```python
import yfinance as yf
import pandas as pd

# Download data
apple_data = yf.download('AAPL', start='2021-01-01', end='2023-12-31', interval='1d')
sp500_data = yf.download('^GSPC', start='2021-01-01', end='2023-12-31', interval='1d')
sp500_it_data = yf.download('XLK', start='2021-01-01', end='2023-12-31', interval='1d')

# Process the data
apple_data['Apple_Returns'] = apple_data['Adj Close'].pct_change()
sp500_data['SP500_Returns'] = sp500_data['Adj Close'].pct_change()
sp500_it_data['SP500_IT_Returns'] = sp500_it_data['Adj Close'].pct_change()

# Combine the data into one dataframe
combined_data = pd.DataFrame({
    'Apple_Returns': apple_data['Apple_Returns'],
    'SP500_Returns': sp500_data['SP500_Returns'],
    'SP500_IT_Returns': sp500_it_data['SP500_IT_Returns']
})

# Drop missing values
combined_data.dropna(inplace=True)

# Save to a CSV
combined_data.to_csv('Cleaned_Combined_Data_2021_2023.csv')
print("\nCleaned and combined data saved as 'Cleaned_Combined_Data_2021_2023.csv'")
```

```
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed


Cleaned and combined data saved as 'Cleaned_Combined_Data_2021_2023.csv'
```

```python
combined_data = pd.read_csv('Cleaned_Combined_Data_2021_2023.csv', index_col=0)
print(combined_data.head())
```

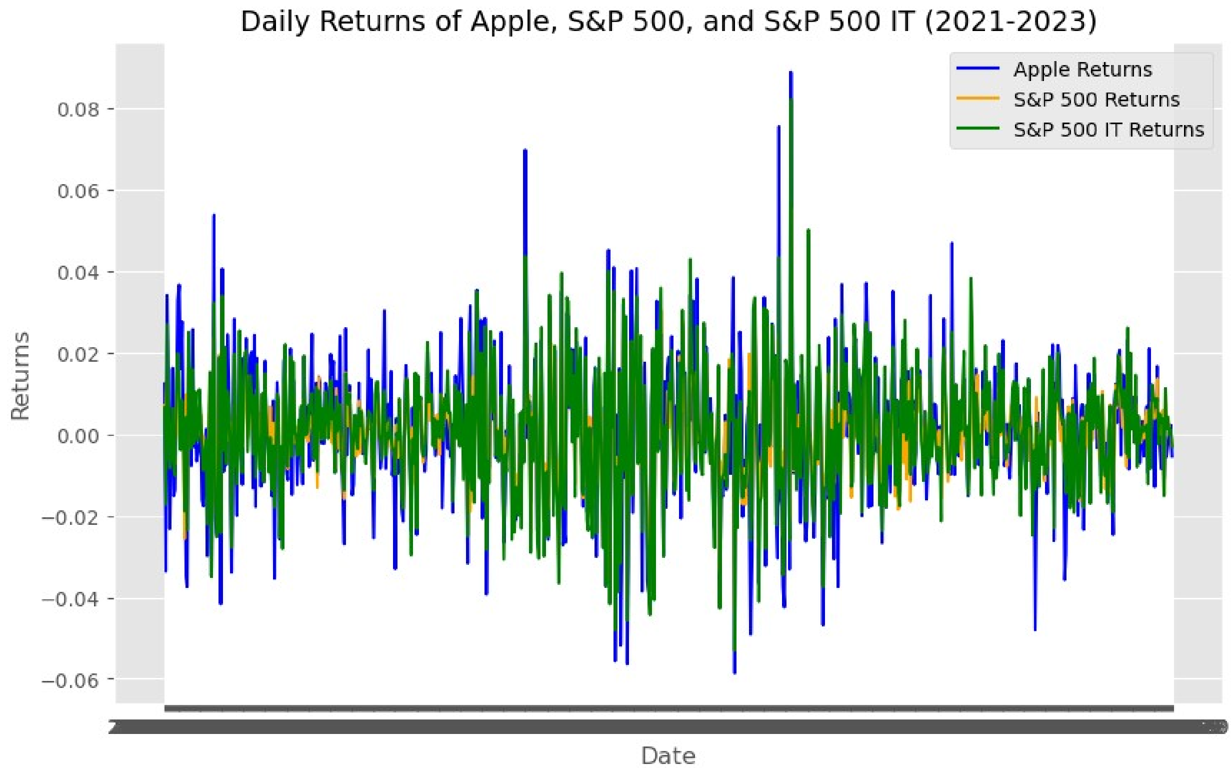
```
            Apple_Returns  SP500_Returns  SP500_IT_Returns
Date
2021-01-05       0.012364       0.007083          0.006489
2021-01-06      -0.033661       0.005710         -0.017245
2021-01-07       0.034123       0.014847          0.026954
```

```
2021-01-08       0.008631       0.005492          0.006466
2021-01-11      -0.023249      -0.006555         -0.008259
```

```python
# Calculate descriptive statistics
print("Descriptive Statistics:")
print(combined_data.describe())
```

```
Descriptive Statistics:
       Apple_Returns  SP500_Returns  SP500_IT_Returns
count     752.000000     752.000000        752.000000
mean        0.000705       0.000399          0.000697
std         0.017511       0.011083          0.015435
min        -0.058680      -0.043237         -0.053084
25%        -0.008891      -0.005863         -0.008470
50%         0.000776       0.000393          0.000582
75%         0.011262       0.006944          0.010097
max         0.088975       0.055434          0.082176
```

```python
import matplotlib.pyplot as plt

# Use an available style
plt.style.use('ggplot')

# Plot time-series data
plt.figure(figsize=(10, 6))
plt.plot(combined_data.index, combined_data['Apple_Returns'],
label='Apple Returns', color='blue')
plt.plot(combined_data.index, combined_data['SP500_Returns'],
label='S&P 500 Returns', color='orange')
plt.plot(combined_data.index, combined_data['SP500_IT_Returns'],
label='S&P 500 IT Returns', color='green')

# Add titles and labels
plt.title("Daily Returns of Apple, S&P 500, and S&P 500 IT (2021-
2023)", fontsize=14)
plt.xlabel("Date", fontsize=12)
plt.ylabel("Returns", fontsize=12)

# Add legend and grid
plt.legend()
plt.grid(True)
plt.show()
```




```python
import statsmodels.api as sm

# ===== Simple OLS Regression =====
# Independent variable: SP500 Returns
X_simple = combined_data['SP500_Returns']
# Dependent variable: Apple Returns
y = combined_data['Apple_Returns']

# Add a constant (intercept) to the model
X_simple = sm.add_constant(X_simple)

# Fit the regression model
simple_model = sm.OLS(y, X_simple).fit()

# Display the summary
print("\n===== Simple OLS Regression =====")
print(simple_model.summary())
```

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

================================================================================
========
Dep. Variable:          Apple_Returns   R-squared:
0.650
```

```
Model:                            OLS   Adj. R-squared:
0.649
Method:                 Least Squares   F-statistic:
1390.
Date:                Mon, 16 Dec 2024   Prob (F-statistic):
6.24e-173
Time:                        13:59:08   Log-Likelihood:
2369.5
No. Observations:                 752   AIC:
-4735.
Df Residuals:                     750   BIC:
-4726.
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
===========
                   coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
const            0.0002      0.000      0.519      0.604      -0.001
0.001
SP500_Returns    1.2733      0.034     37.284      0.000       1.206
1.340
======================================================================
========
Omnibus:                       62.545   Durbin-Watson:
1.845
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
329.299
Skew:                           0.010   Prob(JB):
3.12e-72
Kurtosis:                       6.242   Cond. No.
90.3
======================================================================
========

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

# Compute the correlation matrix
correlation_matrix = combined_data.corr()

# Display the correlation matrix
print("Correlation Matrix:")
print(correlation_matrix)
```

```
Correlation Matrix:
                  Apple_Returns  SP500_Returns  SP500_IT_Returns
Apple_Returns          1.000000       0.805943          0.876018
SP500_Returns          0.805943       1.000000          0.933453
SP500_IT_Returns       0.876018       0.933453          1.000000
```

```
import pandas as pd
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import
variance_inflation_factor

# Assuming combined_data is your processed dataset with returns
# Create the predictor matrix
X = combined_data[['SP500_Returns', 'SP500_IT_Returns']]

# Add a constant for the intercept
X = sm.add_constant(X)

# Calculate VIF for each predictor
vif_data = pd.DataFrame()
vif_data['Variable'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in
range(X.shape[1])]

# Display VIF values
print("Variance Inflation Factor (VIF) for Predictors:")
print(vif_data)
```

```
Variance Inflation Factor (VIF) for Predictors:
           Variable       VIF
0             const  1.002338
1     SP500_Returns  7.772100
2  SP500_IT_Returns  7.772100
```

```
print("Columns in combined_data:", combined_data.columns)
```

```
Columns in combined_data: Index(['Apple_Returns', 'SP500_Returns',
'SP500_IT_Returns'], dtype='object')
```

```
# ===== Multiple OLS Regression =====
# Independent variables: SP500 Returns and SP500 IT Returns
X_multiple = combined_data[['SP500_Returns', 'SP500_IT_Returns']]
# Dependent variable: Apple Returns
y = combined_data['Apple_Returns']

# Add a constant (intercept) to the model
X_multiple = sm.add_constant(X_multiple)

# Fit the regression model
multiple_model = sm.OLS(y, X_multiple).fit()
```

```python
# Display the summary
print("\n===== Multiple OLS Regression =====")
print(multiple_model.summary())
```

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

==============================================================================
========
Dep. Variable:          Apple_Returns   R-squared:
0.768
Model:                            OLS   Adj. R-squared:
0.768
Method:                 Least Squares   F-statistic:
1243.
Date:                Mon, 16 Dec 2024   Prob (F-statistic):
1.08e-238
Time:                        13:59:21   Log-Likelihood:
2525.4
No. Observations:                 752   AIC:
-5045.
Df Residuals:                     749   BIC:
-5031.
Df Model:                           2

Covariance Type:            nonrobust

==============================================================================
==============
                      coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
--------------
const            1.914e-06      0.000      0.006      0.995      -
0.001       0.001
SP500_Returns      -0.1446      0.077     -1.868      0.062      -
0.297       0.007
SP500_IT_Returns    1.0908      0.056     19.616      0.000
0.982       1.200
==============================================================================
========
Omnibus:                       43.059   Durbin-Watson:
1.916
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
153.562
Skew:                          -0.054   Prob(JB):
4.51e-34
Kurtosis:                       5.211   Cond. No.
305.
```

```
==============================================================================
========

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

```python
# Residuals from the simple regression
residuals_simple = simple_model.resid

# Residuals from the multiple regression
residuals_multiple = multiple_model.resid

from scipy.stats import jarque_bera

jb_test_simple = jarque_bera(residuals_simple)
jb_test_multiple = jarque_bera(residuals_multiple)

print("Jarque-Bera Test for Simple Regression:", jb_test_simple)
print("Jarque-Bera Test for Multiple Regression:", jb_test_multiple)
```

```
Jarque-Bera Test for Simple Regression:
SignificanceResult(statistic=329.2988288682313,
pvalue=3.1165052487790823e-72)
Jarque-Bera Test for Multiple Regression:
SignificanceResult(statistic=153.56183080365957,
pvalue=4.513070579913583e-34)
```

```python
from statsmodels.stats.stattools import durbin_watson

dw_stat_simple = durbin_watson(residuals_simple)
dw_stat_multiple = durbin_watson(residuals_multiple)

print("Durbin-Watson for Simple Regression:", dw_stat_simple)
print("Durbin-Watson for Multiple Regression:", dw_stat_multiple)
```

```
Durbin-Watson for Simple Regression: 1.8453927398290495
Durbin-Watson for Multiple Regression: 1.9158310974958823
```

```python
from statsmodels.stats.api import het_white

# Robust covariance matrix
robust_cov = multiple_model.get_robustcov_results(cov_type="HAC",
maxlags=1)
print(robust_cov.summary())
```

```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:          Apple_Returns   R-squared:
0.768
```

```
Model:                            OLS   Adj. R-squared:
0.768
Method:                 Least Squares   F-statistic:
931.0
Date:                Tue, 17 Dec 2024   Prob (F-statistic):
7.85e-204
Time:                        08:39:25   Log-Likelihood:
2525.4
No. Observations:                 752   AIC:
-5045.
Df Residuals:                     749   BIC:
-5031.
Df Model:                           2

Covariance Type:                  HAC

======================================================================
==============
                       coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
--------------
const             1.914e-06      0.000      0.006      0.995      -
0.001       0.001
SP500_Returns       -0.1446      0.111     -1.297      0.195      -
0.364       0.074
SP500_IT_Returns     1.0908      0.085     12.859      0.000
0.924       1.257
======================================================================
========
Omnibus:                       43.059   Durbin-Watson:
1.916
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
153.562
Skew:                          -0.054   Prob(JB):
4.51e-34
Kurtosis:                       5.211   Cond. No.
305.
======================================================================
========

Notes:
[1] Standard Errors are heteroscedasticity and autocorrelation robust
(HAC) using 1 lags and without small sample correction
```

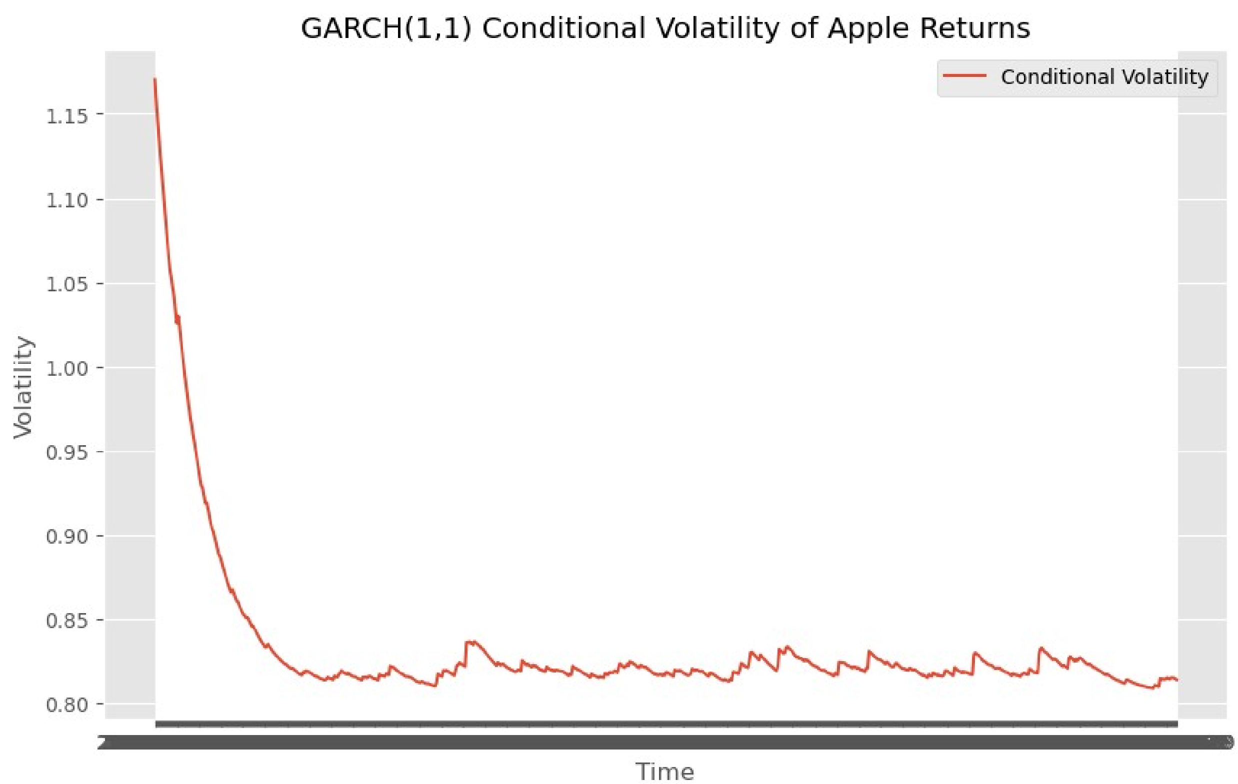
```
from arch import arch_model

# Fit GARCH(1,1) model
residuals_hac = multiple_model.resid  # Residuals from the adjusted
regression
```

```
scaled_residuals_hac = residuals_hac * 100  # Scale residuals for better optimization

garch_model_hac = arch_model(scaled_residuals_hac, vol='Garch', p=1, q=1)
garch_results_hac = garch_model_hac.fit()

print(garch_results_hac.summary())
```

```
Iteration:      1,   Func. Count:      6,   Neg. LLF: 1715284.261092082
Iteration:      2,   Func. Count:     14,   Neg. LLF: 3095.590090631951
Iteration:      3,   Func. Count:     21,   Neg. LLF: 1183.411581073603
Iteration:      4,   Func. Count:     29,   Neg. LLF: 1370.5534682336702
Iteration:      5,   Func. Count:     35,   Neg. LLF: 1261.7497085208604
Iteration:      6,   Func. Count:     41,   Neg. LLF: 1224.8210608022048
Iteration:      7,   Func. Count:     47,   Neg. LLF: 1155.4260061277664
Iteration:      8,   Func. Count:     53,   Neg. LLF: 996.9167173594652
Iteration:      9,   Func. Count:     59,   Neg. LLF: 1029.6951125816108
Iteration:     10,   Func. Count:     65,   Neg. LLF: 984.9868031416943
Iteration:     11,   Func. Count:     71,   Neg. LLF: 959.7513084994887
Iteration:     12,   Func. Count:     77,   Neg. LLF: 938.672728439954
Iteration:     13,   Func. Count:     83,   Neg. LLF: 932.7711014256965
Iteration:     14,   Func. Count:     88,   Neg. LLF: 932.6920535666313
Iteration:     15,   Func. Count:     93,   Neg. LLF: 932.4747109494589
Iteration:     16,   Func. Count:     98,   Neg. LLF: 932.4225904846908
Iteration:     17,   Func. Count:    103,   Neg. LLF: 932.4201725766571
Iteration:     18,   Func. Count:    108,   Neg. LLF: 932.4183675894262
Iteration:     19,   Func. Count:    113,   Neg. LLF: 932.418176297936
Iteration:     20,   Func. Count:    118,   Neg. LLF: 932.4181455539419
Iteration:     21,   Func. Count:    122,   Neg. LLF: 932.4181455583173
Optimization terminated successfully    (Exit mode 0)
```

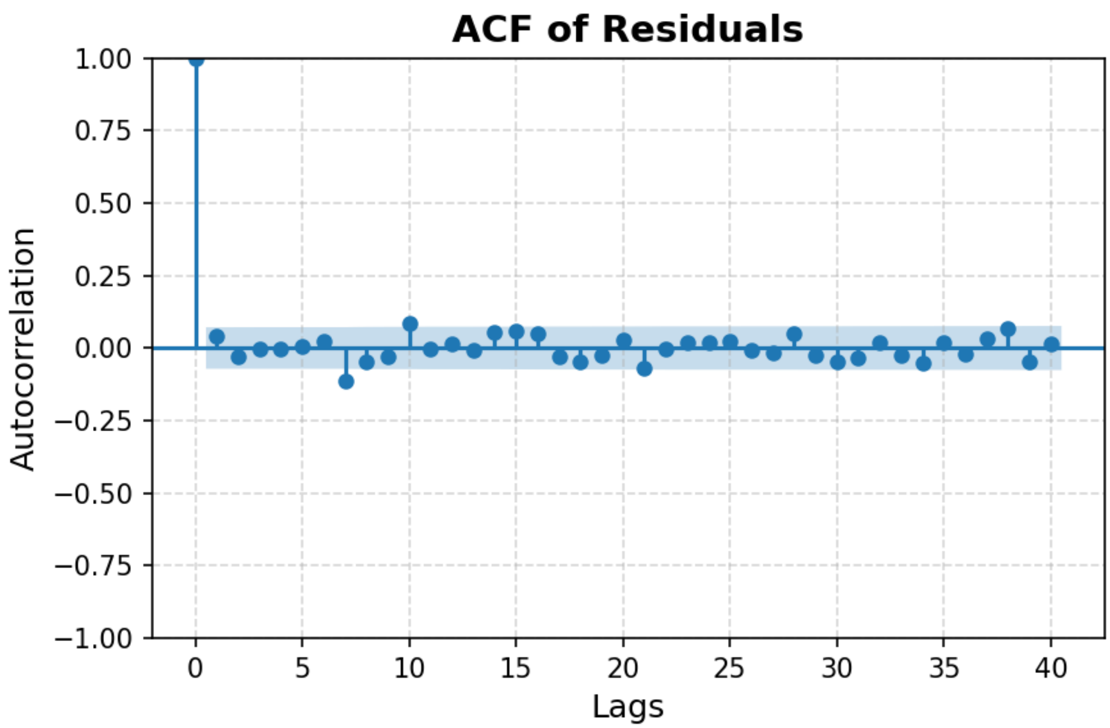
```
            Current function value: 932.4181455539419
            Iterations: 21
            Function evaluations: 122
            Gradient evaluations: 21
                     Constant Mean - GARCH Model Results

======================================================================
========
Dep. Variable:                   None   R-squared:
0.000
Mean Model:             Constant Mean   Adj. R-squared:
0.000
Vol Model:                      GARCH   Log-Likelihood:
-932.418
Distribution:                  Normal   AIC:
1872.84
Method:            Maximum Likelihood   BIC:
1891.33
                                        No. Observations:
752
Date:                Tue, Dec 17 2024   Df Residuals:
751
Time:                        08:57:31   Df Model:
1
                                  Mean Model

======================================================================
=======
                 coef    std err          t      P>|t|       95.0%
Conf. Int.
----------------------------------------------------------------------
-------
mu         2.0360e-03  3.027e-02  6.726e-02      0.946 [-5.729e-
02,6.137e-02]
                               Volatility Model

======================================================================
=======
                 coef    std err          t      P>|t|       95.0%
Conf. Int.
----------------------------------------------------------------------
-------
omega          0.0257  1.184e-02      2.171  2.991e-02  [2.503e-
03,4.893e-02]
alpha[1]   1.7561e-03  1.903e-02  9.229e-02      0.926 [-3.554e-
02,3.905e-02]
beta[1]        0.9599  3.375e-02     28.443 5.998e-178      [  0.894,
1.026]
======================================================================
=======
```

```
Covariance estimator: robust

import matplotlib.pyplot as plt

# Plot the conditional volatility
conditional_volatility = garch_results_hac.conditional_volatility
plt.figure(figsize=(10, 6))
plt.plot(conditional_volatility, label="Conditional Volatility")
plt.title("GARCH(1,1) Conditional Volatility of Apple Returns")
plt.xlabel("Time")
plt.ylabel("Volatility")
plt.legend()
plt.show()
```



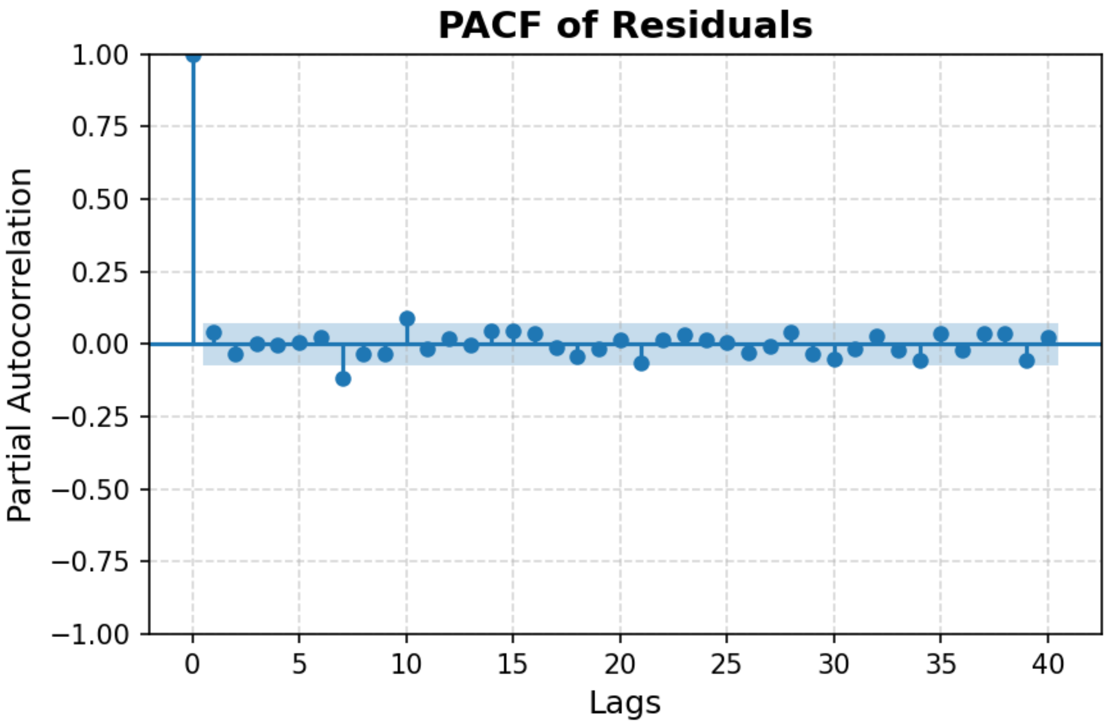

```
from statsmodels.graphics.tsaplots import plot_acf
import matplotlib.pyplot as plt


plt.style.use('default')

# Plot ACF
fig, ax = plt.subplots(figsize=(6, 4), dpi=150, facecolor='white')
plot_acf(residuals_hac, lags=40, alpha=0.05, title="ACF of Residuals",
color='tab:blue', ax=ax)
```

```python
# Refine aesthetics
ax.set_facecolor("white")  # Set axes background to white
plt.grid(True, linestyle='--', alpha=0.5)
plt.xlabel("Lags", fontsize=12)
plt.ylabel("Autocorrelation", fontsize=12)
plt.title("ACF of Residuals", fontsize=14, weight='bold')
plt.tight_layout()
plt.show()
```




```python
from statsmodels.graphics.tsaplots import plot_pacf
import matplotlib.pyplot as plt

# Set plot style and figure size
plt.style.use('default')  # Default clean style
fig, ax = plt.subplots(figsize=(6, 4), dpi=150, facecolor='white')  #
White figure background

# Plot PACF with clean aesthetics
plot_pacf(residuals_hac, lags=40, alpha=0.05, title="PACF of
Residuals", color='tab:blue', ax=ax)

# Customize aesthetics
ax.set_facecolor("white")  # Set axes background to white
plt.grid(True, linestyle='--', alpha=0.5)  # Subtle gridlines
plt.xlabel("Lags", fontsize=12)  # X-axis label
```

```
plt.ylabel("Partial Autocorrelation", fontsize=12)  # Y-axis label
plt.title("PACF of Residuals", fontsize=14, weight='bold')  # Improved
title
plt.tight_layout()
plt.show()
```




```
from statsmodels.tsa.arima.model import ARIMA

# Fit ARIMA model to residuals
arima_model = ARIMA(residuals_hac, order=(1, 0, 1))
arima_results = arima_model.fit()

print(arima_results.summary())

C:\Users\shatakshi bansode\anaconda3\Lib\site-packages\statsmodels\
tsa\base\tsa_model.py:473: ValueWarning: A date index has been
provided, but it has no associated frequency information and so will
be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\shatakshi bansode\anaconda3\Lib\site-packages\statsmodels\
tsa\base\tsa_model.py:473: ValueWarning: A date index has been
provided, but it has no associated frequency information and so will
be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\shatakshi bansode\anaconda3\Lib\site-packages\statsmodels\
tsa\base\tsa_model.py:473: ValueWarning: A date index has been
```

```
provided, but it has no associated frequency information and so will
be ignored when e.g. forecasting.
  self._init_dates(dates, freq)

                               SARIMAX Results

======================================================================
========
Dep. Variable:                      y   No. Observations:
752
Model:                 ARIMA(1, 0, 1)   Log Likelihood
2526.281
Date:                Tue, 17 Dec 2024   AIC                          -
5044.562
Time:                        09:59:20   BIC                          -
5026.071
Sample:                             0   HQIC                         -
5037.438
                                - 752

Covariance Type:                  opg

======================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
----------------------------------------------------------------------
--------
const      -9.934e-18      0.000  -3.14e-14      1.000      -0.001
0.001
ar.L1         -0.4508      0.539     -0.836      0.403      -1.507
0.606
ma.L1          0.4976      0.527      0.944      0.345      -0.536
1.531
sigma2      7.069e-05   2.51e-06     28.129      0.000    6.58e-05
7.56e-05
======================================================================
=============
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):
155.58
Prob(Q):                              0.91   Prob(JB):
0.00
Heteroskedasticity (H):               0.89   Skew:
-0.05
Prob(H) (two-sided):                  0.36   Kurtosis:
5.23
======================================================================
=============

Warnings:
```

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

C:\Users\shatakshi bansode\anaconda3\Lib\site-packages\statsmodels\
base\model.py:607: ConvergenceWarning: Maximum Likelihood optimization
failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "

# 1. OLS captures linear relationships.
# 2. ARIMA ensures that residuals are white noise.
# 3. GARCH captures volatility clustering, which is a key feature of
financial returns.
# 4. Model selection was based on AIC, BIC, and volatility clustering.
```