In [1]:
```python
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
import yfinance as yf
import matplotlib.pyplot as plt
```

In [2]:
```python
# Extraemos los dos DataSets

ibm_walmart = yf.download(tickers = 'IBM WMT', period = '5y', interval = '1mo', rounding = True)
ibm_walmart.head()
```

```
[*********************100%***********************]  2 of 2 completed
```

Out[2]:

Price	Adj Close		Close		High		Low		Open		Volume	
Ticker	IBM	WMT	IBM	WMT	IBM	WMT	IBM	WMT	IBM	WMT	IBM	WMT
Date												
2019-11-01 00:00:00+00:00	101.47	36.75	128.54	39.70	133.02	41.79	126.91	39.03	128.59	39.31	67751825	349861800
2019-12-01 00:00:00+00:00	102.35	36.67	128.15	39.61	130.42	40.71	124.94	39.14	128.54	39.72	75159179	295268100
2020-01-01 00:00:00+00:00	109.75	35.48	137.41	38.16	139.38	39.96	127.34	37.56	129.06	39.62	118459187	383722500
2020-02-01 00:00:00+00:00	99.38	33.37	124.43	35.89	151.77	39.98	120.80	34.79	137.91	38.30	123581342	397242300
2020-03-01 00:00:00+00:00	85.59	35.22	106.05	37.87	130.11	42.69	86.58	34.00	125.00	35.87	198819809	956864400

In [3]:
```python
ibm_walmart = ibm_walmart['Close']
ibm_walmart.head()
```

Out[3]:

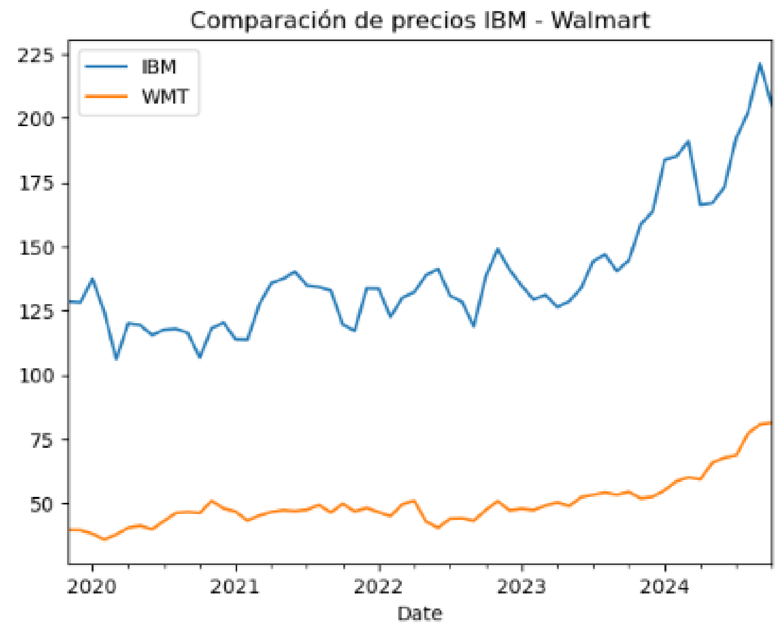
Ticker	IBM	WMT
Date		
2019-11-01 00:00:00+00:00	128.54	39.70
2019-12-01 00:00:00+00:00	128.15	39.61
2020-01-01 00:00:00+00:00	137.41	38.16
2020-02-01 00:00:00+00:00	124.43	35.89
2020-03-01 00:00:00+00:00	106.05	37.87

In [34]:
```python
rendimientos = IBM.pct_change()
rendimientos = rendimientos.dropna()
rendimientos
```

Out[34]:

Ticker	IBM
Date	
2019-11-01 00:00:00+00:00	0.013453
2019-11-04 00:00:00+00:00	0.015822
2019-11-05 00:00:00+00:00	0.001596
2019-11-06 00:00:00+00:00	0.006448

In [4]:
```python
# graficamos
ibm_walmart['IBM'].plot()
ibm_walmart['WMT'].plot()
plt.legend(['IBM', 'WMT'])
plt.title('Comparación de precios IBM - Walmart')
plt.show()
```



In [6]:
```python
# Rendimientos
rend_ibm_wmt = ibm_walmart.pct_change()
rend_ibm_wmt
```

Out[6]:

Ticker	IBM	WMT
Date		
2019-11-01 00:00:00+00:00	NaN	NaN
2019-12-01 00:00:00+00:00	-0.003034	-0.002267
2020-01-01 00:00:00+00:00	0.072259	-0.038607
2020-02-01 00:00:00+00:00	-0.094462	-0.059486

In [7]:
```python
# eliminamos los NAN

rend_ibm_wmt = rend_ibm_wmt.dropna()
rend_ibm_wmt
```

Out[7]:

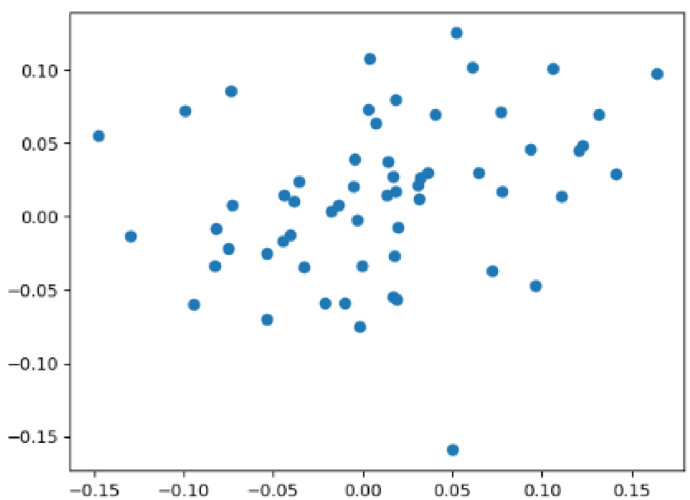
Ticker	IBM	WMT
Date		
2019-12-01 00:00:00+00:00	-0.003034	-0.002267
2020-01-01 00:00:00+00:00	0.072259	-0.036607
2020-02-01 00:00:00+00:00	-0.094462	-0.059486
2020-03-01 00:00:00+00:00	-0.147714	0.055169
2020-04-01 00:00:00+00:00	0.131919	0.069976

Aplicamos la Nomenclatura y componentes de las series de tiempo

In [8]:
```python
# Calculamos la correalción

correlacion = rend_ibm_wmt['IBM'].corr(rend_ibm_wmt['WMT'])
print('Correlación entre IBM y Walmart: ',correlacion)
```

```
Correlación entre IBM y Walmart:  0.2770463660898834
```

In [9]:
```python
# graficamos
plt.scatter(rend_ibm_wmt['IBM'], rend_ibm_wmt['WMT'])
plt.show()
```



- ¿Existe alguna correlación entre los precios de las acciones de ambas empresas?
- Observando la Gráfica y la correlación, vemos que no hay relación entre los precios de ambas acciones

In [11]:
```
# podemos corroborar esta correlación con el modelo de regresión simple
import statsmodels.api as sm
rend_ibm_wmt = sm.add_constant(rend_ibm_wmt)
rend_ibm_wmt
```

Out[11]:

Date	const	IBM	WMT
2019-12-01 00:00:00+00:00	1.0	-0.003034	-0.002267
2020-01-01 00:00:00+00:00	1.0	0.072259	-0.036607
2020-02-01 00:00:00+00:00	1.0	-0.094462	-0.059486
2020-03-01 00:00:00+00:00	1.0	-0.147714	0.055169

In [12]:
```
regresion = sm.OLS(rend_ibm_wmt['IBM'], rend_ibm_wmt[['const', 'WMT']]).fit()
```

In [13]:
```
print(regresion.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    IBM   R-squared:                       0.077
Model:                            OLS   Adj. R-squared:                  0.061
Method:                 Least Squares   F-statistic:                     4.739
Date:                Wed, 30 Oct 2024   Prob (F-statistic):             0.0336
Time:                        21:40:01   Log-Likelihood:                 77.323
No. Observations:                  59   AIC:                            -150.6
Df Residuals:                      57   BIC:                            -146.5
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0054      0.009      0.610      0.544      -0.012       0.023
WMT            0.3491      0.160      2.177      0.034       0.028       0.670
==============================================================================
Omnibus:                        0.243   Durbin-Watson:                   2.003
Prob(Omnibus):                  0.886   Jarque-Bera (JB):                0.198
Skew:                          -0.131   Prob(JB):                        0.906
Kurtosis:                       2.892   Cond. No.                         18.6
==============================================================================

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

In [14]:
```
# calculamos el indice de correlación
autocorrelacion = rend_ibm_wmt['IBM'].autocorr()
autocorrelacion
```

Out[14]: -0.014759191403178598

In [19]:
```python
autocorrelacion = ibm_walmart['IBM'].autocorr()
autocorrelacion
```
Out[19]:
```
0.9267057150281207
```

In [20]:
```python
IBM = yf.download(tickers = 'IBM', period = '5y', interval = '1d', rounding = True)
IBM = IBM['Close']
```
```
[*********************100%***********************]  1 of 1 completed
```

In [22]:
```python
# aplicamos las diferencias consecutivas
IBM_diff = IBM.diff()
IBM_diff
```
Out[22]:

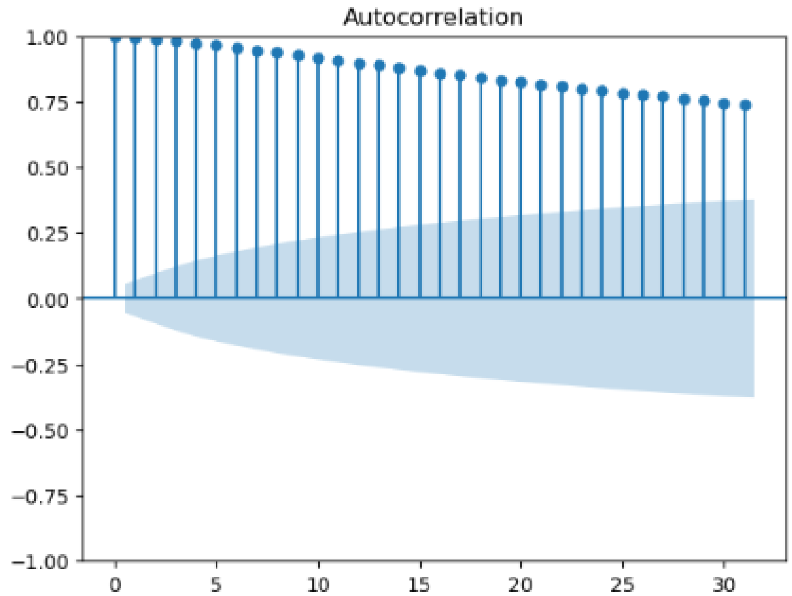
Ticker	IBM
Date	
2019-10-31 00:00:00+00:00	NaN
2019-11-01 00:00:00+00:00	1.72
2019-11-04 00:00:00+00:00	2.05

In [24]:
```python
autocorr_diff = IBM_diff['IBM'].autocorr()
autocorr_diff
```
Out[24]:
```
-0.0291691800424556
```

In [26]:
```python
# generacion de la funcion de utocorrelacion
from statsmodels.tsa.stattools import acf
from statsmodels.graphics.tsaplots import plot_acf
```

In [27]:
```python
acf_array = acf(IBM)
acf_array
```
Out[27]:
```
array([1.        , 0.99345266, 0.98670695, 0.97950292, 0.97211519,
       0.96441491, 0.95518912, 0.9463187 , 0.93675462, 0.92763549,
       0.91782713, 0.9077393 , 0.89782   , 0.88793764, 0.87833055,
       0.86865654, 0.85938242, 0.85033942, 0.84149532, 0.8327977 ,
       0.82426098, 0.81624398, 0.80811862, 0.80021112, 0.79196781,
       0.78383544, 0.77621711, 0.76869266, 0.76093226, 0.75337665,
       0.74611517])
```

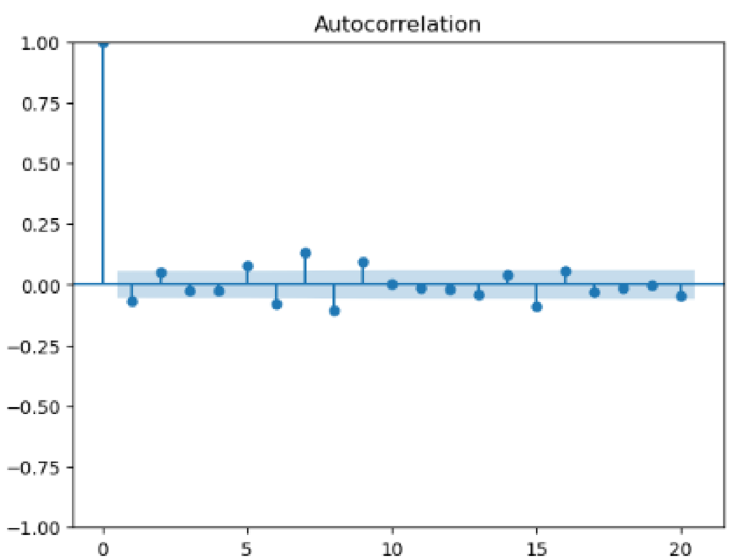
In [28]:
```
plot_acf(IBM, alpha = 0.05)
plt.show()
```



In [35]:
```
rendimientos = rendimientos.dropna()
acf_rend = acf(rendimientos)
print(acf_rend)
```

```
[ 1.00000000e+00 -6.88977982e-02  5.26747789e-02 -2.36832375e-02
 -2.45647724e-02  7.65622144e-02 -7.96770841e-02  1.34745538e-01
 -1.06537573e-01  9.48817480e-02  2.36408333e-05 -1.31366271e-02
 -1.90885706e-02 -4.21350835e-02  4.16877608e-02 -9.06925715e-02
  5.64904688e-02 -3.00199264e-02 -1.45474234e-02 -4.64945311e-03
 -4.55443796e-02  2.22553267e-02 -6.55883319e-02  4.64812027e-02
 -4.35328914e-02 -5.05222615e-02 -2.08037798e-02  3.28265723e-02
 -7.18823228e-03  1.74159733e-02 -3.66072399e-02]
```

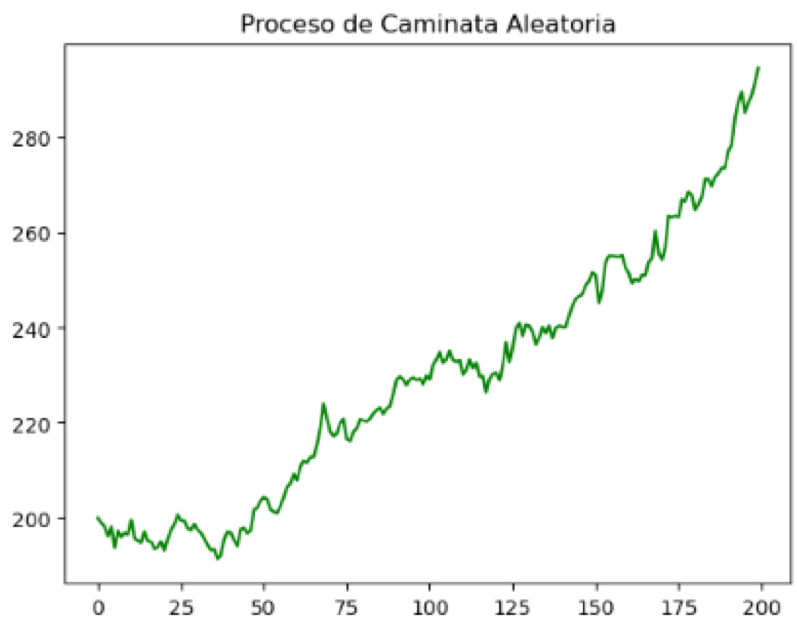
In [36]:
```
plot_acf(rendimientos, alpha = 0.05, lags = 20)
plt.show()
```



In [58]:
```
# Prueba de caminata aleatoria, hay 2 hipotesis
# H0: Se tiene un proceso de Caminata Aleatoria
# Ha: No se tiene un proceso de Caminata Aleatoria.

from statsmodels.tsa.stattools import adfuller
import numpy as np

# generación de 500 pasos aleatorios

np.random.seed(1)
steps = np.random.normal(loc = 0.001, scale = 0.01, size = 200) +1
```

In [95]:
```
steps[0] = 2
p = 100 * np.cumprod(steps)
```

In [96]:
```
# Graficamos los precios simulados

plt.plot(p, color = 'green')
plt.title('Proceso de Caminata Aleatoria')
plt.show()
```



In [97]:
```
resultado = adfuller(p)
print('El resultado de p en la prueba es :', resultado[1])
```

```
El resultado de p en la prueba es : 0.9989986444709306
```

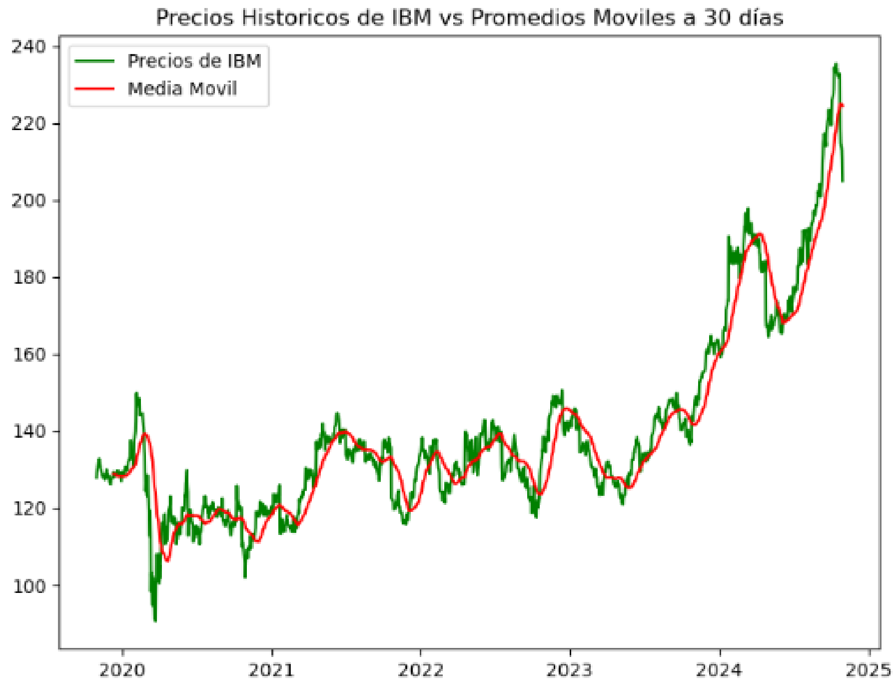
0.99, indica que no hay suficiente evidencia para rechazar la hipótesis nula de que la serie no es estacionaria.

In [98]:
```
# Prueba Dickey Fuller para los precios de IBM
resultado = adfuller(IBM)
print('El resultado de p en la prueba es:', resultado[1])
```

```
El resultado de p en la prueba es: 0.7347657589182868
```

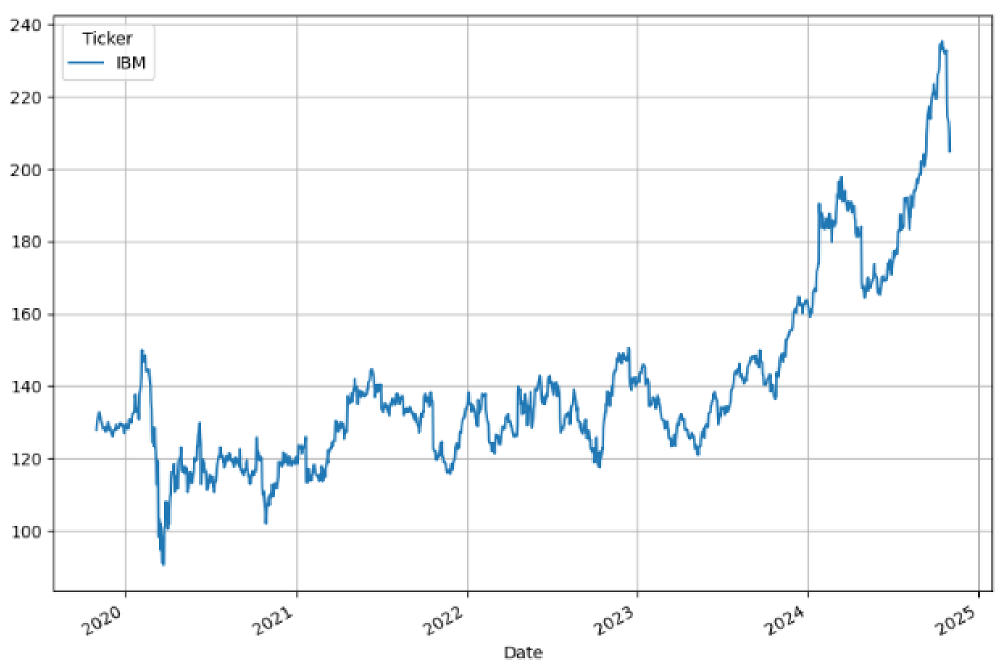
In [99]:

```
rolling_ibm = IBM.rolling(30).mean()

plt.figure(figsize=(8,6))
plt.plot(IBM, label = 'Precios de IBM', color = 'green')
plt.plot(rolling_ibm, label = 'Media Movil', color = 'red')
plt.title('Precios Historicos de IBM vs Promedios Moviles a 30 días')
plt.legend()
plt.show()
```



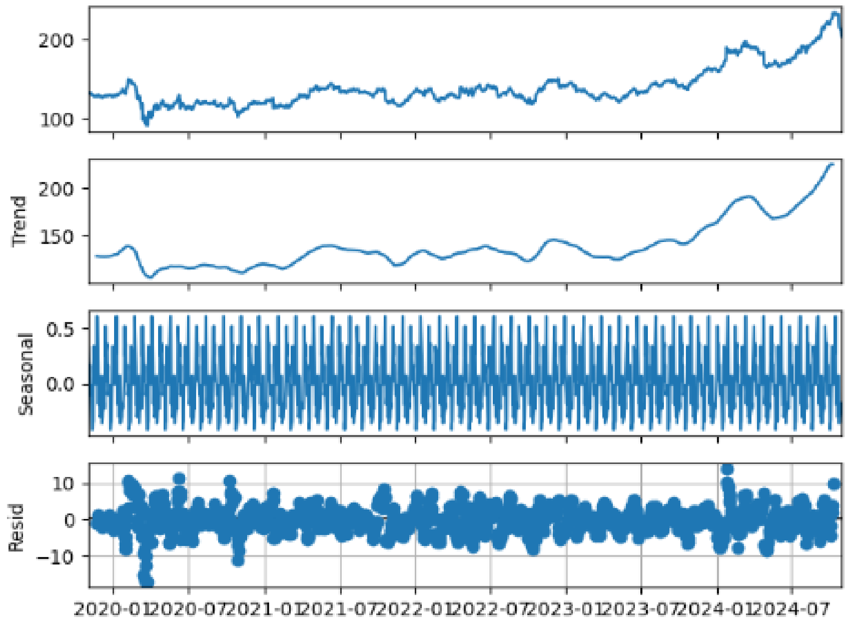
In [100]:

```
# Descomposición de la serie de tiempo
IBM.plot(figsize=(10,7)).grid()
```



In [101]:
```
decomposed_ibm = sm.tsa.seasonal_decompose(IBM, period = 30)
```

In [102]:
```
figure = decomposed_ibm.plot()
plt.grid()
plt.show()
```



Realizamos Predicciones

** Predicción Simple mediante promedios moviles

In [103]:
```
IBM.shape
```
Out[103]: (1258, 1)

In [104]:
```
len_train = int(1259 * 0.8)
len_train
```
Out[104]: 1007

In [105]:
```
# Grupos de entrenamiento y prueba
train = IBM[0:len_train]
test = IBM[len_train:]
```

In [106]:
```
len(train)
```
Out[106]: 1007

In [107]:
```
len(test)
```
Out[107]: 251

In [137]:
```
#y_pred = IBM.copy()
#y_pred = pd.DataFrame(y_pred)
ibm_data = IBM.copy()
ibm_data = pd.DataFrame(ibm_data)
```

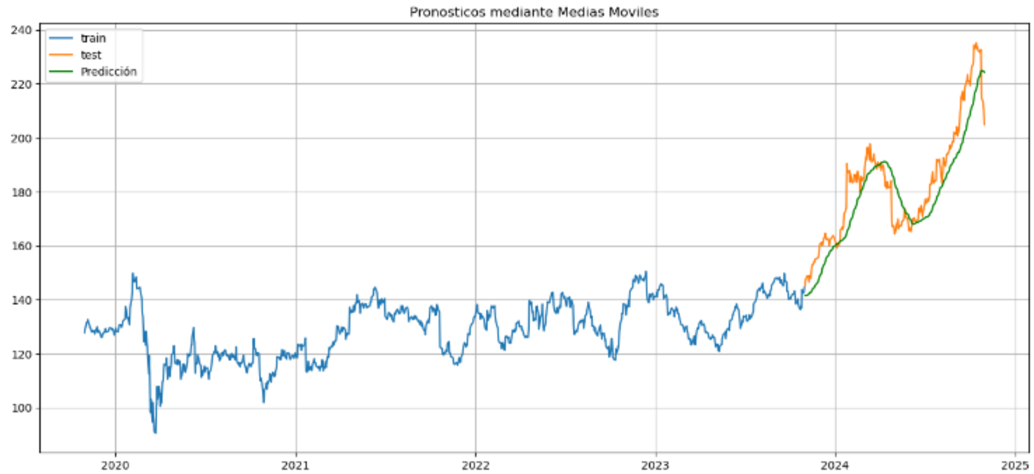
In [138]:
```
ibm_data['promedio_movil'] = ibm_data.rolling(30).mean()
```

In [112]:
```
y_pred = ibm_data.copy()
y_pred['pronostico'][29] = 'NaN'
for contador in range(30, 1258):
    y_pred['pronostico'][contador] = y_pred['pronostico'][contador]
y_pred[0:35]
```
Out[112]:

In [113]:
```
y_pred = pd.DataFrame(y_pred['pronostico'][1007:])
y_pred
```
Out[113]:

	pronostico
Date	
2023-11-01 00:00:00+00:00	141.566
2023-11-02 00:00:00+00:00	141.553667
2023-11-03 00:00:00+00:00	141.586667
2023-11-06 00:00:00+00:00	141.669667
2023-11-07 00:00:00+00:00	141.856

In [114]:
```python
# Gtraficamos
plt.figure(figsize = (16,7))
plt.grid()
plt.plot(train, label = 'train')
plt.plot(test, label= 'test')
plt.plot(y_pred['pronostico'], label = 'Predicción', color = 'green')
plt.legend()
plt.title('Pronosticos mediante Medias Moviles')
plt.show()
```



In [115]:
```python
test = pd.DataFrame(test)
```

In [116]:
```python
res = pd.concat([test.reset_index(drop=True), y_pred.reset_index(drop=True)], axis=1)
res.columns = ['Observado', 'pronostico']
```

In [118]:
```python
# Evaluamos los pronosticos

from sklearn.metrics import mean_squared_error
```

In [119]:
```python
# primero obtenemos el rmse (raiz cuadradico medio,  mean_squared_error)

rmse = np.sqrt(mean_squared_error(test, y_pred)).round(2)
mape = np.round(np.mean(np.abs((test['IBM'] - y_pred['pronostico']) / test['IBM'])) * 100, 2)
```

In [120]:
```python
print('RMSE: ', rmse, 'Mape: ', mape)
```

```
RMSE:  9.58 Mape:  4.34
```

En promedio cuando hacemos pronosticos, nos equivocamos 9.58 dlls y eso equivale a 4.34% que es nuestro error promedio absuloto hacia arriba o hacia abajo

In [134]:
```python
# Pronóstico: tomar el último valor calculado del promedio móvil como estimación para el siguiente día
ultimo_promedio_movil = ibm_data['promedio_movil'].iloc[-1]

# Crear una fecha adicional para el 1 de noviembre de 2024
proximo_dia = pd.Timestamp('2024-11-01')

# Crear un nuevo DataFrame para almacenar la fecha y el pronóstico
pronostico = pd.DataFrame({'Close': [np.nan], 'promedio_movil': [ultimo_promedio_movil]}, index=[proximo_dia])

# Concatenar el pronóstico al final de los datos existentes
ibm_data = pd.concat([ibm_data, pronostico])

# Imprimir el pronóstico
print("Pronóstico para el 1 de noviembre de 2024:",ultimo_promedio_movil)
```

```
Pronóstico para el 1 de noviembre de 2024: 224.29266666666666
```