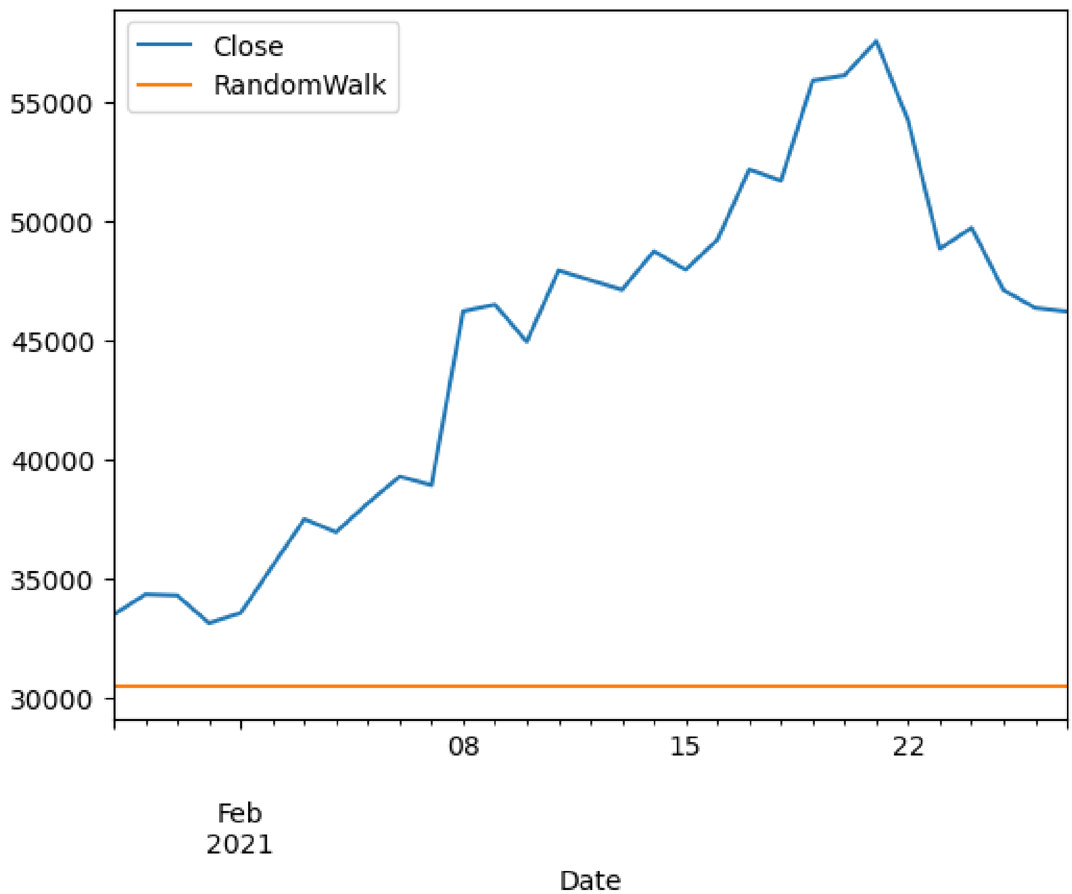
Ploteo de las predicciones vs las series reales, en train y test:

[30]:
```
df_train["RandomWalk"] = df_train.CloseShift
df_train.plot(kind="line", y = ["Close", "RandomWalk"]);
```



[31]:
```
df_test["RandomWalk"] = pd.Series(df_train["Close"][-1], index=df_test.index)
```

[32]:
```
df_test.plot(kind="line", y = ["Close", "RandomWalk"]);
```



Se calcula el MAPE + RMSE y se almacena

[33]:
```
model_MAPE = mean_absolute_percentage_error (df_test.Close , df_test.RandomWalk)
```

[34]:
```
df_Results.loc[1, "Model"] = "Random Walk"
df_Results.loc[1, "RMSE"] = RMSE(df_test.RandomWalk, df_test.Close)
df_Results.loc[1, "MAPE"] = model_MAPE
df_Results
```

[34]:

	Model	RMSE	MAPE
0	Mean	40968.433969	89.845161
1	Random Walk	16049.403917	30.009555

[35]:
```
# Para un resumen, se utiliza el Summary:
model_linear = smf.ols('Close ~ timeIndex', data = df_train).fit()
```

[36]:
```
model_linear.summary()
```

[36]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Close   R-squared:                       0.582
Model:                            OLS   Adj. R-squared:                  0.582
Method:                 Least Squares   F-statistic:                     3945.
Date:                Tue, 08 Aug 2023   Prob (F-statistic):               0.00
Time:                        21:29:28   Log-Likelihood:                -27197.
No. Observations:                2831   AIC:                         5.440e+04
Df Residuals:                    2829   BIC:                         5.441e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept  -2939.2871    135.218    -21.737      0.000   -3204.423   -2674.151
timeIndex      5.1977      0.083     62.811      0.000       5.035       5.360
==============================================================================
Omnibus:                     2081.927   Durbin-Watson:                   0.008
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            43129.622
Skew:                           3.304   Prob(JB):                         0.00
Kurtosis:                      20.943   Cond. No.                     3.27e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.27e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

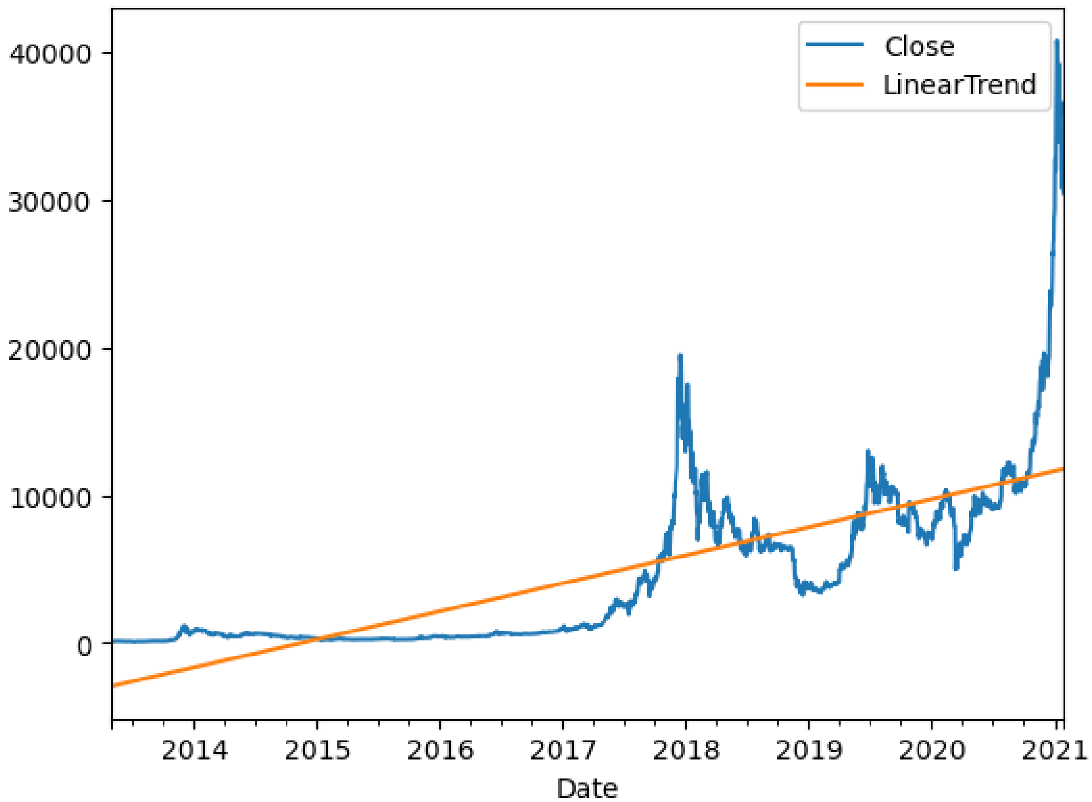
2.3 c) Linear Trend

Se crea una columna en train con el predict:

[37]:
```
df_train["LinearTrend"] = model_linear.predict(df_train.timeIndex)
```

Ploteo de las predicciones vs las series reales, en train y test:

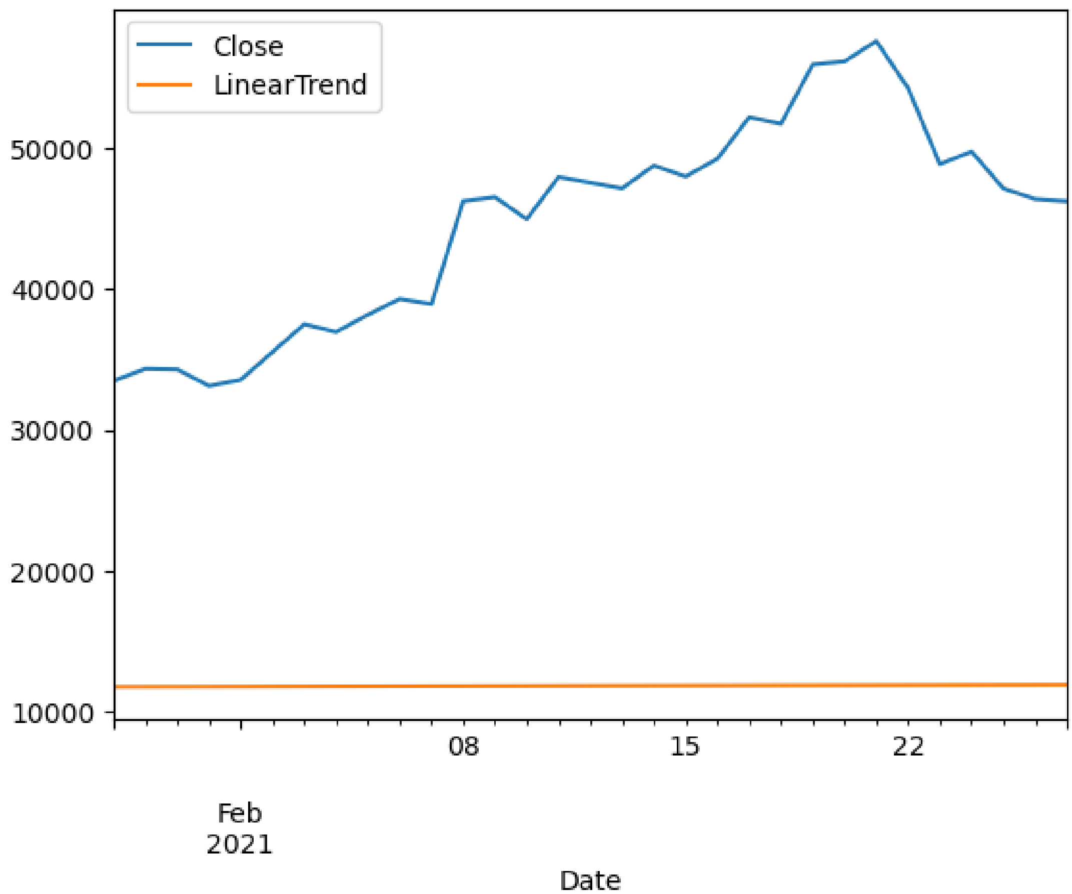
[38]:
```
df_train.plot(kind = "line", y = ["Close","LinearTrend"]);
```



Se repete en Test:

[39]:
```
df_test["LinearTrend"] = model_linear.predict(df_test.timeIndex)
```

[40]:
```
df_test.plot(kind = "line", y = ["Close","LinearTrend"]);
```



Se calcula el MAPE + RMSE y se almacena

[41]:
```
model_MAPE = mean_absolute_percentage_error (df_test.Close , df_test.
  ↪LinearTrend)
```

[42]:
```
df_Results.loc[2, "Model"] = "LinearTrend"
df_Results.loc[2, "RMSE"] = RMSE(df_test.LinearTrend, df_test.Close)
df_Results.loc[2, "MAPE"] = model_MAPE
df_Results
```

[42]:

	Model	RMSE	MAPE
0	Mean	40968.433969	89.845161
1	Random Walk	16049.403917	30.009555
2	LinearTrend	33666.922165	72.755041

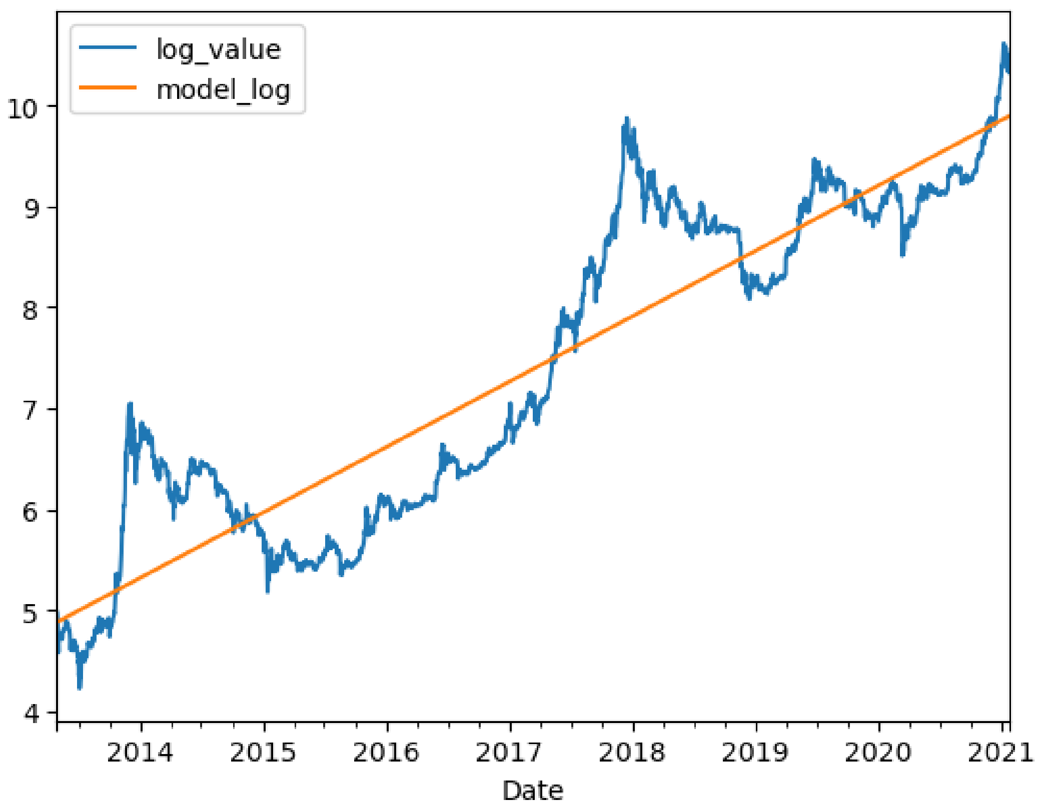
2.4 d) Transf Log

[43]:
```
df_train['model_log'] = model_log.predict(df_train[["timeIndex"]])
df_test['model_log'] = model_log.predict(df_test[["timeIndex"]])
```

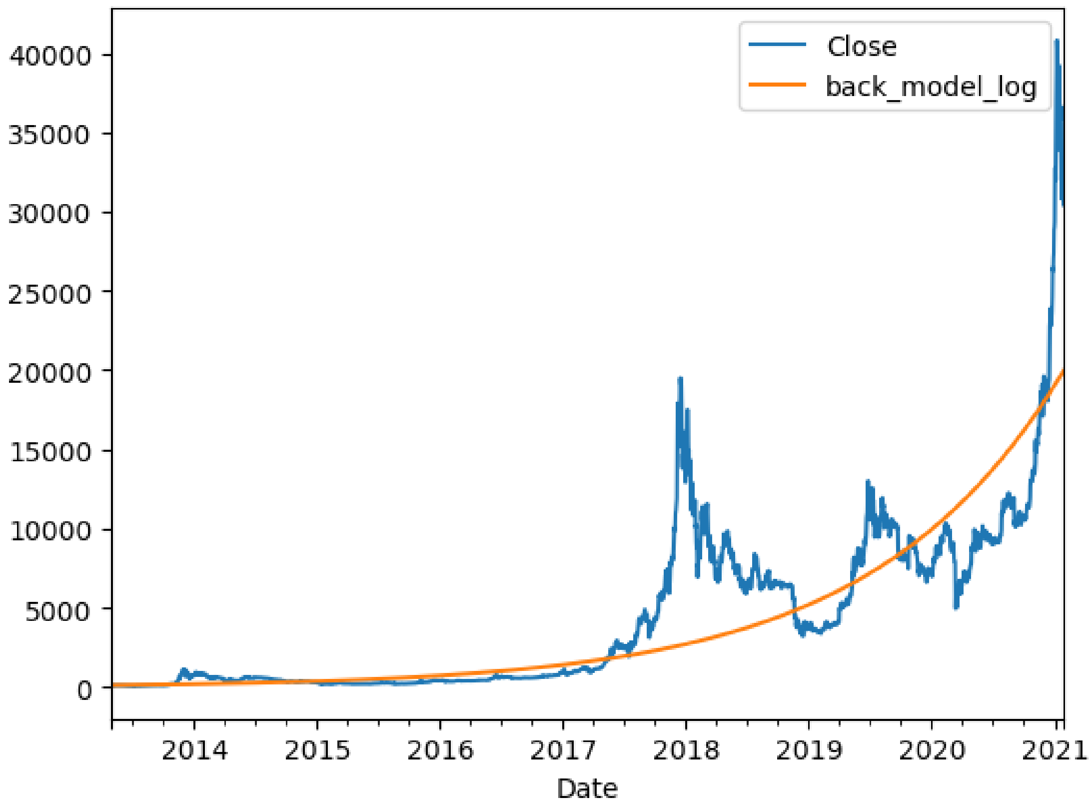
[44]:
```
df_train['back_model_log'] = np.exp(df_train['model_log'])
df_test['back_model_log'] = np.exp(df_test['model_log'])
```

Ploteo de las predicciones vs las series reales, en train y test:

[45]:
```
df_train.plot(kind = "line", x = "Date", y = ['log_value', 'model_log']);
```

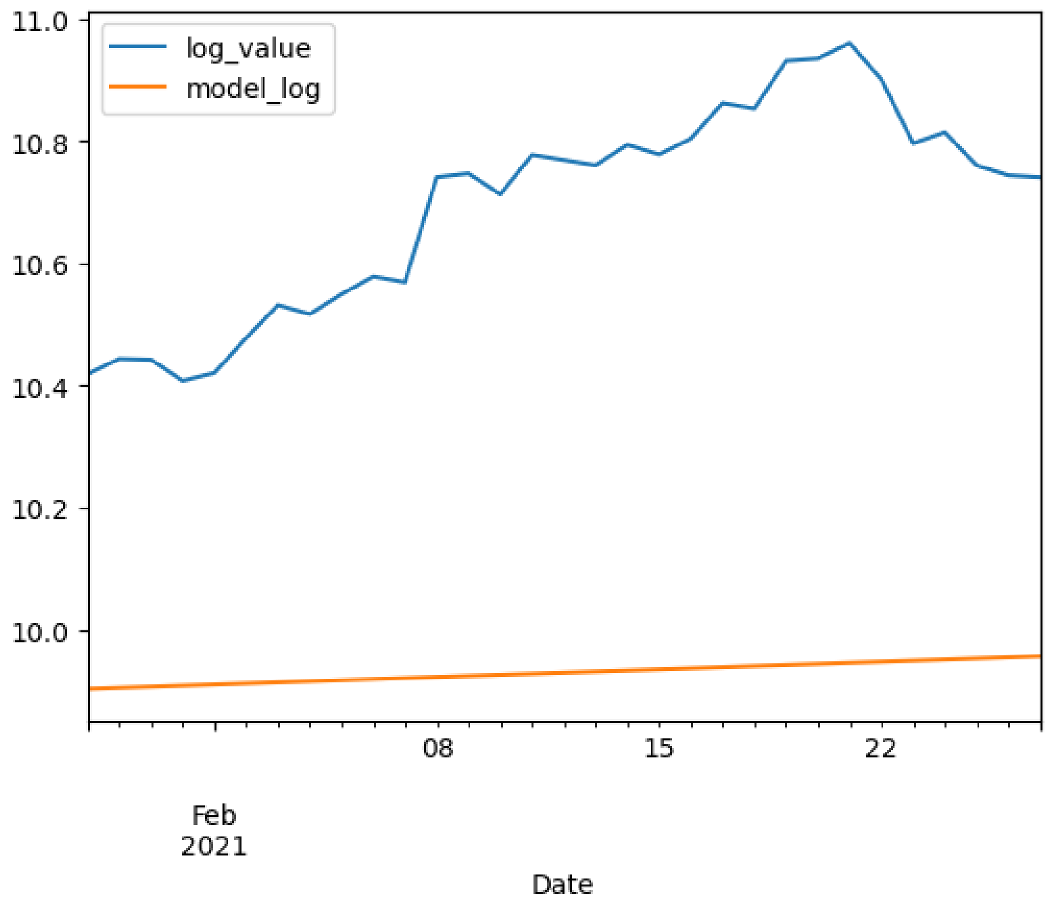


[46]:
```
df_train.plot(kind = "line", x = "Date", y = ['Close', 'back_model_log']);
```

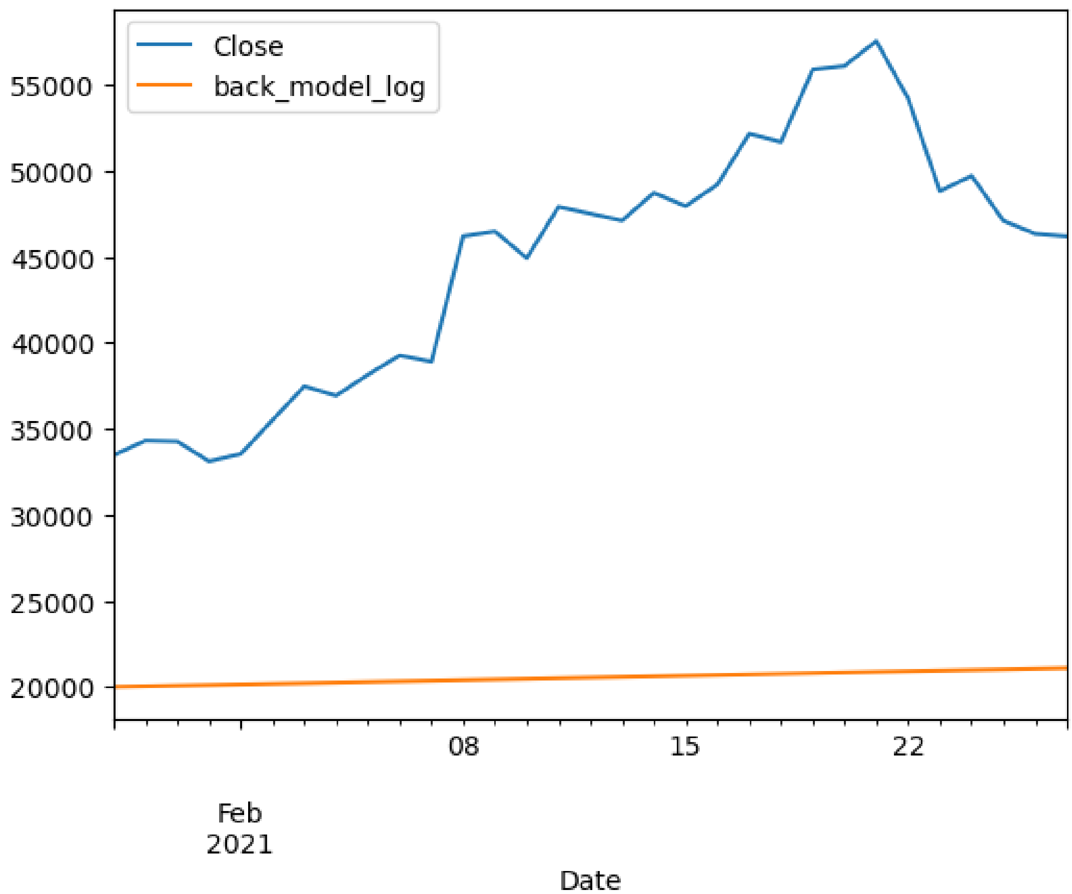


[47]:

```
df_test.plot(kind = "line", x = "Date", y = ['log_value', 'model_log']);
```




```
[48]: df_test.plot(kind = "line", x = "Date", y = ['Close', 'back_model_log']);
```



Se calcula el MAPE + RMSE y se almacena

[49]:
```
model_MAPE = mean_absolute_percentage_error (df_test.Close , df_test.
  ↪back_model_log)
```

[50]:
```
df_Results.loc[3, "Model"] = "Transf Log"
df_Results.loc[3, "RMSE"] = RMSE(df_test['back_model_log'], df_test['Close'])
df_Results.loc[3, "MAPE"] = model_MAPE
df_Results
```

[50]:

	Model	RMSE	MAPE
0	Mean	40968.433969	89.845161
1	Random Walk	16049.403917	30.009555
2	LinearTrend	33666.922165	72.755041
3	Transf Log	25190.683145	52.878589

2.5 e) Transf Log + Est

[51]:
```
model_log_est = smf.ols('log_value ~ timeIndex + Month_2 + Month_3 + Month_4 +␣
↪Month_5 + Month_6 + Month_7 + Month_8 + Month_9 + Month_11 + Month_12',\
                          data = df_train).fit()
```

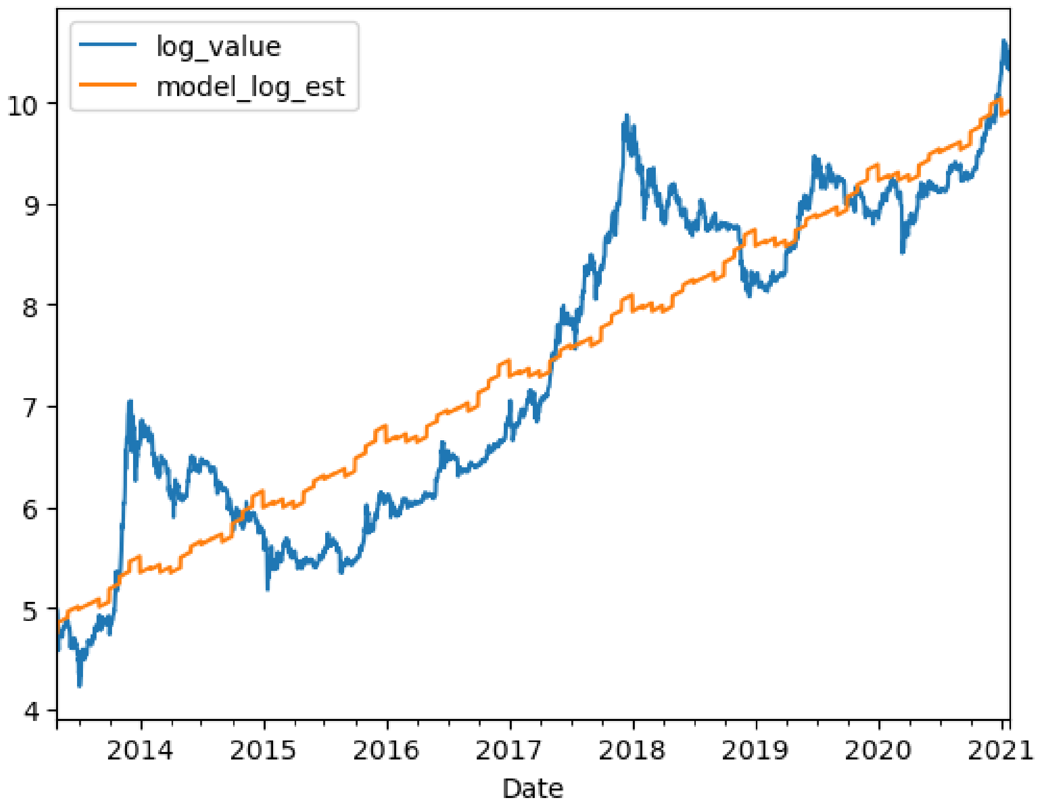
[52]:
```
df_train['model_log_est'] = model_log_est.predict(df_train[["timeIndex",\
                                              "Month_2", "Month_3", "Month_4",␣
↪"Month_5",\
                                               "Month_6","Month_7", "Month_8",␣
↪"Month_9","Month_10","Month_11","Month_12"]])


df_test['model_log_est'] = model_log_est.predict(df_test[["timeIndex",\
                                               "Month_2", "Month_3", "Month_4",␣
↪"Month_5",\
                                               "Month_6","Month_7", "Month_8",␣
↪"Month_9","Month_10","Month_11","Month_12"]])
```

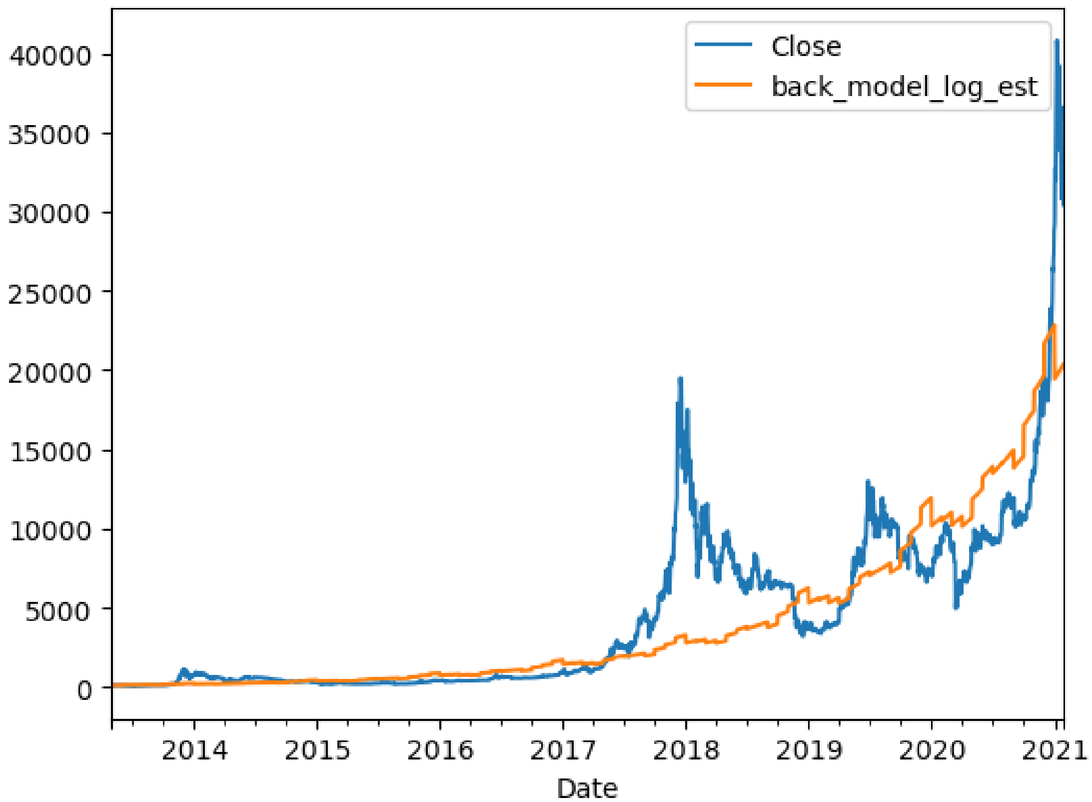
[53]:
```
df_train['back_model_log_est'] = np.exp(df_train['model_log_est'])
df_test['back_model_log_est'] = np.exp(df_test['model_log_est'])
```

Ploteo de las predicciones vs las series reales, en train y test:

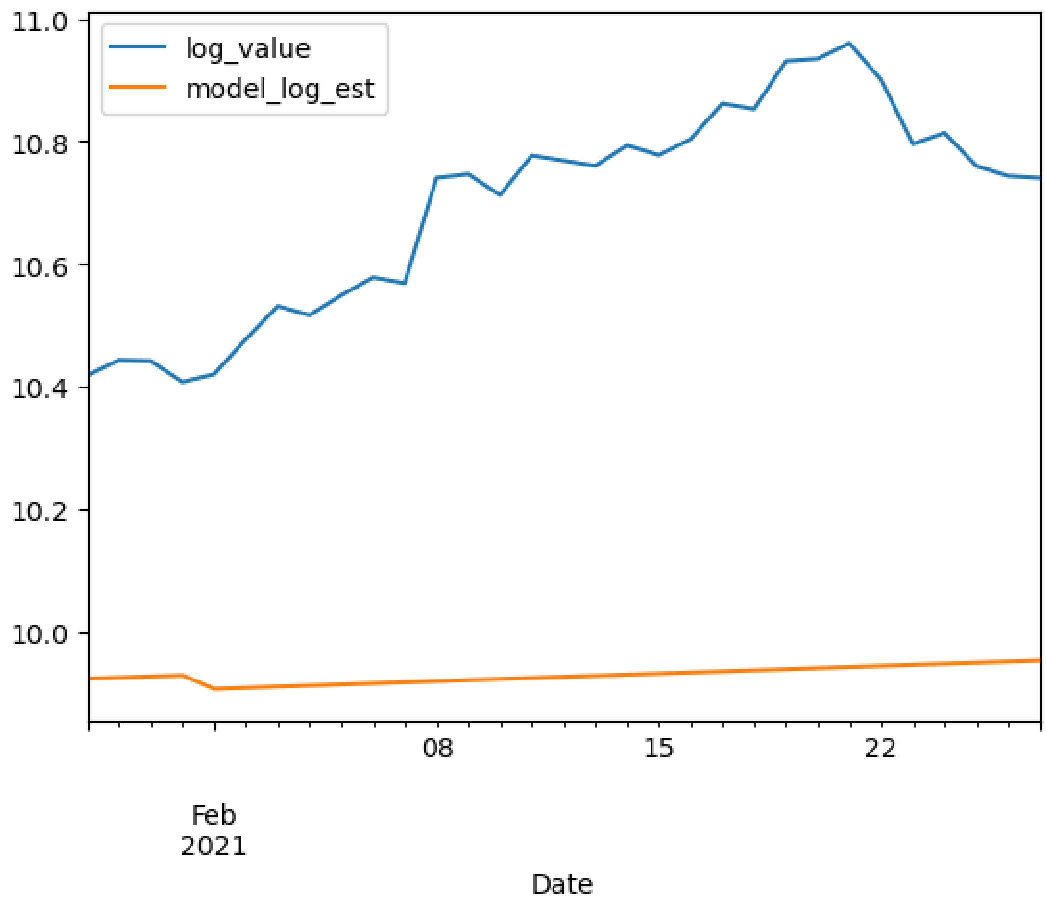
[54]:
```
df_train.plot(kind = "line", x = "Date", y = ['log_value', 'model_log_est']);
```



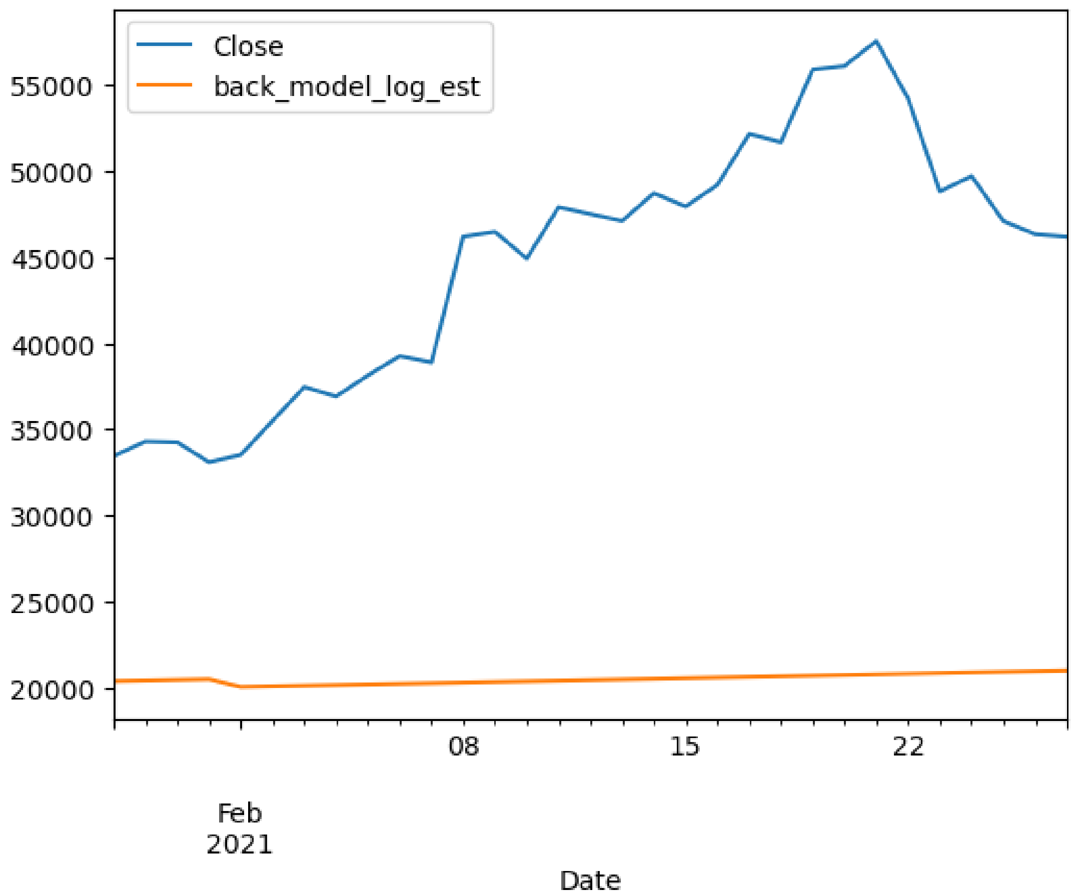
[55]:
```
df_train.plot(kind = "line", x = "Date", y = ['Close', 'back_model_log_est']);
```



[56]:
```
df_test.plot(kind = "line", x = "Date", y = ['log_value', 'model_log_est']);
```



[57]:
```
df_test.plot(kind = "line", x = "Date", y = ['Close', 'back_model_log_est']);
```



Se calcula el MAPE + RMSE y se almacena

[58]:
```
model_MAPE = mean_absolute_percentage_error (df_test.Close , df_test.
  ↪back_model_log_est)
```

[59]:
```
df_Results.loc[4, "Model"] = "Transf Log + est"
df_Results.loc[4, "RMSE"] = RMSE(df_test['back_model_log_est'],␣
  ↪df_test['Close'])
df_Results.loc[4, "MAPE"] = model_MAPE
df_Results
```

[59]:

	Model	RMSE	MAPE
0	Mean	40968.433969	89.845161
1	Random Walk	16049.403917	30.009555
2	LinearTrend	33666.922165	72.755041
3	Transf Log	25190.683145	52.878589
4	Transf Log + est	25219.962947	52.844384

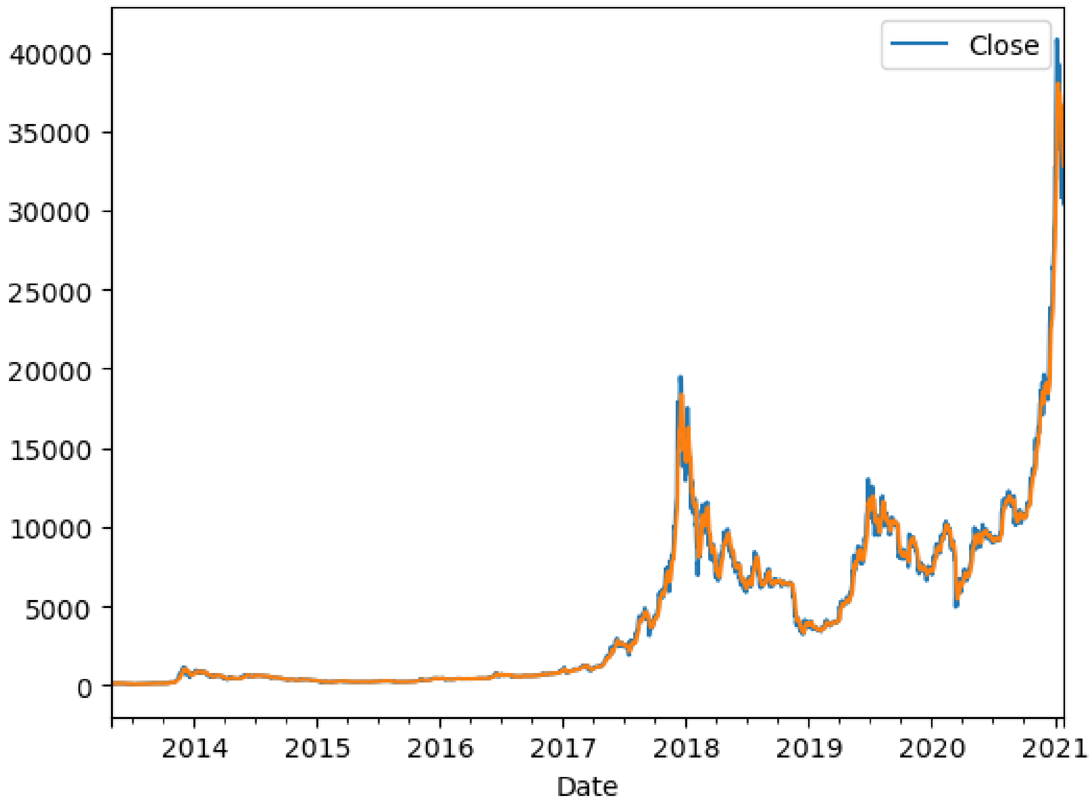
2.6 f) Simple Smoothing

Fiteo del modelo:

[60]:
```
model_exp_smoothing = SimpleExpSmoothing(df_train.Close).fit(smoothing_level=0.
↪3, optimized=False)
```

Ploteo de las predicciones vs las series reales, en train y test:

[61]:
```
df_train.plot(kind = "line", y = "Close")
model_exp_smoothing.fittedvalues.plot();
```



[62]:
```
# Se define cantidad de splits:
tscv = TimeSeriesSplit(n_splits=5)
```

[63]:
```
for train_index, val_index in tscv.split(df_train):
    print("TRAIN:", train_index, "VAL:", val_index)
```

```
TRAIN: [   0    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16   17
  18   19   20   21   22   23   24   25   26   27   28   29   30   31   32   33   34   35
  36   37   38   39   40   41   42   43   44   45   46   47   48   49   50   51   52   53
  54   55   56   57   58   59   60   61   62   63   64   65   66   67   68   69   70   71
  72   73   74   75   76   77   78   79   80   81   82   83   84   85   86   87   88   89
  90   91   92   93   94   95   96   97   98   99  100  101  102  103  104  105  106  107
```

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 1157 1158 1159 1160 1161 1162 1163 1164 1165 1166 1167 1168 1169 1170
 1171 1172 1173 1174 1175 1176 1177 1178 1179 1180 1181 1182 1183 1184
 1185 1186 1187 1188 1189 1190 1191 1192 1193 1194 1195 1196 1197 1198
 1199 1200 1201 1202 1203 1204 1205 1206 1207 1208 1209 1210 1211 1212
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 1395 1396 1397 1398 1399 1400 1401 1402 1403 1404 1405 1406 1407 1408
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TRAIN: [   0    1    2 … 1415 1416 1417] VAL: [1418 1419 1420 1421 1422 1423
1424 1425 1426 1427 1428 1429 1430 1431
 1432 1433 1434 1435 1436 1437 1438 1439 1440 1441 1442 1443 1444 1445
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 1516 1517 1518 1519 1520 1521 1522 1523 1524 1525 1526 1527 1528 1529
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 1852 1853 1854 1855 1856 1857 1858 1859 1860 1861 1862 1863 1864 1865
 1866 1867 1868 1869 1870 1871 1872 1873 1874 1875 1876 1877 1878 1879
 1880 1881 1882 1883 1884 1885 1886 1887 1888]
TRAIN: [   0    1    2 … 1886 1887 1888] VAL: [1889 1890 1891 1892 1893 1894
1895 1896 1897 1898 1899 1900 1901 1902
 1903 1904 1905 1906 1907 1908 1909 1910 1911 1912 1913 1914 1915 1916
 1917 1918 1919 1920 1921 1922 1923 1924 1925 1926 1927 1928 1929 1930
 1931 1932 1933 1934 1935 1936 1937 1938 1939 1940 1941 1942 1943 1944
 1945 1946 1947 1948 1949 1950 1951 1952 1953 1954 1955 1956 1957 1958
 1959 1960 1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972
 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986
 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000
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 2043 2044 2045 2046 2047 2048 2049 2050 2051 2052 2053 2054 2055 2056
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 2071 2072 2073 2074 2075 2076 2077 2078 2079 2080 2081 2082 2083 2084
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 2253 2254 2255 2256 2257 2258 2259 2260 2261 2262 2263 2264 2265 2266
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 2309 2310 2311 2312 2313 2314 2315 2316 2317 2318 2319 2320 2321 2322
 2323 2324 2325 2326 2327 2328 2329 2330 2331 2332 2333 2334 2335 2336
 2337 2338 2339 2340 2341 2342 2343 2344 2345 2346 2347 2348 2349 2350
 2351 2352 2353 2354 2355 2356 2357 2358 2359]
TRAIN: [   0    1    2 … 2357 2358 2359] VAL: [2360 2361 2362 2363 2364 2365
2366 2367 2368 2369 2370 2371 2372 2373
 2374 2375 2376 2377 2378 2379 2380 2381 2382 2383 2384 2385 2386 2387
 2388 2389 2390 2391 2392 2393 2394 2395 2396 2397 2398 2399 2400 2401
 2402 2403 2404 2405 2406 2407 2408 2409 2410 2411 2412 2413 2414 2415
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 2444 2445 2446 2447 2448 2449 2450 2451 2452 2453 2454 2455 2456 2457
 2458 2459 2460 2461 2462 2463 2464 2465 2466 2467 2468 2469 2470 2471
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 2640 2641 2642 2643 2644 2645 2646 2647 2648 2649 2650 2651 2652 2653
 2654 2655 2656 2657 2658 2659 2660 2661 2662 2663 2664 2665 2666 2667
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 2682 2683 2684 2685 2686 2687 2688 2689 2690 2691 2692 2693 2694 2695
 2696 2697 2698 2699 2700 2701 2702 2703 2704 2705 2706 2707 2708 2709
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 2794 2795 2796 2797 2798 2799 2800 2801 2802 2803 2804 2805 2806 2807
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 2822 2823 2824 2825 2826 2827 2828 2829 2830]
```

Creación de una función para aplicar Cross Validation

[64]:
```
def timeseriesCVscore_exp_smoot(alpha, series):
    """
        Devuelve errores en CV

        slen - longitud de la sesión para modelo Holt-Winters
    """
    # Se crea un array de errores:
    errors = []
    values = series.values

    # Se instancia el objeto que realiza el tscv:
    tscv = TimeSeriesSplit(n_splits=5)

    # Se aplica cross validation:
    for train, test in tscv.split(values):

        model = SimpleExpSmoothing(values[train]).fit(smoothing_level = alpha,␣
 ↪optimized=False)
        predictions = model.forecast(len(test))
        actual = values[test]

        error = mean_squared_error(predictions, actual)
        errors.append(error)

    return np.mean(np.array(errors))
```

Aplicación de la función

[65]:
```
alphas = [0.001, 0.01, 0.1, 0.2, 0.3, 0.35, 0.4, 0.5, 0.7]
errors = []

for alpha in alphas:
    error = timeseriesCVscore_exp_smoot(alpha, df_train.Close)
    errors.append(error)

print('Alpha óptimo:', alphas[np.argmin(errors)])
```

```
Alpha óptimo: 0.1
```

[66]:
```
model_exp_smoothing = SimpleExpSmoothing(df_train.Close).
 ↪fit(smoothing_level=alphas[np.argmin(errors)], optimized=False)
```

[67]:
```
df_test["Simple_Smoothing"] = model_exp_smoothing.forecast(len(df_test))
df_test.head()
```

[67]:
```
                SNo     Name Symbol       Date         High          Low  \
Date
2021-01-28  2832  Bitcoin    BTC 2021-01-28  33858.31099  30023.20683
2021-01-29  2833  Bitcoin    BTC 2021-01-29  38406.26096  32064.81419
2021-01-30  2834  Bitcoin    BTC 2021-01-30  34834.70830  32940.18691
2021-01-31  2835  Bitcoin    BTC 2021-01-31  34288.33148  32270.17602
2021-02-01  2836  Bitcoin    BTC 2021-02-01  34638.21349  32384.22811

                   Open        Close        Volume     Marketcap  …  \
Date                                                              …
2021-01-28  30441.04182  33466.09636  7.651716e+10  6.229100e+11  …
2021-01-29  34318.67169  34316.38765  1.178950e+11  6.387690e+11  …
2021-01-30  34295.93504  34269.52154  6.514183e+10  6.379250e+11  …
2021-01-31  34270.87759  33114.35775  5.275454e+10  6.164530e+11  …
2021-02-01  33114.57724  33537.17682  6.140040e+10  6.243490e+11  …

            log_value         Mean   CloseShift   RandomWalk   LinearTrend  \
Date
2021-01-28  10.418288  4415.425613   2831.00000  30432.54708  11775.336020
2021-01-29  10.443378  4415.425613  33466.09636  30432.54708  11780.533697
2021-01-30  10.442012  4415.425613  34316.38765  30432.54708  11785.731374
2021-01-31  10.407722  4415.425613  34269.52154  30432.54708  11790.929051
2021-02-01  10.420410  4415.425613  33114.35775  30432.54708  11796.126727

            model_log  back_model_log  model_log_est  back_model_log_est  \
Date
2021-01-28   9.903266    19995.562080       9.923727        20408.903014
2021-01-29   9.905039    20031.053582       9.925496        20445.051836
2021-01-30   9.906812    20066.608080       9.927266        20481.264685
2021-01-31   9.908586    20102.225685       9.929035        20517.541675
2021-02-01   9.910359    20137.906512       9.907257        20075.524059

            Simple_Smoothing
Date
2021-01-28       33347.84119
2021-01-29       33347.84119
2021-01-30       33347.84119
2021-01-31       33347.84119
2021-02-01       33347.84119

[5 rows x 34 columns]
```

Se calcula el MAPE + RMSE y se almacena

[68]:
```
model_MAPE = mean_absolute_percentage_error(df_test.Close , df_test.
  ↪Simple_Smoothing)
```

[69]:
```
# Calculamos el RMSE y almacenamos los resultados
df_Results.loc[5, "Model"] = "Simple Smoothing"
df_Results.loc[5, "RMSE"] = RMSE(df_test["Simple_Smoothing"], df_test.Close)
df_Results.loc[5, "MAPE"] = model_MAPE

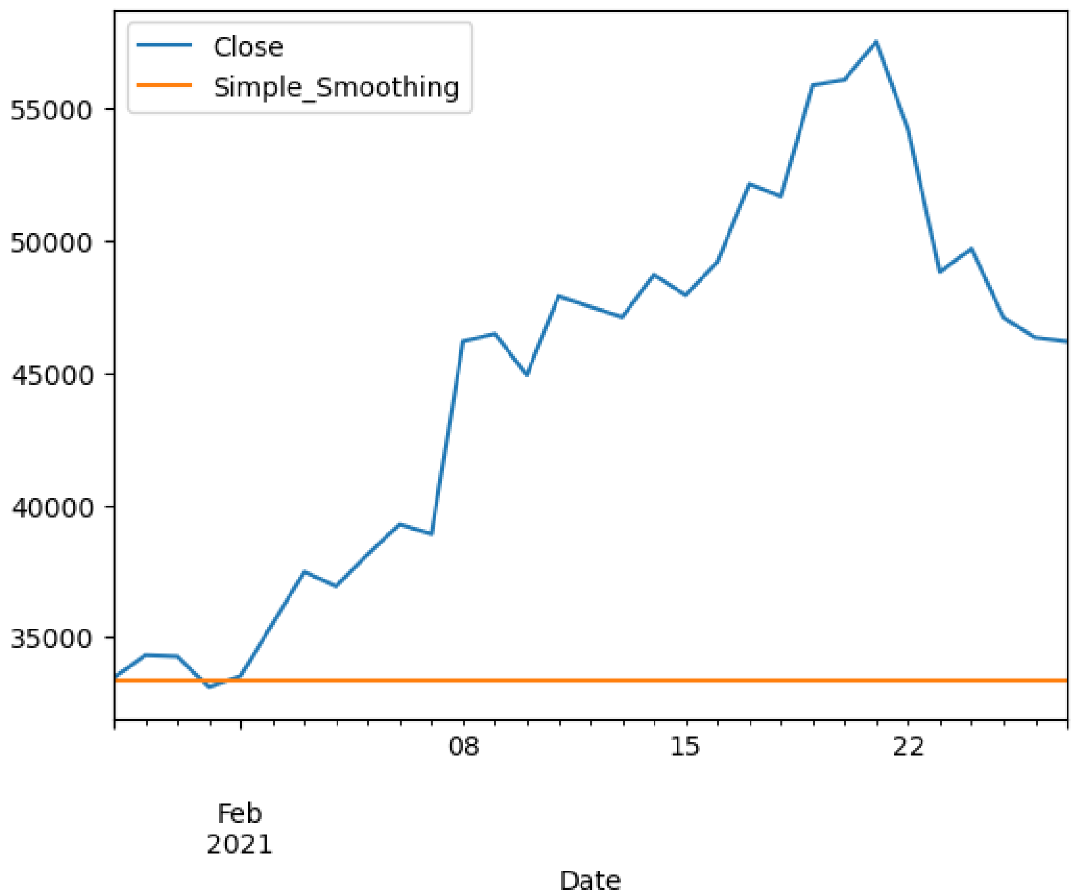
df_Results
```

[69]:

	Model	RMSE	MAPE
0	Mean	40968.433969	89.845161
1	Random Walk	16049.403917	30.009555
2	LinearTrend	33666.922165	72.755041
3	Transf Log	25190.683145	52.878589
4	Transf Log + est	25219.962947	52.844384
5	Simple Smoothing	13517.463589	23.350291

Ploteo de las predicciones vs las series reales, en train y test:

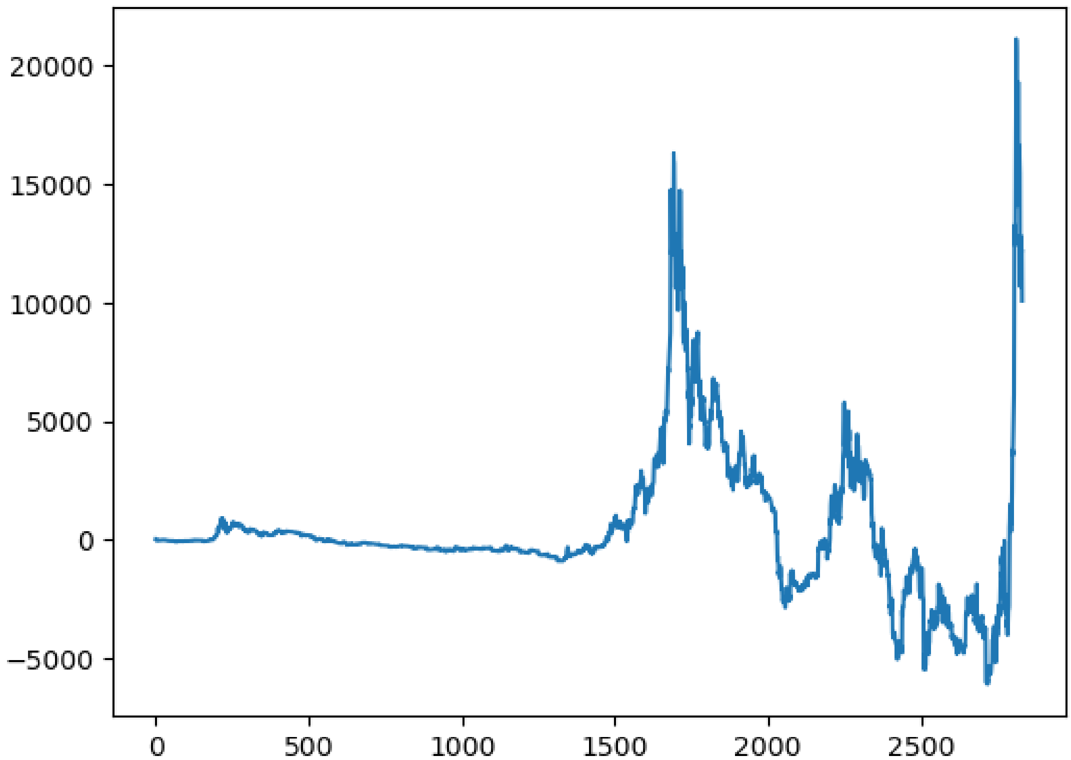
[70]:
```
df_test.plot(kind="line", y = ["Close", "Simple_Smoothing"]);
```



2.7 g) Dickey Fuller + Autocorrelación

Se prueba si los residuos son estacionarios

[71]:
```
residuo = df_train['Close'] - df_train['back_model_log_est']
plt.plot(df_train.timeIndex, residuo, '-');
```



Aplicación de Dickey Fuller al residuo:

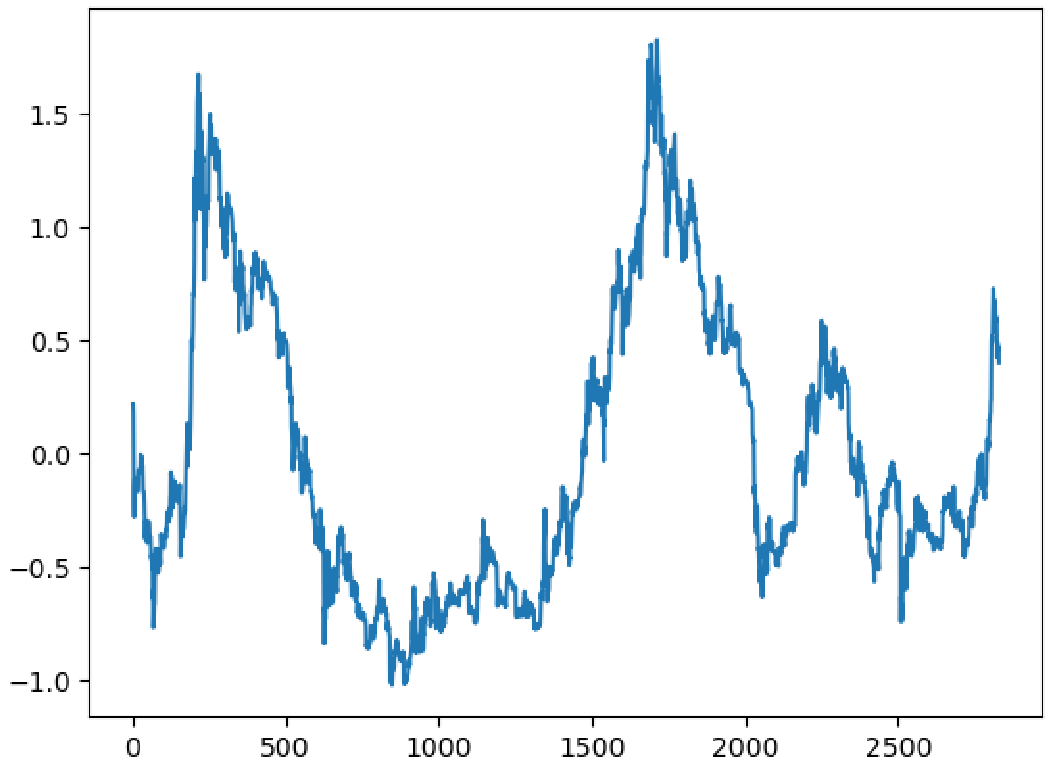
[72]:
```
result = adfuller(residuo)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
for key, value in  result[4].items():
    print('Valor crítico %s: %.2f' % (key,value))
```

```
ADF Statistic: -2.831115
p-value: 0.053965
Valor crítico 1%: -3.43
Valor crítico 5%: -2.86
Valor crítico 10%: -2.57
```

No se puede rechazar la H0 con un nivel de significación del 5%.

[73]:
```
# Se prueba ahora con los residuos antes de realizar back transform:
res_log_est = df_train['log_value'] - df_train['model_log_est']
```

```
plt.plot(df_train.timeIndex, res_log_est, '-');
```



Segundo testeo de la estacionalidad de los residuos:

[74]:
```
from statsmodels.tsa.stattools import adfuller

result = adfuller(res_log_est)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
for key, value in  result[4].items():
    print('Valor crítico %s: %.2f' % (key,value))
```

```
ADF Statistic: -2.176515
p-value: 0.214879
Valor crítico 1%: -3.43
Valor crítico 5%: -2.86
Valor crítico 10%: -2.57
```

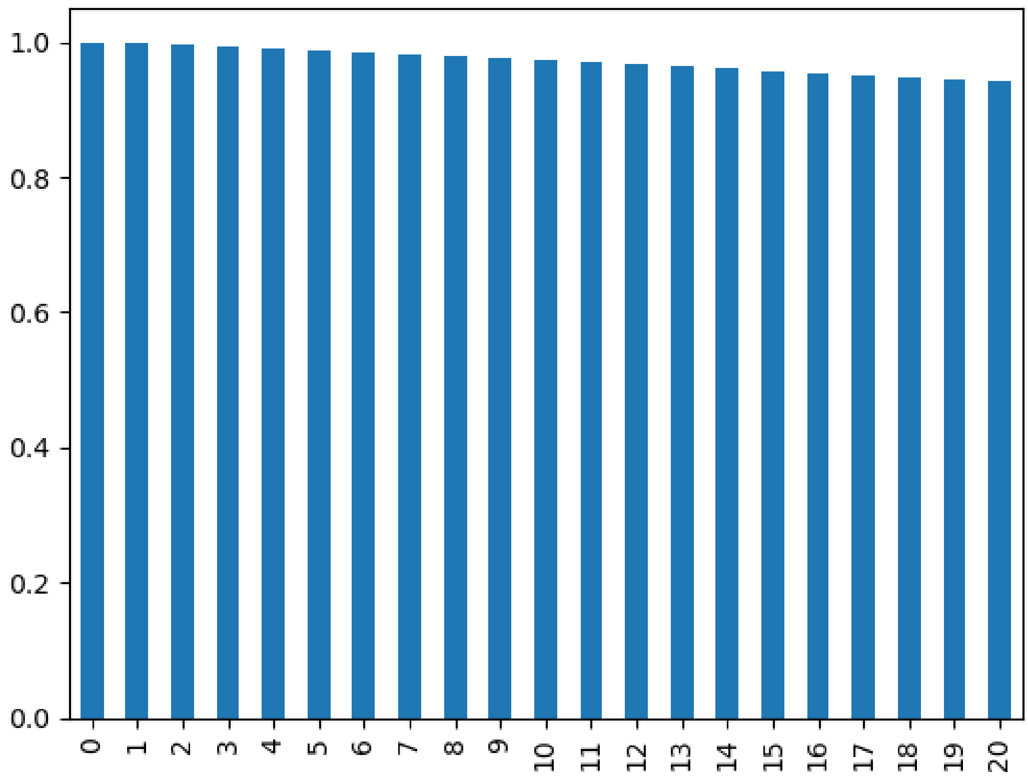
Aún no se puede rechazar la H0, pero se continúa el análisis

[75]:
```
# Cálculo del res_log con 20 rezagos:
lag_acf = acf(res_log_est, nlags = 20)
lag_acf
```

[75]: array([1.   , 0.9973684 , 0.99471906, 0.99215484, 0.98968734,
        0.98710619, 0.98434791, 0.98131918, 0.97840278, 0.97558444,
        0.97280571, 0.969828 , 0.96671826, 0.9635972 , 0.96047466,
        0.95735437, 0.95426951, 0.95116815, 0.94768699, 0.94429688,
        0.94100531])

Se almacena la serie ACF y se plotea:

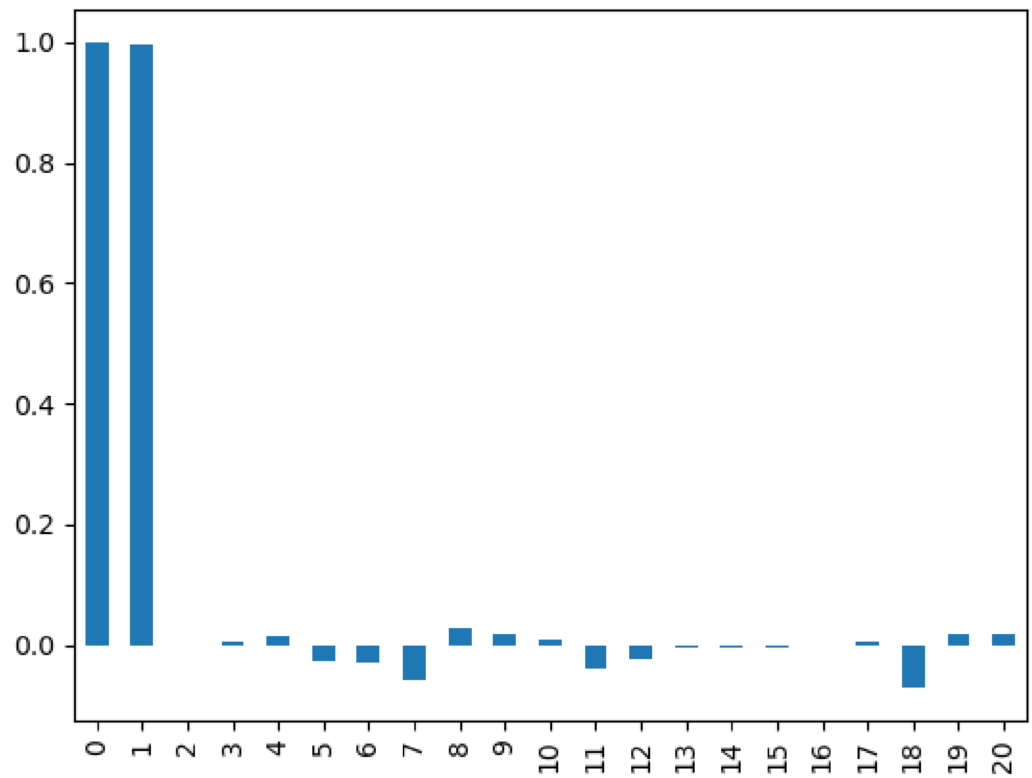
[76]:
```
ACF = pd.Series(lag_acf)
ACF.plot(kind = "bar");
```



Se repiten los pasos anteriores pero con PACF:

[77]:
```
lag_pacf = pacf(res_log_est, nlags=20, method='ols');
```

[78]:
```
PACF = pd.Series(lag_pacf)
PACF.plot(kind = "bar");
```



Se puede concluir de este análisis que la correlación indirecta es alta, pero la parcial que considera solo influencia directa de cada período es absoluta en tan solo un mes antes del momento a analizar: esto habla de la alta volatilidad del caso a analizar, ya que se deduce de la herramienta y los datos que es de poca utilidad para la predicción de valores en las criptomonedas la utilización de información de más de un mes atrás

Se crea una función para plotear una serie con información sobre los ACF y PACF y su estacionalidad:

[79]:
```
def tsplot(y, lags=None, figsize=(12, 7), style='bmh'):
    """
        Plotea la serie de tiempo, el ACF y PACF y el test de Dickey-Fuller

        y - serie de tiempo
        lags - cuántos lags incluir para el cálculo de la ACF y PACF

    """
    if not isinstance(y, pd.Series):
        y = pd.Series(y)

    with plt.style.context(style):
        fig = plt.figure(figsize=figsize)
        layout = (2, 2)
```

```
    # Se definen ejes
    ts_ax = plt.subplot2grid(layout, (0, 0), colspan=2)
    acf_ax = plt.subplot2grid(layout, (1, 0))
    pacf_ax = plt.subplot2grid(layout, (1, 1))

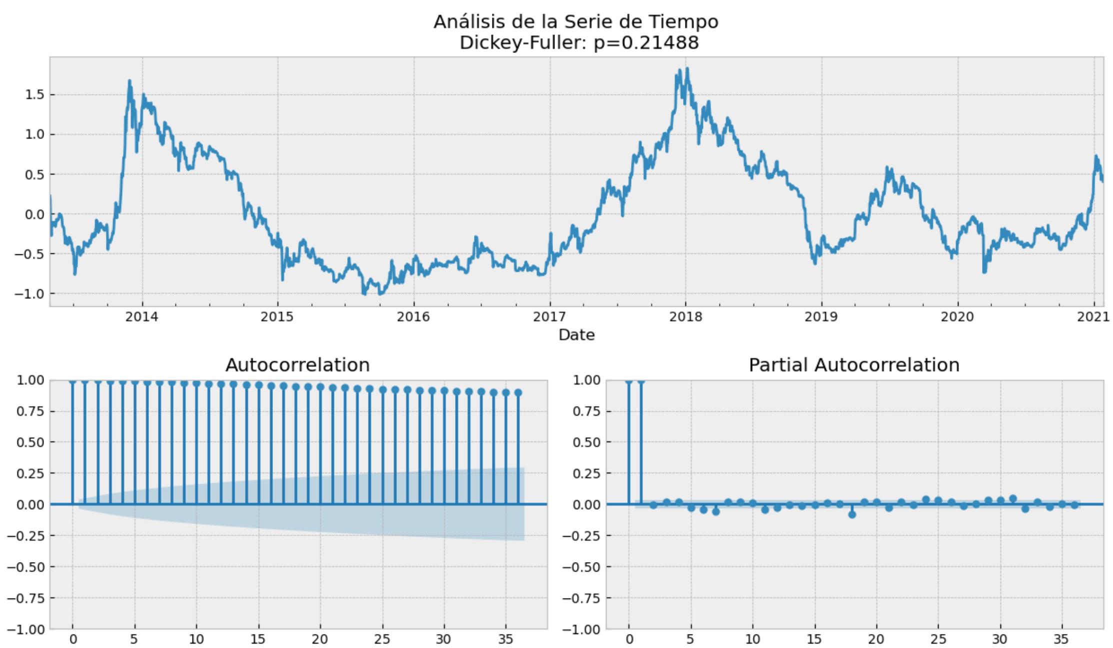
    y.plot(ax=ts_ax)

    # Se obtiene el p-value con H0: raiz unitaria presente
    p_value = sm.tsa.stattools.adfuller(y)[1]

    ts_ax.set_title('Análisis de la Serie de Tiempo\n Dickey-Fuller: p={0:.
↪5f}'\
                    .format(p_value))

    # Plot de autocorrelacion
    smt.graphics.plot_acf(y, lags=lags, ax=acf_ax)
    # Plot de autocorrelacion parcial
    smt.graphics.plot_pacf(y, lags=lags, ax=pacf_ax)
    plt.tight_layout()
```

[80]:
```
# Aplicación de la función con la serie res_log:
tsplot(res_log_est, lags=36)
```



2.8 h) ARIMA

Se aplica el auto_arima sobre res_log_est

[81]:
```
stepwise_fit = auto_arima(res_log_est, trace=True, suppress_warnings=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=-9444.242, Time=1.04 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=-9452.140, Time=0.38 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=-9450.140, Time=0.55 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=-9450.140, Time=1.20 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=-9454.135, Time=0.23 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=-9448.140, Time=0.55 sec

Best model:  ARIMA(0,1,0)(0,0,0)[0]
Total fit time: 3.955 seconds
```

Como se obtuvo mejores resultados con p=2 y q=1, s aplica:

[82]:
```
model_ARIMA = ARIMA(res_log_est, order=(2,0,1))

# Estimación del modelo:
results_ARIMA = model_ARIMA.fit()
results_ARIMA.fittedvalues.head()
```

[82]:
```
Date
2013-04-29    0.037648
2013-04-30    0.221391
2013-05-01    0.181000
2013-05-02   -0.091703
2013-05-03   -0.202132
Freq: D, dtype: float64
```

Se observa el summary:

[83]:
```
print(results_ARIMA.summary())
```

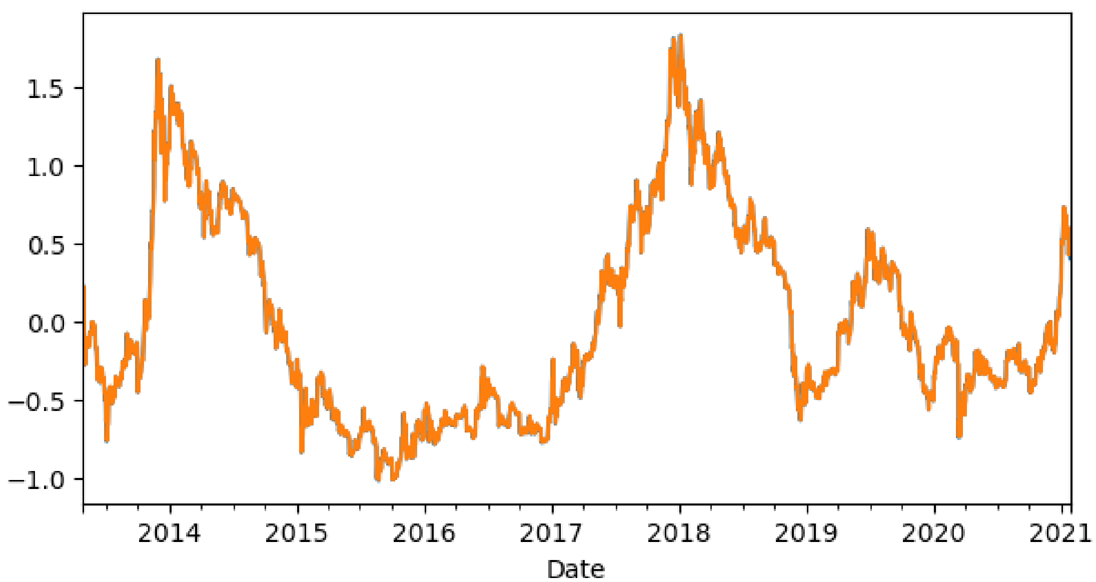
```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 2831
Model:                 ARIMA(2, 0, 1)   Log Likelihood                4729.821
Date:                Tue, 08 Aug 2023   AIC                          -9449.641
Time:                        21:29:45   BIC                          -9419.899
Sample:                    04-29-2013   HQIC                         -9438.911
                         - 01-27-2021
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0376      0.308      0.122      0.903      -0.567       0.642
ar.L1          0.0797      0.115      0.694      0.488      -0.145       0.305
```

```
ar.L2          0.9147      0.114      7.997      0.000      0.691      1.139
ma.L1          0.9094      0.119      7.652      0.000      0.677      1.142
sigma2         0.0021   2.26e-05     91.558      0.000      0.002      0.002
================================================================================
===
Ljung-Box (L1) (Q):                   0.30   Jarque-Bera (JB):
12186.52
Prob(Q):                              0.59   Prob(JB):
0.00
Heteroskedasticity (H):               0.65   Skew:
-0.45
Prob(H) (two-sided):                  0.00   Kurtosis:
13.12
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

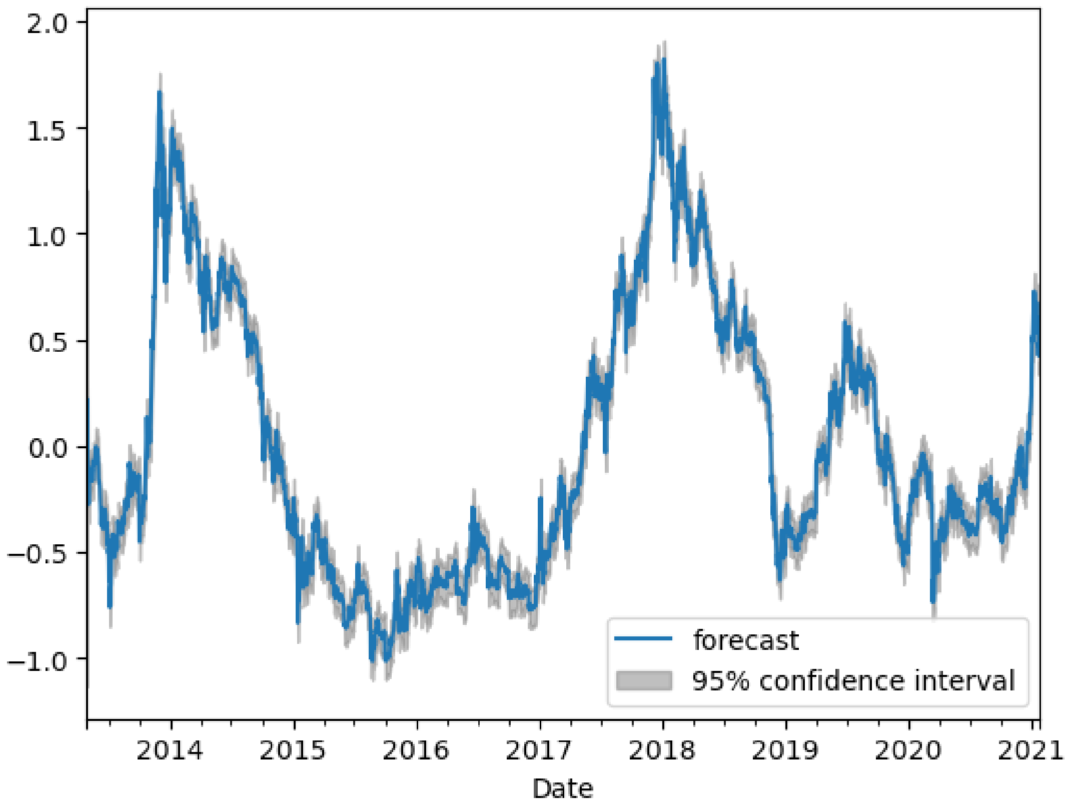
Ploteo de resultados:

[84]:
```
plt.figure(figsize=(7,3.5))
res_log_est.plot()
results_ARIMA.fittedvalues.plot();
```

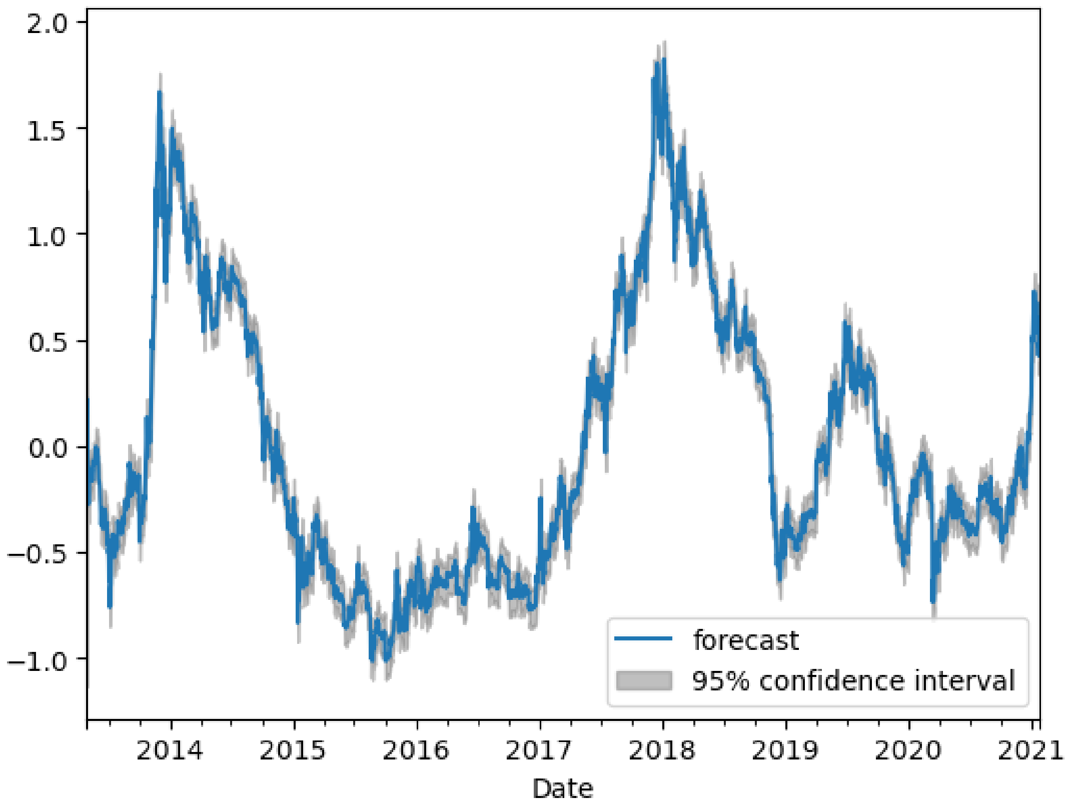


[85]:
```
plot_predict(results_ARIMA)
```

[85]:



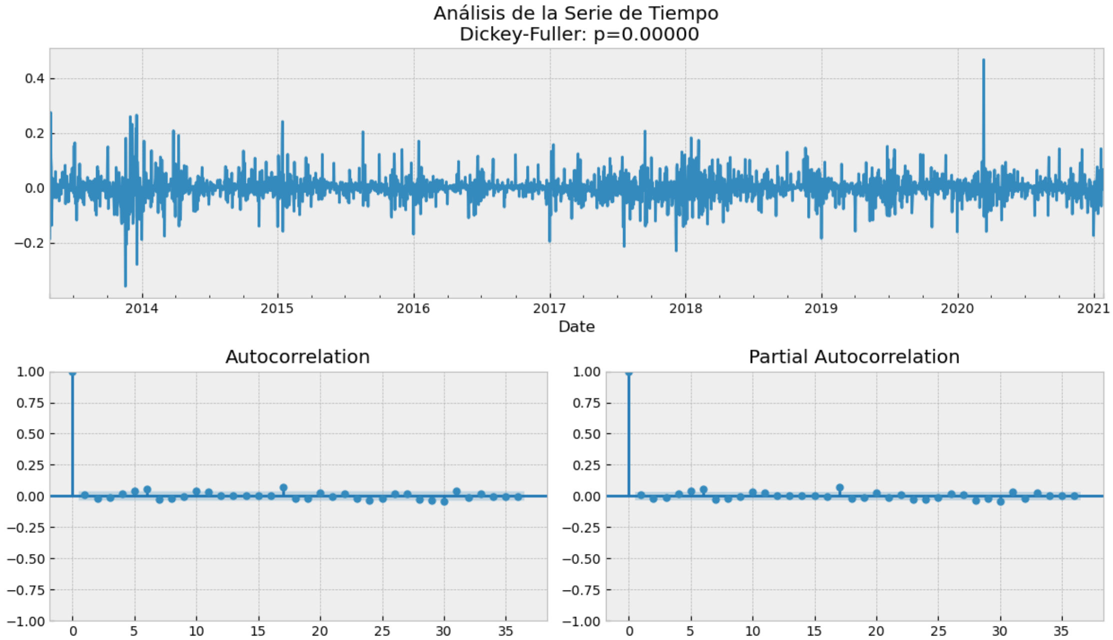
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
forecast
95% confidence interval
2014
2015
2016
2017
2018
2019
2020
2021
Date



Análisis de los residuos del modelo ARIMA:

[86]:
```
res_ARIMA =  results_ARIMA.fittedvalues - res_log_est
```

[87]:
```
tsplot(res_ARIMA, lags=36)
```



Aplicación del método Forecast:

[88]:
```
forecast = results_ARIMA.forecast(len(df_test['Close']), alpha=0.05)
print(forecast)
```

```
2021-01-28    0.401940
2021-01-29    0.399350
2021-01-30    0.399719
2021-01-31    0.397379
2021-02-01    0.397529
2021-02-02    0.395401
2021-02-03    0.395369
2021-02-04    0.393420
2021-02-05    0.393235
2021-02-06    0.391437
2021-02-07    0.391125
2021-02-08    0.389455
2021-02-09    0.389037
2021-02-10    0.387476
2021-02-11    0.386969
2021-02-12    0.385501
2021-02-13    0.384919
2021-02-14    0.383530
2021-02-15    0.382888
2021-02-16    0.381566
2021-02-17    0.380873
2021-02-18    0.379608
```

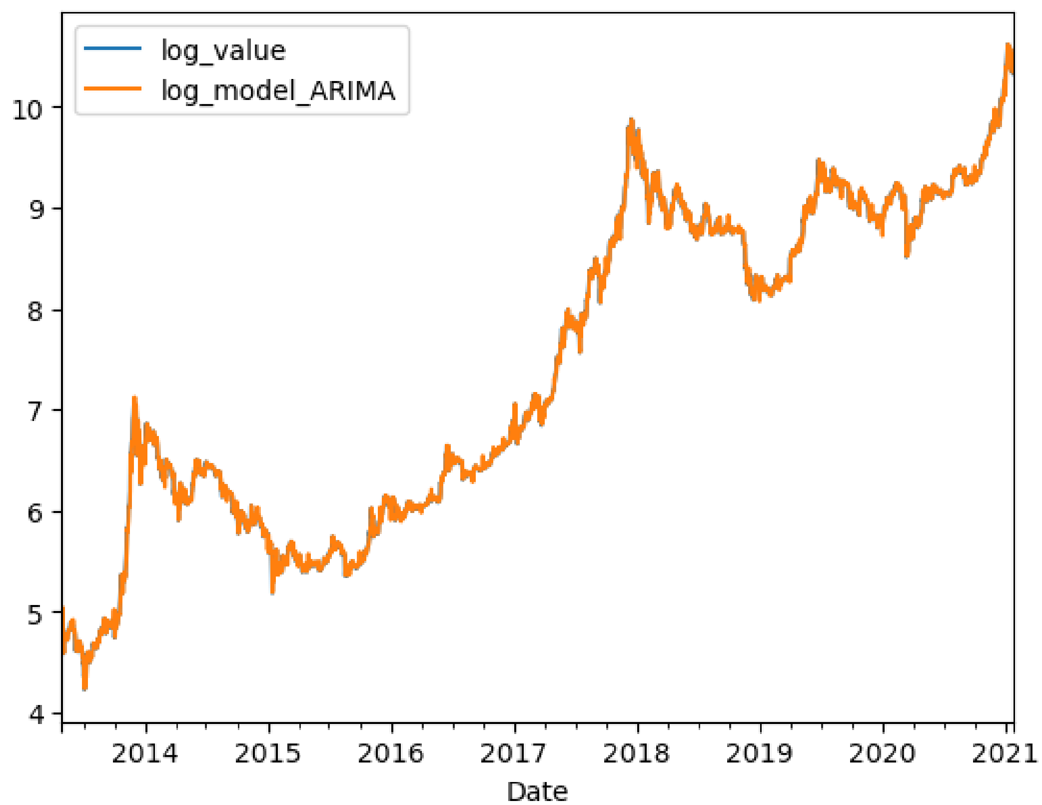
```
2021-02-19    0.378874
2021-02-20    0.377658
2021-02-21    0.376889
2021-02-22    0.375716
2021-02-23    0.374919
2021-02-24    0.373783
2021-02-25    0.372963
2021-02-26    0.371858
2021-02-27    0.371021
Freq: D, Name: predicted_mean, dtype: float64
```

[89]:
```
# Se crea una variable para el train y otra para el test:

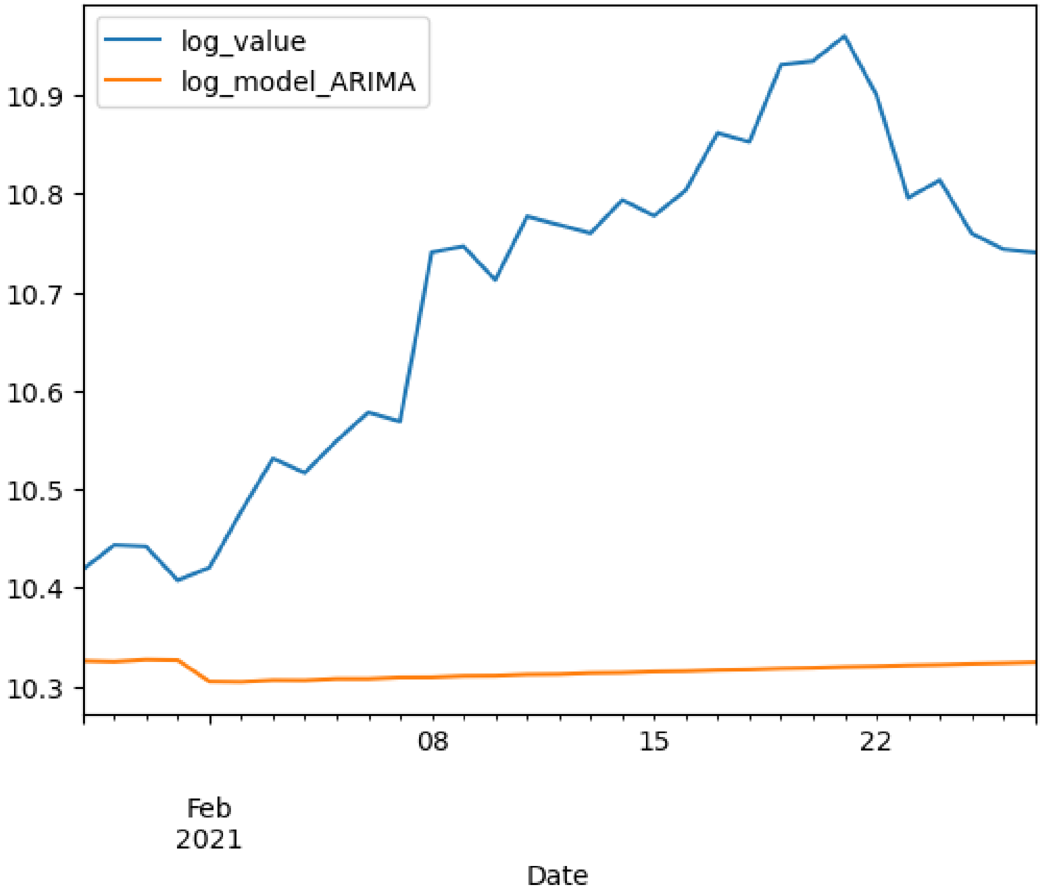
df_train['log_model_ARIMA'] = df_train['model_log_est'] + results_ARIMA.
 ↪fittedvalues
df_test['log_model_ARIMA'] = df_test['model_log_est'] + forecast
```

Ploteo de las predicciones vs las series reales, en train y test:

[90]:
```
df_train.plot(kind = "line", y = ['log_value', 'log_model_ARIMA']);
```



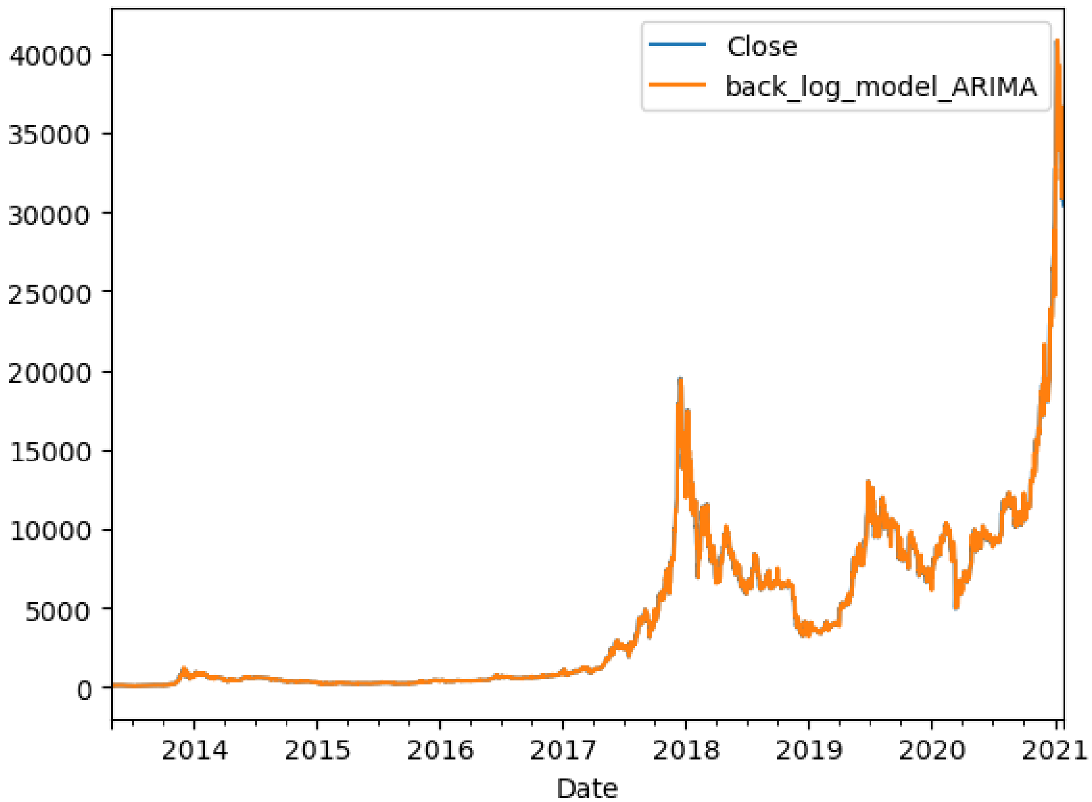
[91]:
```
df_test.plot(kind = "line", y = ['log_value', 'log_model_ARIMA']);
```



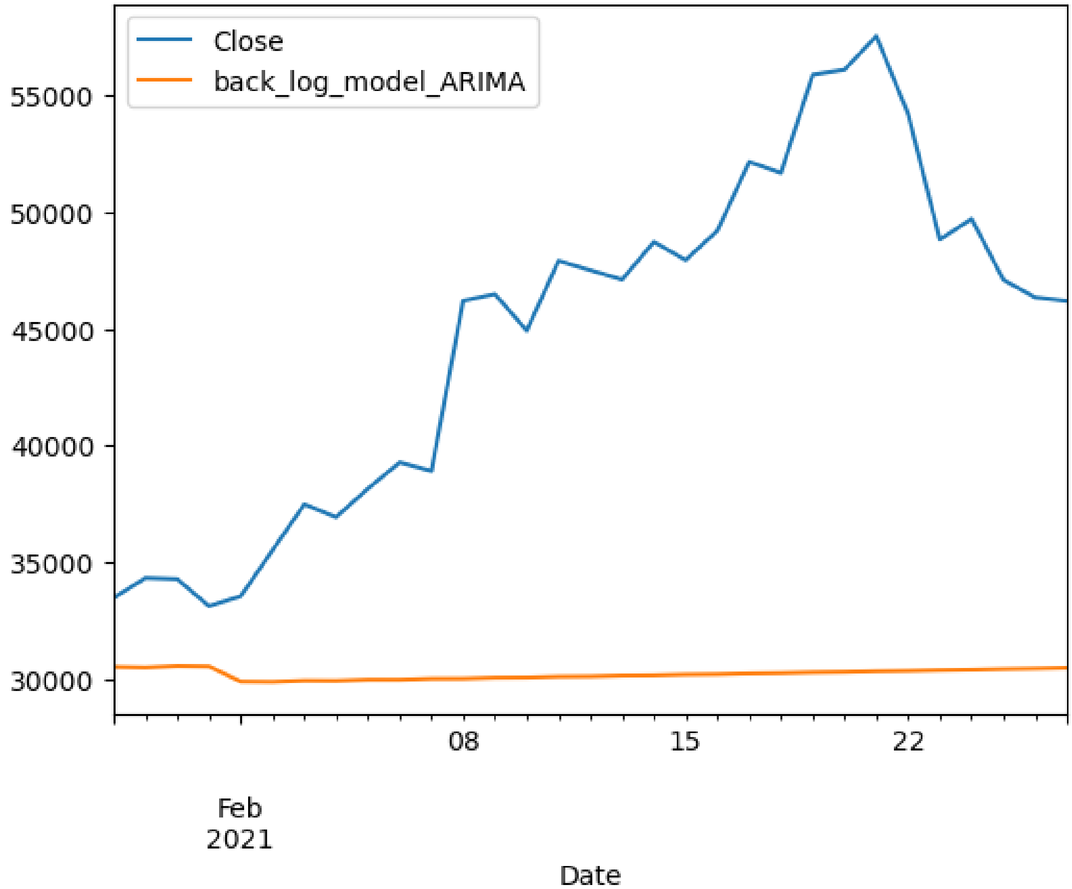
[92]:
```
# Se repite el proceso con back transformation del modelo log:

df_train['back_log_model_ARIMA'] = np.exp(df_train['log_model_ARIMA'])
df_test['back_log_model_ARIMA'] = np.exp(df_test['log_model_ARIMA'])

df_train.plot(kind = "line", y = ['Close', 'back_log_model_ARIMA']);
df_test.plot(kind = "line", y = ['Close', 'back_log_model_ARIMA']);
```



Close
back_log_model_ARIMA
40000
35000
30000
25000
20000
15000
10000
5000
0
2014
2015
2016
2017
2018
2019
2020
2021
Date



Se calcula el MAPE + RMSE y se almacena

[93]:
```
model_MAPE = mean_absolute_percentage_error (df_test.Close , df_test.
    ↪back_log_model_ARIMA)
```

[94]:
```
df_Results.loc[6, "Model"] = "Log Model + est + ARIMA"
df_Results.loc[6, "RMSE"] = RMSE(df_test['back_log_model_ARIMA'],␣
    ↪df_test['Close'])
df_Results.loc[6, "MAPE"] = model_MAPE
```

2.9 I) Prophet

En la 3ra y última notebook se prueba una herramienta no vista en el curso. Se separó para ser planteada como un anexo, debido a nuestra incertidumbre con respecto a sus resultados.

[95]:
```
# Como en esta notebook no se analiza esa herramienta, los resultados son␣
    ↪ingresados manualmente

df_Results.loc[7, "Model"] = "Prophet"
```

```python
df_Results.loc[7, "RMSE"] = 6997.16
df_Results.loc[7, "MAPE"] = 15.54

df_Results
```

[95]:

	Model	RMSE	MAPE
0	Mean	40968.433969	89.845161
1	Random Walk	16049.403917	30.009555
2	LinearTrend	33666.922165	72.755041
3	Transf Log	25190.683145	52.878589
4	Transf Log + est	25219.962947	52.844384
5	Simple Smoothing	13517.463589	23.350291
6	Log Model + est + ARIMA	16242.023902	30.550652
7	Prophet	6997.16	15.54

3 3) Comparación de resultados

Análisis de RMSE y MAPE visualizado

[96]:
```python
df_Results
```

[96]:

	Model	RMSE	MAPE
0	Mean	40968.433969	89.845161
1	Random Walk	16049.403917	30.009555
2	LinearTrend	33666.922165	72.755041
3	Transf Log	25190.683145	52.878589
4	Transf Log + est	25219.962947	52.844384
5	Simple Smoothing	13517.463589	23.350291
6	Log Model + est + ARIMA	16242.023902	30.550652
7	Prophet	6997.16	15.54

[97]:
```python
fig, ax1 = plt.subplots(figsize=(22, 13))
ax1.set_xlabel('Modelos', fontsize=22)
ax1.set_ylabel('MAPE', fontsize=20, color='b')
ax1.bar(df_Results.index - 0.2, df_Results.MAPE, width=0.4, color='b',␣
 ↪linewidth=2, label = "MAPE")
ax1.tick_params(axis='y', labelcolor='b', labelsize = 17)
ax1.tick_params(axis='x', labelsize = 15)
ax1.set_ylim([0, 99])

ax2 = ax1.twinx()
ax2.set_ylabel('RMSE', fontsize=20, color='r')
ax2.bar(df_Results.index + 0.2, df_Results.RMSE, width=0.4, color='r',␣
 ↪linewidth=2, label = "RMSE")
ax2.tick_params(axis='y', labelcolor='r', labelsize = 17)
ax2.set_ylim([0, 50000])

plt.axvline(x='Means', color="grey", linestyle="--", lw=1.3)
```

```
plt.axvline(x='Random Walk',color="grey", linestyle="--", lw=1.3)
plt.axvline(x='LinearTrend', color="grey", linestyle="--", lw=1.3)
plt.axvline(x='Transf Log' , color="grey", linestyle="--", lw=1.3)
plt.axvline(x='Transf Log + est', color="grey", linestyle="--", lw=1.3)
plt.axvline(x='S. Smoothing', color="grey", linestyle="--", lw=1.3)
plt.axvline(x='Log_est_ARIMA', color="grey", linestyle="--", lw=1.3)
plt.axvline(x='Prophet', color="grey", linestyle="--", lw=1.3)

plt.grid(which='major', axis='y', color='black', lw=0.4, alpha=0.6)
plt.suptitle("Comparación de resultados", fontsize=24, y=0.94)
legend1 = ax1.legend(loc=(0.86, 0.9), fontsize = 18)
legend2 = ax2.legend(loc=(0.86, 0.82), fontsize = 18)

plt.show()
```