In [1]:
```
import yfinance as yf
import pandas as pd
import sweetviz as sv
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
```

1. Analiza la evolución de los datos:

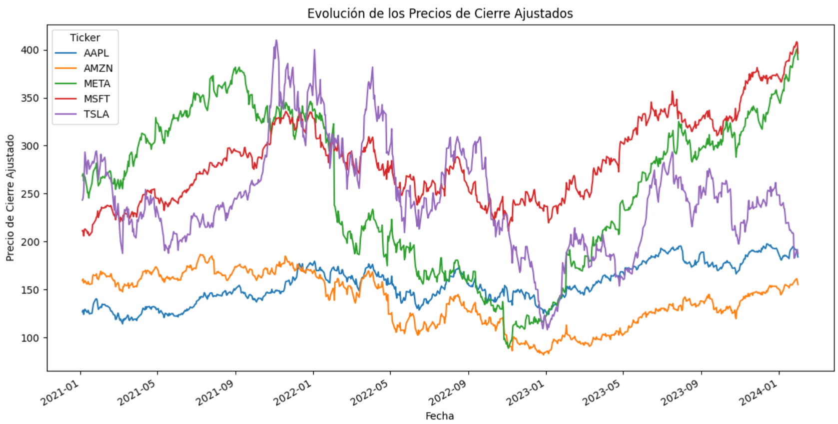
In [2]:
```
# Definir los tickers y el periodo de tiempo de retorno
tickers = ["AMZN", "AAPL", "TSLA", "META", "MSFT"]
start_date = "2021-01-01"
end_date = "2024-02-01"

# Obtener los datos históricos de los tickers
data = yf.download(tickers, start=start_date, end=end_date)["Adj Close"]
data.head()
```

```
[*********************100%%**********************]  5 of 5 completed
```

Out[2]:

Ticker	AAPL	AMZN	META	MSFT	TSLA
Date					
2021-01-04	126.830070	159.331497	268.654968	211.224289	243.256668
2021-01-05	128.398193	160.925507	270.682800	211.428085	245.036667
2021-01-06	124.076088	156.919006	263.030914	205.945862	251.993332
2021-01-07	128.309982	158.108002	268.455170	211.806503	272.013336
2021-01-08	129.417465	159.134995	267.286407	213.097015	293.339996

In [3]:
```
data.plot(figsize=(14, 7))
plt.title('Evolución de los Precios de Cierre Ajustados')
plt.ylabel('Precio de Cierre Ajustado')
plt.xlabel('Fecha')
plt.legend(title='Ticker')
plt.show()
```



In [4]:
```
print(data.describe())
```

```
Ticker        AAPL        AMZN        META        MSFT        TSLA
count   774.000000  774.000000  774.000000  774.000000  774.000000
mean    155.328509  138.698511  257.310001  284.443793  246.076809
std      20.662072   27.212948   79.664535   43.929686   55.151301
min     114.210655   81.820000   88.815765  205.945862  108.099998
25%     140.345200  115.401375  186.522106  247.555931  210.007496
50%     152.195824  142.435005  273.634674  279.698730  240.474998
```

```
75%      172.349945  163.153381  327.170380  320.037910  277.849998
max      197.589523  186.570496  400.594940  408.227386  409.970001
```

2. ¿Hay correlación entre los stocks?

In [5]:
```
# Calcular los retornos diarios
returns = data.pct_change()

# Calcular la matriz de correlación de los retornos
correlation_matrix = returns.corr()
print(correlation_matrix)
```

```
Ticker       AAPL      AMZN      META      MSFT      TSLA
Ticker
AAPL     1.000000  0.607974  0.551687  0.720267  0.535235
AMZN     0.607974  1.000000  0.590752  0.669459  0.456775
META     0.551687  0.590752  1.000000  0.584624  0.355462
MSFT     0.720267  0.669459  0.584624  1.000000  0.442584
TSLA     0.535235  0.456775  0.355462  0.442584  1.000000
```

In [6]:
```
# Generar un reporte usando Sweetviz
report = sv.analyze(data)
report.show_html('../reports/Stock_Report.html')  # Salida en HTML
```

```
|
…

Report ../reports/Stock_Report.html was generated! NOTEBOOK/COLAB USERS: t
he web browser MAY not pop up, regardless, the report IS saved in your not
ebook/colab files.
```

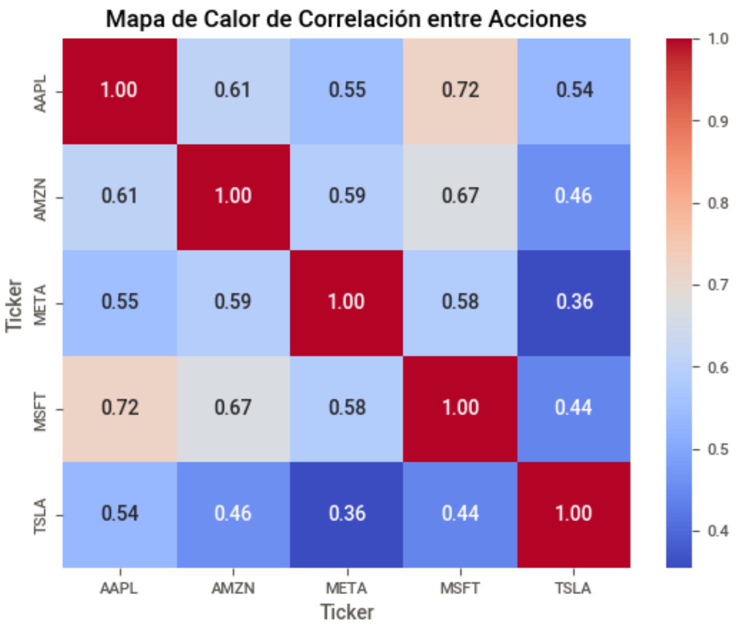
In [7]:
```
print(returns.head())
```

```
Ticker           AAPL      AMZN      META      MSFT      TSLA
Date
2021-01-04        NaN       NaN       NaN       NaN       NaN
2021-01-05   0.012364  0.010004  0.007548  0.000965  0.007317
2021-01-06  -0.033662 -0.024897 -0.028269 -0.025929  0.028390
2021-01-07   0.034123  0.007577  0.020622  0.028457  0.079447
2021-01-08   0.008631  0.006496 -0.004354  0.006093  0.078403
```

In [8]:
```
returns.dtypes
```

Out[8]:
```
Ticker
AAPL    float64
AMZN    float64
META    float64
MSFT    float64
TSLA    float64
dtype: object
```

In [9]:
```
# Asumiendo que 'correlation_matrix' es tu DataFrame de Pandas
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Mapa de Calor de Correlación entre Acciones')
plt.show()
```



In [10]:
```
adj_amz = data['AMZN']
adj_amz
```

Out[10]:
```
Date
2021-01-04    159.331497
2021-01-05    160.925507
2021-01-06    156.919006
2021-01-07    158.108002
2021-01-08    159.134995
                 ...
2024-01-25    157.750000
2024-01-26    159.119995
2024-01-29    161.259995
2024-01-30    159.000000
2024-01-31    155.199997
Name: AMZN, Length: 774, dtype: float64
```

4. A partir de este momento seleccionamos la columna de Amazon. Crea una columna llamada Return calculada con la función pct_change() a partir de la columna Adj_Close().

In [11]:
```
# Calcular los retornos diarios solo de AMZ
returns_amz = data['AMZN'].pct_change()
returns_amz.head()
```

Out[11]:
```
Date
2021-01-04         NaN
2021-01-05    0.010004
2021-01-06   -0.024897
2021-01-07    0.007577
2021-01-08    0.006496
Name: AMZN, dtype: float64
```

In [12]:
```
# Comprobando valores faltantes en el conjunto de datos
missing_values = returns_amz.isnull().sum()
missing_values
```

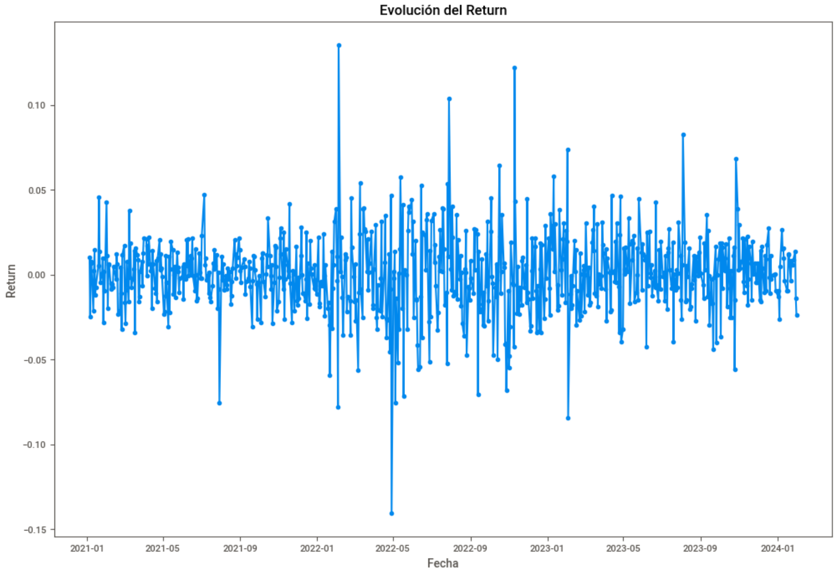
Out[12]: 1

In [13]:
```
returns_amz
```

Out[13]:
```
Date
2021-01-04         NaN
2021-01-05    0.010004
2021-01-06   -0.024897
2021-01-07    0.007577
2021-01-08    0.006496
                ...
2024-01-25    0.005610
2024-01-26    0.008685
2024-01-29    0.013449
2024-01-30   -0.014015
2024-01-31   -0.023899
Name: AMZN, Length: 774, dtype: float64
```

In [14]:
```
# Convertir los datos a un DataFrame
df_amz = pd.DataFrame(list(returns_amz.items()), columns=['Date', 'Return
df_amz['Date'] = pd.to_datetime(df_amz['Date'])

# Crear figura y eje
fig, ax = plt.subplots(figsize=(12, 8))

# Graficar los datos
ax.plot(df_amz['Date'], df_amz['Return'], marker='o')

# Añadir título y etiquetas
ax.set_title('Evolución del Return')
```

```
ax.set_xlabel('Fecha')
ax.set_ylabel('Return')

# Añadir anotación en un punto específico
ax.annotate('Punto destacado', xy=(pd.to_datetime('2021-01-06'), 156.9190
            xytext=(pd.to_datetime('2021-01-07'), 117.5),
            arrowprops=dict(facecolor='black', arrowstyle='->'))

# Mostrar el gráfico
plt.show()
```



In [15]:
```
df_amz.Return.describe()
```

Out[15]:
```
count    773.000000
mean       0.000238
std        0.023342
min       -0.140494
25%       -0.012566
50%        0.000313
75%        0.012696
max        0.135359
Name: Return, dtype: float64
```

5. Argumenta si las series temporales son estacionarias o no con los datos de la columna Return.

In [16]:
```
from statsmodels.tsa.stattools import adfuller
```

In [17]:
```
df_amz.dtypes
```

Out[17]:
```
Date      datetime64[ns]
Return           float64
dtype: object
```

In [18]:
```
# Realizar la prueba de Dickey-Fuller aumentada
df_amz_clean = df_amz.dropna()
```

```python
df_amz_clean['Return'].dropna(inplace=True)


result = adfuller(df_amz_clean['Return'])

# Imprimir los resultados de la prueba
print('ADF Statistic:', result[0])
print('p-value:', result[1])
print('Critical Values:')
for key, value in result[4].items():
    print(f'   {key}: {value}')
```

```
ADF Statistic: -27.77390308652727
p-value: 0.0
Critical Values:
   1%: -3.4388489336836003
   5%: -2.865291103159288
   10%: -2.568767459327767
```

```
/var/folders/fj/dm38xwzd6bz39y7f15ykw6sc0000gn/T/ipykernel_32603/324899025
0.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_amz_clean['Return'].dropna(inplace=True)
```

In [19]:

```python
adj_amz
```

Out[19]:

```
Date
2021-01-04    159.331497
2021-01-05    160.925507
2021-01-06    156.919006
2021-01-07    158.108002
2021-01-08    159.134995
                 ...
2024-01-25    157.750000
2024-01-26    159.119995
2024-01-29    161.259995
2024-01-30    159.000000
2024-01-31    155.199997
Name: AMZN, Length: 774, dtype: float64
```

In [20]:

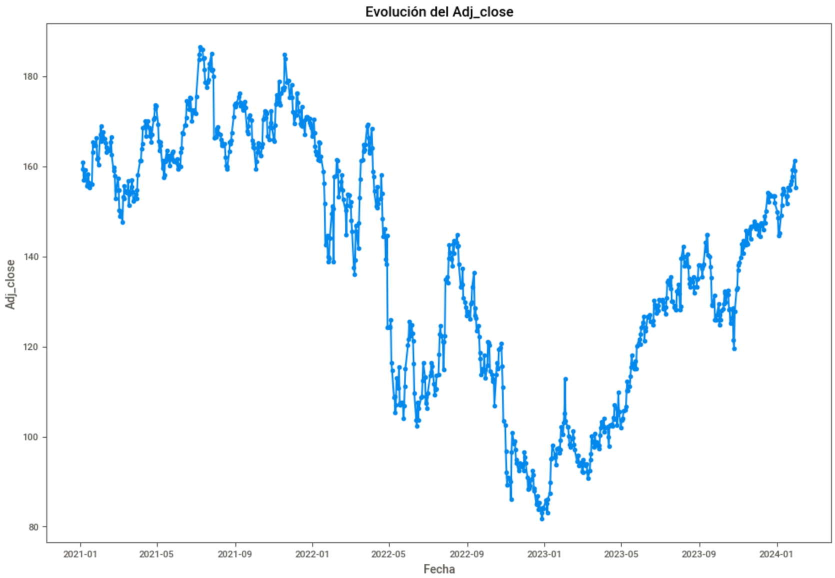
```python
# Convertir los datos a un DataFrame
adj_amz = pd.DataFrame(list(adj_amz.items()), columns=['Date', 'Adj_close
adj_amz['Date'] = pd.to_datetime(adj_amz['Date'])
# Realizar la prueba de Dickey-Fuller aumentada
adj_amz = adj_amz.dropna()

print(adj_amz)

result = adfuller(adj_amz['Adj_close'])

# Imprimir los resultados de la prueba
print('ADF Statistic:', result[0])
print('p-value:', result[1])
print('Critical Values:')
for key, value in result[4].items():
    print(f'   {key}: {value}')
```

```
          Date   Adj_close
0   2021-01-04  159.331497
1   2021-01-05  160.925507
2   2021-01-06  156.919006
3   2021-01-07  158.108002
4   2021-01-08  159.134995
..         ...         ...
769 2024-01-25  157.750000
770 2024-01-26  159.119995
771 2024-01-29  161.259995
772 2024-01-30  159.000000
773 2024-01-31  155.199997

[774 rows x 2 columns]
ADF Statistic: -1.5925997801740708
p-value: 0.48730982269373996
Critical Values:
   1%: -3.438837902109151
   5%: -2.8652862410999114
   10%: -2.568764869203001
```

In [21]:

```python
# Crear figura y eje
fig, ax = plt.subplots(figsize=(12, 8))
```

```
# Graficar los datos
ax.plot(adj_amz['Date'], adj_amz['Adj_close'], marker='o')

# Añadir título y etiquetas
ax.set_title('Evolución del Adj_close')
ax.set_xlabel('Fecha')
ax.set_ylabel('Adj_close')

# Añadir anotación en un punto específico
#ax.annotate('Punto destacado', xy=(pd.to_datetime('2021-01-06'), 156.919
#             xytext=(pd.to_datetime('2021-01-07'), 117.5),
#             arrowprops=dict(facecolor='black', arrowstyle='->'))

# Mostrar el gráfico
plt.show()
```



In [22]:
```
adj_amz.Adj_close.describe()
```

Out[22]:
```
count    774.000000
mean     138.698511
std       27.212948
min       81.820000
25%      115.401375
50%      142.435005
75%      163.153381
max      186.570496
Name: Adj_close, dtype: float64
```

In [23]:
```
missing_values = df_amz_clean.isnull().sum()
missing_values
```

Out[23]:
```
Date      0
Return    0
dtype: int64
```

In [24]:
```
df_amz_clean
```

Out[24]:

	Date	Return
1	2021-01-05	0.010004
2	2021-01-06	-0.024897
3	2021-01-07	0.007577
4	2021-01-08	0.006496
5	2021-01-11	-0.021519
...	...	...
769	2024-01-25	0.005610
770	2024-01-26	0.008685
771	2024-01-29	0.013449
772	2024-01-30	-0.014015
773	2024-01-31	-0.023899

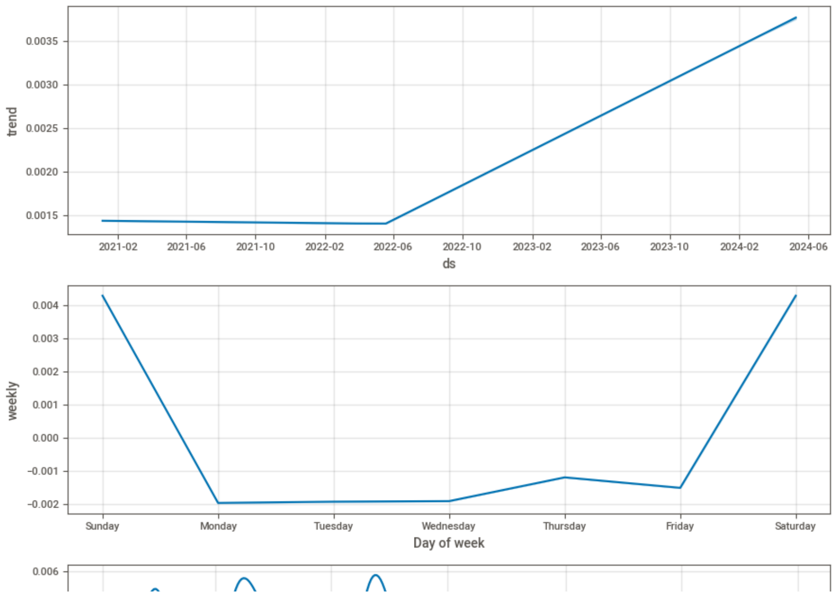
773 rows × 2 columns

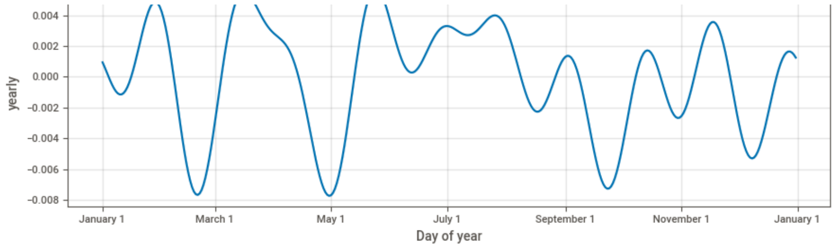
6. Utilizando el paquete fbprophet, descompón la serie temporal de la columna Return en su tendencia y su parte estacional.

In [25]:

```
from prophet import Prophet

df_amz_clean.columns = ['ds', 'y']  # Cambiar los nombres de las columnas

# Crear y ajustar el modelo
model = Prophet()
model.fit(df_amz_clean)

# Hacer la descomposición
future = model.make_future_dataframe(periods=100)
forecast = model.predict(future)

# Plotear los componentes (tendencia y estacionalidad)
fig = model.plot_components(forecast)
plt.show()
```

```
Importing plotly failed. Interactive plots will not work.
13:34:21 - cmdstanpy - INFO - Chain [1] start processing
13:34:21 - cmdstanpy - INFO - Chain [1] done processing
```





In [26]:
```
df_amz_clean
```

Out[26]:

	ds	y
1	2021-01-05	0.010004
2	2021-01-06	-0.024897
3	2021-01-07	0.007577
4	2021-01-08	0.006496
5	2021-01-11	-0.021519
...	...	...
769	2024-01-25	0.005610
770	2024-01-26	0.008685
771	2024-01-29	0.013449
772	2024-01-30	-0.014015
773	2024-01-31	-0.023899

773 rows × 2 columns

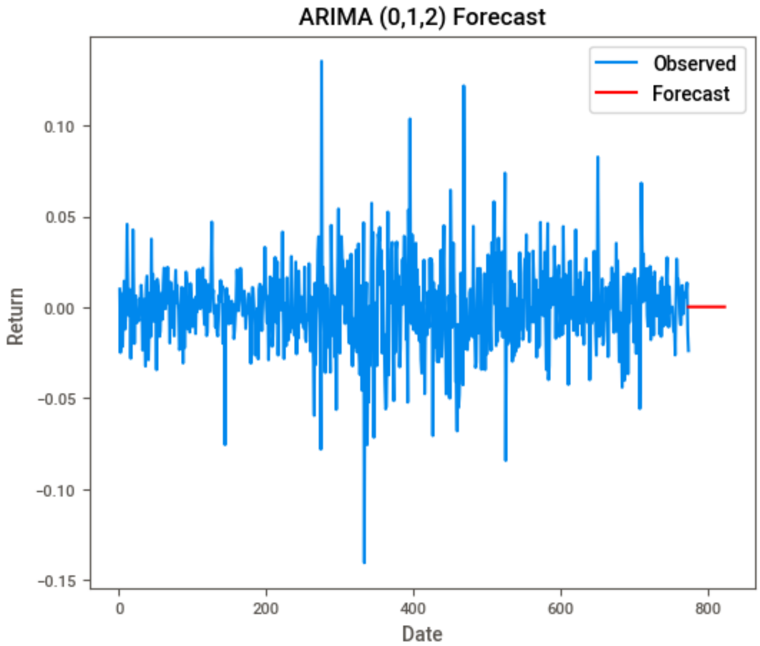
7. Predice con ARIMA (0,1,2) y los datos de la columna Return la evolución de los stocks de Amazon.

In [27]:
```
from statsmodels.tsa.arima.model import ARIMA
import warnings

# Ignorar todos los warnings
warnings.filterwarnings('ignore')

from matplotlib import pyplot

# Ajustar el modelo ARIMA (0,1,2)
model = ARIMA(df_amz_clean['y'], order=(0,1,2))
model_fit = model.fit()

# Realizar la predicción
forecast_steps = 50  # Número de pasos a predecir
forecast = model_fit.forecast(steps=forecast_steps)

# Imprimir resumen del modelo y las predicciones
print(model_fit.summary())
print(forecast)

# Graficar los resultados
```

```
plt.figure(figsize=(6, 5))
plt.plot(df_amz_clean['y'], label='Observed')
plt.plot(forecast, label='Forecast', color='red')

plt.title('ARIMA (0,1,2) Forecast')
plt.xlabel('Date')
plt.ylabel('Return')
plt.legend()
plt.show()

# summary of fit model
print(model_fit.summary())
# line plot of residuals
#residuals = DataFrame(model_fit.resid)
#residuals.plot()
#pyplot.show()
# density plot of residuals
#residuals.plot(kind='kde')
#pyplot.show()
# summary stats of residuals
#print(residuals.describe())
```

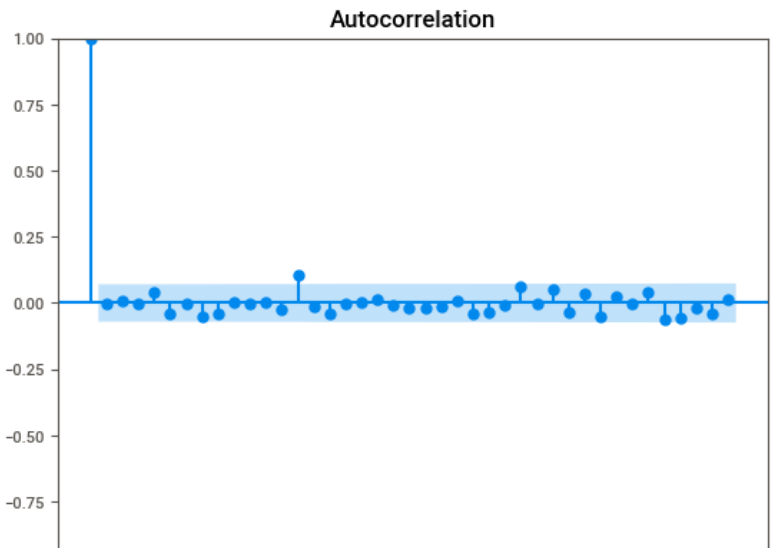
```
                              SARIMAX Results
==========================================================================
====
Dep. Variable:                      y   No. Observations:
773
Model:                 ARIMA(0, 1, 2)   Log Likelihood                180
2.044
Date:                Fri, 31 May 2024   AIC                          -359
8.088
Time:                        13:34:22   BIC                          -358
4.141
Sample:                             0   HQIC                         -359
2.721
                                - 773
Covariance Type:                  opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
ma.L1         -1.0001      0.152     -6.591      0.000      -1.297      -
0.703
ma.L2          0.0002      0.030      0.006      0.995      -0.058
0.058
sigma2         0.0005   8.41e-05      6.477      0.000       0.000
0.001
==========================================================================
=========
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
738.38
Prob(Q):                              0.98   Prob(JB):
0.00
Heteroskedasticity (H):               1.75   Skew:
0.12
Prob(H) (two-sided):                  0.00   Kurtosis:
7.79

==========================================================================
=========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (com
plex-step).
773    0.000243
774    0.000239
775    0.000239
776    0.000239
777    0.000239
778    0.000239
779    0.000239
780    0.000239
781    0.000239
782    0.000239
783    0.000239
784    0.000239
785    0.000239
786    0.000239
787    0.000239
788    0.000239
789    0.000239
790    0.000239
```

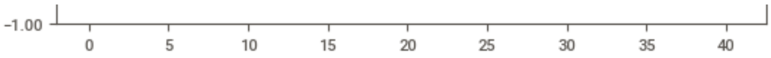
```
790     0.000239
791     0.000239
792     0.000239
793     0.000239
794     0.000239
795     0.000239
796     0.000239
797     0.000239
798     0.000239
799     0.000239
800     0.000239
801     0.000239
802     0.000239
803     0.000239
804     0.000239
805     0.000239
806     0.000239
807     0.000239
808     0.000239
809     0.000239
810     0.000239
811     0.000239
812     0.000239
813     0.000239
814     0.000239
815     0.000239
816     0.000239
817     0.000239
818     0.000239
819     0.000239
820     0.000239
821     0.000239
822     0.000239
Name: predicted_mean, dtype: float64
```

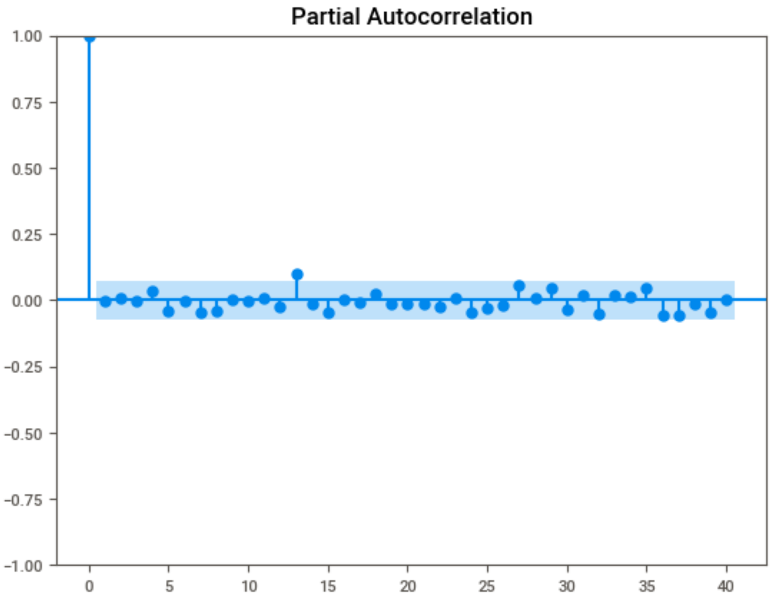


```
                               SARIMAX Results
==============================================================================
====
Dep. Variable:                      y   No. Observations:
773
Model:                 ARIMA(0, 1, 2)   Log Likelihood                 180
2.044
Date:                Fri, 31 May 2024   AIC                           -359
8.088
Time:                        13:34:22   BIC                           -358
4.141
Sample:                             0   HQIC                          -359
2.721
                                - 773
Covariance Type:                  opg
==============================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
------------------------------------------------------------------------------
----
ma.L1         -1.0001      0.152     -6.591      0.000      -1.297      -
0.703
ma.L2          0.0002      0.030      0.006      0.995      -0.058
0.058
sigma2         0.0005   8.41e-05      6.477      0.000       0.000
0.001
==============================================================================
=========
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
738.38
Prob(Q):                              0.98   Prob(JB):
0.00
Heteroskedasticity (H):               1.75   Skew:
0.12
Prob(H) (two-sided):                  0.00   Kurtosis:
7.79
==============================================================================
=========

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

In [28]:
```python
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
plot_acf(df_amz_clean['y'], lags=40)
plot_pacf(df_amz_clean['y'], lags=40)
plt.show()
```







In [29]:
```
from pmdarima import auto_arima
stepwise_fit = auto_arima(df_amz_clean['y'], trace=True, suppress_warning
```

```
Performing stepwise search to minimize aic
 ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=-3604.915, Time=0.28 sec
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=-3612.416, Time=0.04 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=-3610.418, Time=0.02 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=-3610.417, Time=0.02 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=-3614.335, Time=0.02 sec
 ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=-3608.659, Time=0.09 sec

Best model:  ARIMA(0,0,0)(0,0,0)[0]
Total fit time: 0.477 seconds
```

In [30]:
```
df_amz_clean
```

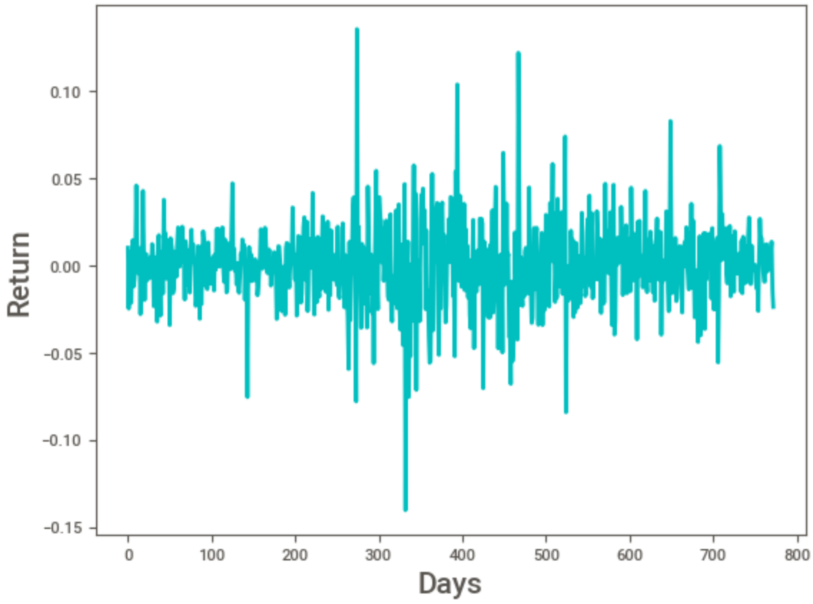
Out[30]:

	ds	y
1	2021-01-05	0.010004
2	2021-01-06	-0.024897
3	2021-01-07	0.007577
4	2021-01-08	0.006496
5	2021-01-11	-0.021519
...	...	...
769	2024-01-25	0.005610
770	2024-01-26	0.008685
771	2024-01-29	0.013449
772	2024-01-30	-0.014015
773	2024-01-31	-0.023899

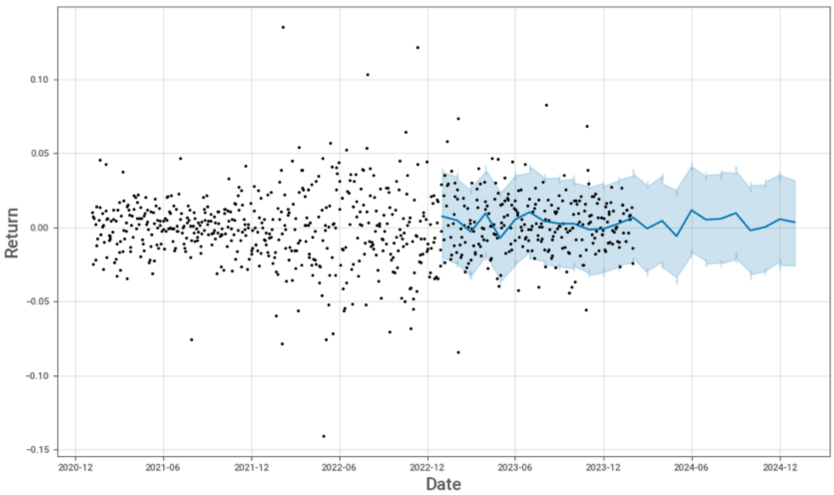
773 rows × 2 columns

In [31]:
```
df = df_amz_clean
n_days = np.arange(len(df))

# plot de la serie temporal
plt.plot(n_days, df['y'],'c-', linewidth = 2)
plt.ylabel("Return", fontsize = 15)
plt.xlabel("Days", fontsize = 15)
plt.show()

from prophet import Prophet

#define el rango de tiempo a predecir
start_date, end_date = "2023-1-01", "2025-01-01"
```

```
# define el modelo
model_fc = Prophet()
# entrena el modelo
model_fc.fit(df)
# define el periodo para predecir
future = list()

date_generated = pd.period_range(start=start_date, end=end_date, freq='d'
future = list()
future=date_generated.strftime("%Y%m")
future = future.to_list()
future = pd.DataFrame(future)
future.columns = ['ds']
future['ds']= pd.to_datetime(future['ds'], format='%Y%m')
# hacemos el forecast
forecast_fc = model_fc.predict(future)
# summarize the forecast
print(forecast_fc[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].head())
# plot forecast
model_fc.plot(forecast_fc)
plt.ylabel("Return", fontsize = 15)
plt.xlabel("Date", fontsize = 15)
pyplot.show()
```




```
13:34:24 - cmdstanpy - INFO - Chain [1] start processing
13:34:24 - cmdstanpy - INFO - Chain [1] done processing
          ds      yhat  yhat_lower  yhat_upper
0 2023-01-01  0.007494   -0.022638    0.039232
1 2023-01-01  0.007494   -0.020713    0.037629
2 2023-01-01  0.007494   -0.023539    0.039740
3 2023-01-01  0.007494   -0.018788    0.037428
4 2023-01-01  0.007494   -0.022364    0.034687
```



In [32]:
```
df_amz_clean
```

Out[32]:

	ds	y
1	2021-01-05	0.010004
2	2021-01-06	-0.024897
3	2021-01-07	0.007577
4	2021-01-08	0.006496
5	2021-01-11	-0.021519
...	...	...
769	2024-01-25	0.005610
770	2024-01-26	0.008685
771	2024-01-29	0.013449
772	2024-01-30	-0.014015
773	2024-01-31	-0.023899

773 rows × 2 columns

In [33]:
```
df_amz_clean_se = df_amz_clean.y.dropna()
df_amz_clean_se
```

Out[33]:
```
1      0.010004
2     -0.024897
3      0.007577
4      0.006496
5     -0.021519
         ...
769    0.005610
770    0.008685
771    0.013449
772   -0.014015
773   -0.023899
Name: y, Length: 773, dtype: float64
```

In [34]:
```
df_amz_clean
```

Out[34]:

	ds	y
1	2021-01-05	0.010004
2	2021-01-06	-0.024897
3	2021-01-07	0.007577
4	2021-01-08	0.006496
5	2021-01-11	-0.021519
...	...	...
769	2024-01-25	0.005610
770	2024-01-26	0.008685
771	2024-01-29	0.013449
772	2024-01-30	-0.014015
773	2024-01-31	-0.023899

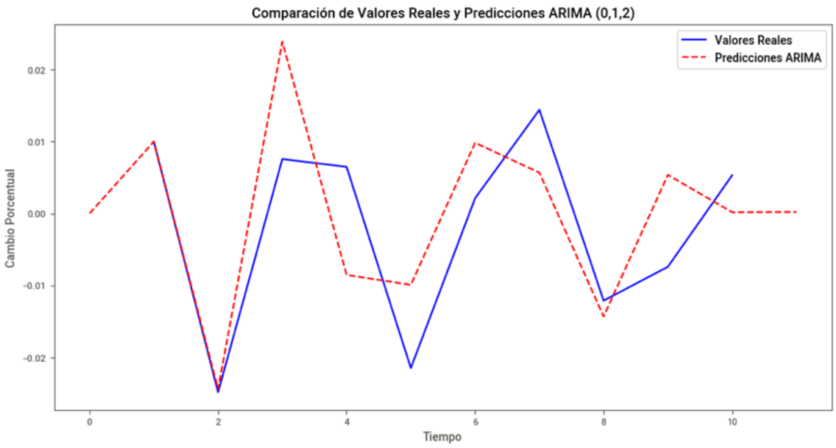
773 rows × 2 columns

In [35]:
```
# Calcular el cambio porcentual
ts = df_amz_clean.y.head(10)
ts_pct_change = ts.dropna()

# Ajustar el modelo ARIMA (aquí se asume p=1, d=0, q=1 como ejemplo)
model = ARIMA(ts_pct_change, order=(0, 1, 2))
model_fit = model.fit()

# Resumen del modelo
print(model_fit.summary())
```

```
print(model_fit.summary())

# Hacer predicciones
predictions = model_fit.predict(start=0, end=len(ts_pct_change)+1)

# Crear un DataFrame para comparar predicciones y valores reales

comparison_df = pd.DataFrame({
    'Real': ts_pct_change,
    'Predicted': predictions
})

# Graficar los valores reales y las predicciones
plt.figure(figsize=(12, 6))
plt.plot(comparison_df['Real'], label='Valores Reales', color='blue')
plt.plot(comparison_df['Predicted'], label='Predicciones ARIMA', color='r
plt.title('Comparación de Valores Reales y Predicciones ARIMA (0,1,2)')
plt.xlabel('Tiempo')
plt.ylabel('Cambio Porcentual')
plt.legend()
plt.show()
```

```
                               SARIMAX Results
==========================================================================
====
Dep. Variable:                      y   No. Observations:
10
Model:                 ARIMA(0, 1, 2)   Log Likelihood                  2
3.656
Date:                Fri, 31 May 2024   AIC                            -4
1.311
Time:                        13:34:24   BIC                            -4
0.720
Sample:                             0   HQIC                           -4
2.588
                                 - 10
Covariance Type:                  opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
```

```
ma.L1         -0.1344      8.195     -0.016      0.987     -16.197      1
5.928
ma.L2         -0.8312      7.145     -0.116      0.907     -14.835      1
3.172
sigma2         0.0002      0.002      0.124      0.901      -0.004
0.004
==========================================================================
=========
Ljung-Box (L1) (Q):                   3.56   Jarque-Bera (JB):
0.35
Prob(Q):                              0.06   Prob(JB):
0.84
Heteroskedasticity (H):               0.21   Skew:
0.14
Prob(H) (two-sided):                  0.23   Kurtosis:
2.07
==========================================================================
=========

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



In [36]:
```python
import math
from sklearn.metrics import mean_squared_error, mean_absolute_error
df_amz_clean.columns = ['Date', 'Return']
df_amz_clean.set_index('Date', inplace=True)
df_amz_clean
```

Out[36]:

	Return
Date	
2021-01-05	0.010004
2021-01-06	-0.024897
2021-01-07	0.007577
2021-01-08	0.006496
2021-01-11	-0.021519
...	...
2024-01-25	0.005610
2024-01-26	0.008685
2024-01-29	0.013449
2024-01-30	-0.014015
2024-01-31	-0.023899

773 rows × 1 columns

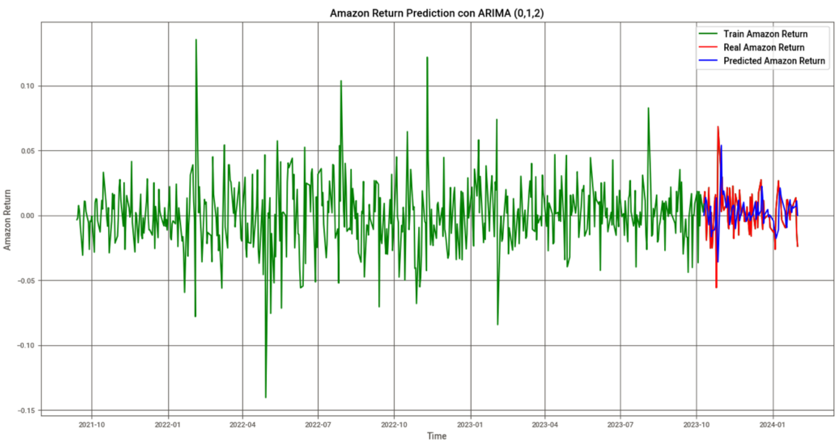
In [37]:
```
train_data, test_data = df_amz_clean[0:int(len(df_amz_clean)*0.9)], df_am

train_arima = train_data['Return']

test_arima = test_data['Return']

history = [x for x in train_arima]
y = test_arima
# make first prediction
predictions = list()
model = ARIMA(history, order=(0,1,2))
model_fit = model.fit()
yhat = model_fit.forecast()[0]
predictions.append(yhat)
history.append(y[0])
```

In [38]:
```
# rolling forecasts

for i in range(1, len(y)):
    # predict
    model = ARIMA(history, order=(1,1,0))
    model_fit = model.fit()
    yhat = model_fit.forecast()[0]
    # invert transformed prediction
    predictions.append(yhat)
    # observation
    obs = y[i]
    history.append(obs)
    warnings.filterwarnings('ignore')
```

In [39]:
```
# report performance
mse = mean_squared_error(y, predictions)
print('MSE: '+str(mse))
mae = mean_absolute_error(y, predictions)
print('MAE: '+str(mae))
rmse = math.sqrt(mean_squared_error(y, predictions))
print('RMSE: '+str(rmse))
```

```
MSE: 0.0004883712372787762
MAE: 0.01584183932364207
RMSE: 0.022099122997955738
```

In [40]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(16,8))
plt.plot(df_amz_clean.index[-600:], df_amz_clean['Return'].tail(600), col
plt.plot(test_data.index, y, color = 'red', label = 'Real Amazon Return')
plt.plot(test_data.index, predictions, color = 'blue', label = 'Predicted
plt.title('Amazon Return Prediction con ARIMA (0,1,2)')
plt.xlabel('Time')
plt.ylabel('Amazon Return')
plt.legend()
plt.grid(True)
plt.savefig('../reports/arima_model.pdf')
plt.show()
```



8. Investiga sobre los factores de Fama French 3

https://mba.tuck.dartmouth.edu/pages/faculty/ken.fre y descarga dichos factores para las fechas acordadas.

• ¿Qué significan los factores Rm-Rf, SMB y HML? ¿Cómo sus variaciones afectan al retorno de las acciones

• Calcula y analiza la regresión OLS para los datos de la columna Return de Amazon en función de los factores FF3. ¿Cómo afecta cada factor a los retornos de la acción de Amazon?

In [41]:

```
import statsmodels.api as sm

# Cargar los datos de los factores Fama-French
ff_factors = pd.read_csv('../data/F-F_Research_Data_Factors_daily.CSV', i

start_date = "2021-01-01"
end_date = "2024-02-01"

ff_factors
```

Out[41]:

tk	Date	Mkt-RF	SMB	HML	RF
NaN	19260701	0.10	-0.25	-0.27	0.009
NaN	19260702	0.45	-0.33	-0.06	0.009
NaN	19260706	0.17	0.30	-0.39	0.009
NaN	19260707	0.09	-0.58	0.02	0.009
NaN	19260708	0.21	-0.38	0.19	0.009
...	...	...	...	...	...
NaN	20240322	-0.23	-0.87	-0.53	0.021
NaN	20240325	-0.26	-0.24	0.88	0.021
NaN	20240326	-0.26	0.09	-0.13	0.021
NaN	20240327	0.88	1.04	0.91	0.021
NaN	20240328	0.10	0.29	0.48	0.021

25710 rows × 5 columns

In [42]:

```
ff_factors['Date'] = pd.to_datetime(ff_factors['Date'], format='%Y%m%d')
ff_factors
```

Out[42]:

tk	Date	Mkt-RF	SMB	HML	RF
NaN	1926-07-01	0.10	-0.25	-0.27	0.009
NaN	1926-07-02	0.45	-0.33	-0.06	0.009
NaN	1926-07-06	0.17	0.30	-0.39	0.009
NaN	1926-07-07	0.09	-0.58	0.02	0.009
NaN	1926-07-08	0.21	-0.38	0.19	0.009
...	...	...	...	...	...
NaN	2024-03-22	-0.23	-0.87	-0.53	0.021
NaN	2024-03-25	-0.26	-0.24	0.88	0.021
NaN	2024-03-26	-0.26	0.09	-0.13	0.021

NaN	2024-03-27	0.88	1.04	0.91	0.021
NaN	2024-03-28	0.10	0.29	0.48	0.021

25710 rows × 5 columns

In [43]:
```
# Filtrar el DataFrame entre las dos fechas
filtered_ff_factors = ff_factors.loc[(ff_factors['Date'] >= start_date) &

print("DataFrame filtrado:")
print(filtered_ff_factors)
```

```
DataFrame filtrado:
           Date  Mkt-RF   SMB   HML     RF
tk
NaN 2021-01-04   -1.41  0.22  0.58  0.000
NaN 2021-01-05    0.86  1.23  0.49  0.000
NaN 2021-01-06    0.79  2.14  3.94  0.000
NaN 2021-01-07    1.76  0.33 -0.83  0.000
NaN 2021-01-08    0.51 -0.75 -1.37  0.000
..          ...     ...   ...   ...    ...
NaN 2024-01-26   -0.02  0.40 -0.27  0.022
NaN 2024-01-29    0.86  1.07 -0.59  0.022
NaN 2024-01-30   -0.13 -1.26  0.84  0.022
NaN 2024-01-31   -1.74 -0.92 -0.30  0.022
NaN 2024-02-01    1.23  0.63 -1.36  0.021

[775 rows x 5 columns]
```

In [44]:
```
df_amz_clean = df_amz_clean.reset_index()
df_amz_clean
```

Out[44]:

	Date	Return
0	2021-01-05	0.010004
1	2021-01-06	-0.024897
2	2021-01-07	0.007577
3	2021-01-08	0.006496
4	2021-01-11	-0.021519
...	...	...
768	2024-01-25	0.005610
769	2024-01-26	0.008685
770	2024-01-29	0.013449
771	2024-01-30	-0.014015
772	2024-01-31	-0.023899

773 rows × 2 columns

In [45]:
```
# Cargar los retornos de Amazon
df_amz_clean.columns = ['Date', 'Return']

# Alinear las fechas y combinar los datos
ff_factors_amz = pd.merge(filtered_ff_factors, df_amz_clean, on='Date', h

print(ff_factors_amz)
```

```
           Date  Mkt-RF   SMB   HML     RF    Return
0   2021-01-05    0.86  1.23  0.49  0.000  0.010004
1   2021-01-06    0.79  2.14  3.94  0.000 -0.024897
2   2021-01-07    1.76  0.33 -0.83  0.000  0.007577
3   2021-01-08    0.51 -0.75 -1.37  0.000  0.006496
4   2021-01-11   -0.51  0.26  1.26  0.000 -0.021519
..         ...     ...   ...   ...    ...       ...
768 2024-01-25    0.46  0.04  0.56  0.022  0.005610
769 2024-01-26   -0.02  0.40 -0.27  0.022  0.008685
770 2024-01-29    0.86  1.07 -0.59  0.022  0.013449
771 2024-01-30   -0.13 -1.26  0.84  0.022 -0.014015
772 2024-01-31   -1.74 -0.92 -0.30  0.022 -0.023899

[773 rows x 6 columns]
```

In [46]:
```
# Definir la variable dependiente (retorno de Amazon) y las independiente
X = ff_factors_amz[['Mkt-RF', 'SMB', 'HML']]
```

```python
X = ff_factors_amz[['Mkt-RF', 'SMB', 'HML']]
y = ff_factors_amz['Return']

# Agregar una constante (intercepto) a las variables independientes
X = sm.add_constant(X)

# Ajustar el modelo OLS
model = sm.OLS(y, X).fit()

# Resumen del modelo
print(model.summary())
```

```
                            OLS Regression Results                            
==========================================================================
====
Dep. Variable:                 Return   R-squared:                       
0.585
Model:                            OLS   Adj. R-squared:                  
0.583
Method:                 Least Squares   F-statistic:                     3
61.3
Date:                Fri, 31 May 2024   Prob (F-statistic):          2.38e
-146
Time:                        13:34:26   Log-Likelihood:                 21
48.1
No. Observations:                 773   AIC:                            -4
288.
Df Residuals:                     769   BIC:                            -4
270.
Df Model:                           3                                         
Covariance Type:            nonrobust                                         
==========================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
--------------------------------------------------------------------------
----
const       4.594e-05      0.001      0.085      0.933      -0.001       
0.001
Mkt-RF         0.0133      0.001     25.072      0.000       0.012       
0.014
SMB           -0.0029      0.001     -3.735      0.000      -0.004      -
0.001
HML           -0.0058      0.001    -10.532      0.000      -0.007      -
0.005
==========================================================================
====
Omnibus:                      217.587   Durbin-Watson:                   
2.030
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             591
2.167
Skew:                           0.639   Prob(JB):                        
0.00
Kurtosis:                      16.488   Cond. No.                        
1.98
==========================================================================
====
```

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