MODS205 - Digital Finance - Project

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Question 1

Comment on the article “Crypto’s Richest Rebel” from Fortune April/May 2022 available on the e-campus website using all keywords and concepts covered in the course.

the Binance story encapsulates the dynamic interplay between **innovation** and **regulation**, a recurrent theme across the digital finance landscape. Binance’s trajectory, from its inception to becoming the world's largest cryptocurrency exchange, underscores the transformative potential of digital platforms. Yet, it also highlights the complexities and challenges these entities face in navigating a global regulatory framework. This duality mirrors foundational course discussions about the need for digital finance platforms to balance groundbreaking technological advancements with adherence to established regulatory standards to ensure market integrity and protect investor interests.

The strategic expansion and diversification of Binance reflect key principles of **portfolio management**, underscoring the importance of **risk management** in a domain characterized by rapid technological evolution and regulatory uncertainties. Binance’s efforts to comply with international regulations illuminate the critical role of robust risk management practices, emphasizing the need for digital finance entities to proactively address potential operational, regulatory, and reputational risks.

Furthermore, the volatility of the cryptocurrency market and the influence of significant news events on market dynamics bring to life the relevance of **financial time series analysis**. This aspect of Binance’s operation highlights the importance of understanding and predicting market movements, a key area of study within the course that gains practical significance in the highly volatile cryptocurrency sector.

Binance's encounters with regulatory challenges embody the real-world complexities of **regulatory compliance** and **consumer protection**. These challenges not only illustrate the tangible consequences of regulatory non-compliance but also emphasize the pivotal role of governance and ethical business practices in maintaining trust and stability in the digital finance ecosystem.

Moreover, Changpeng Zhao’s vision for leveraging **blockchain technology** for **financial innovation** encapsulates the course’s exploration of blockchain's economic implications. The narrative of Binance navigating the promise and perils of blockchain technology underscores its potential to revolutionize financial services, while also highlighting the regulatory, ethical, and operational considerations that accompany such disruptive technologies.

In essence, the stories and insights derived from Binance's journey offer a vivid reflection of the intricate themes explored throughout the Digital Finance course. They underscore the ongoing dialogue between innovation and regulation, the strategic challenges of market navigation, and the profound potential of blockchain technology to reshape the financial services landscape. This analysis not only reinforces key concepts covered in the course but also presents a comprehensive case study on the complexities and opportunities that define the digital finance sector today, offering valuable lessons for stakeholders navigating this rapidly evolving domain.

Question 2

Comment on the article "Binance CEO Changpeng Zhao charged with money laundering" from Fortune Website 2023-11-23 available on the e-campus website using all keywords and concepts covered in the course.

The Binance saga, marked by legal challenges including a substantial settlement with the DOJ and the stepping down of CEO Changpeng Zhao, serves as a pivotal case in the digital finance narrative, illustrating the tension between rapid technological innovation and the imperative for **regulatory compliance**. Binance's journey from a startup to the apex of the cryptocurrency exchange market, while fraught with regulatory oversights, underscores a broader industry-wide challenge: the necessity of integrating robust compliance mechanisms within the fabric of **financial innovation** to ensure **market integrity** and **protect investor interests**.

This case underscores the importance of adherence to anti-money laundering and know-your-customer principles, foundational to the trust and security that underpin the financial markets. It also highlights the complexities of operating within the **global financial ecosystem**, where adherence to international sanctions plays a critical role in maintaining legal and economic stability. The repercussions faced by Binance accentuate the criticality of compliance, not merely as a legal obligation but as a cornerstone of sustainable business growth and market trust.

Moreover, the Binance episode reflects on the strategic necessity for digital finance platforms to balance innovation with compliance. The proactive steps taken by Binance to align with regulatory expectations post-litigation indicate a shift towards prioritizing compliance alongside innovation. This alignment is essential for the continued evolution of the **cryptocurrency sector**, ensuring that it can mature into a stable, trustworthy component of the broader financial system.

In essence, the Binance case is emblematic of the evolving landscape of digital finance, where the interplay between **innovation** and **regulation** is both intricate and indispensable. It highlights the need for ongoing dialogue between innovators and regulators to forge a path forward that nurtures technological advancement while safeguarding the principles of market integrity and investor protection. This dialogue is crucial for the future trajectory of the cryptocurrency sector and the wider digital finance ecosystem, ensuring that they can realize their full potential in a manner that is both innovative and compliant.

Question 3

In [ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from scipy.stats import norm
```

Question 3.1

Import data in Excel (2 stocks, CAC40 index, 5-week interest rate from the US Treasury). Sort data by date and make sure that all dates coincides for all columns. Adjust cells if there are missing values.

In [ ]:
```
# Data for the 2 stocks
air_liquide_stock = pd.read_csv('AI.PA.csv')
peugeot_stock = pd.read_csv('UG.PA.csv')

# Data for the CAC40 index
CAC40 = pd.read_csv('^FCHI.csv')

# Data for 5-week interest rate from the US Treasury
interest_rate = pd.read_csv('^IRX.csv')

# List of the dataframes
df_list = [air_liquide_stock, peugeot_stock, CAC40, interest_rate]
```

In [ ]:
```
# Function to replace the null (nan) values of the datavrframes with the mean of the column
def replace_nan_with_mean(df_list):
    updated_dfs = []
    for df in df_list:
        for col in df.columns:
            if df[col].isnull().any():
                df[col].fillna(df[col].mean(), inplace=True)
        updated_dfs.append(df)
    return updated_dfs

updated_list = replace_nan_with_mean(df_list)
```

In [ ]:
```
# Check if the dataframes had null values and have been updated
if updated_list == df_list:
```

```
    print("The dataframes didn't have null values")
else:
    print("The dataframes had null values and have been updated")
```

```
The dataframes didn't have null values
```

In [ ]:
```
# Dimensions of the dataframes
print(f"Air liquid stock shape = {air_liquide_stock.shape}")
print(f"Peugeot stock shape = {peugeot_stock.shape}")
print(f"CAC40 shape = {CAC40.shape}")
print(f"Interest rate shape = {interest_rate.shape}")
```

```
Air liquid stock shape = (255, 7)
Peugeot stock shape = (255, 7)
CAC40 shape = (255, 7)
Interest rate shape = (252, 7)
```

In [ ]:
```
# Function to convert the date column from string to datetime
def str_to_date(column_name, df_list):
    for df in df_list:
        df[column_name] = pd.to_datetime(df[column_name])
    return df_list
```

In [ ]:
```
# Function to align the dataframes
def align_dataframes(df_list):
    # Create a set with all the dates present in all the dataframes
    dates = set.intersection(*(set(df['Date']) for df in df_list))

    # Criates a new list of dataframes, where each dataframe is filtered to contain only the dates present in all dataframes
    list_aligned_dfs = [df[df['Date'].isin(dates)].sort_values('Date').reset_index(drop=True) for df in df_list]

    # Verifies if all the dates are present in all the dataframes
    for data in dates:
        if not all(data in df['Date'].values for df in list_aligned_dfs):
            # If a date is not present in all dataframes, remove that date from all dataframes
            list_aligned_dfs = [df[df['Date'] != data] for df in list_aligned_dfs]

    return list_aligned_dfs
```

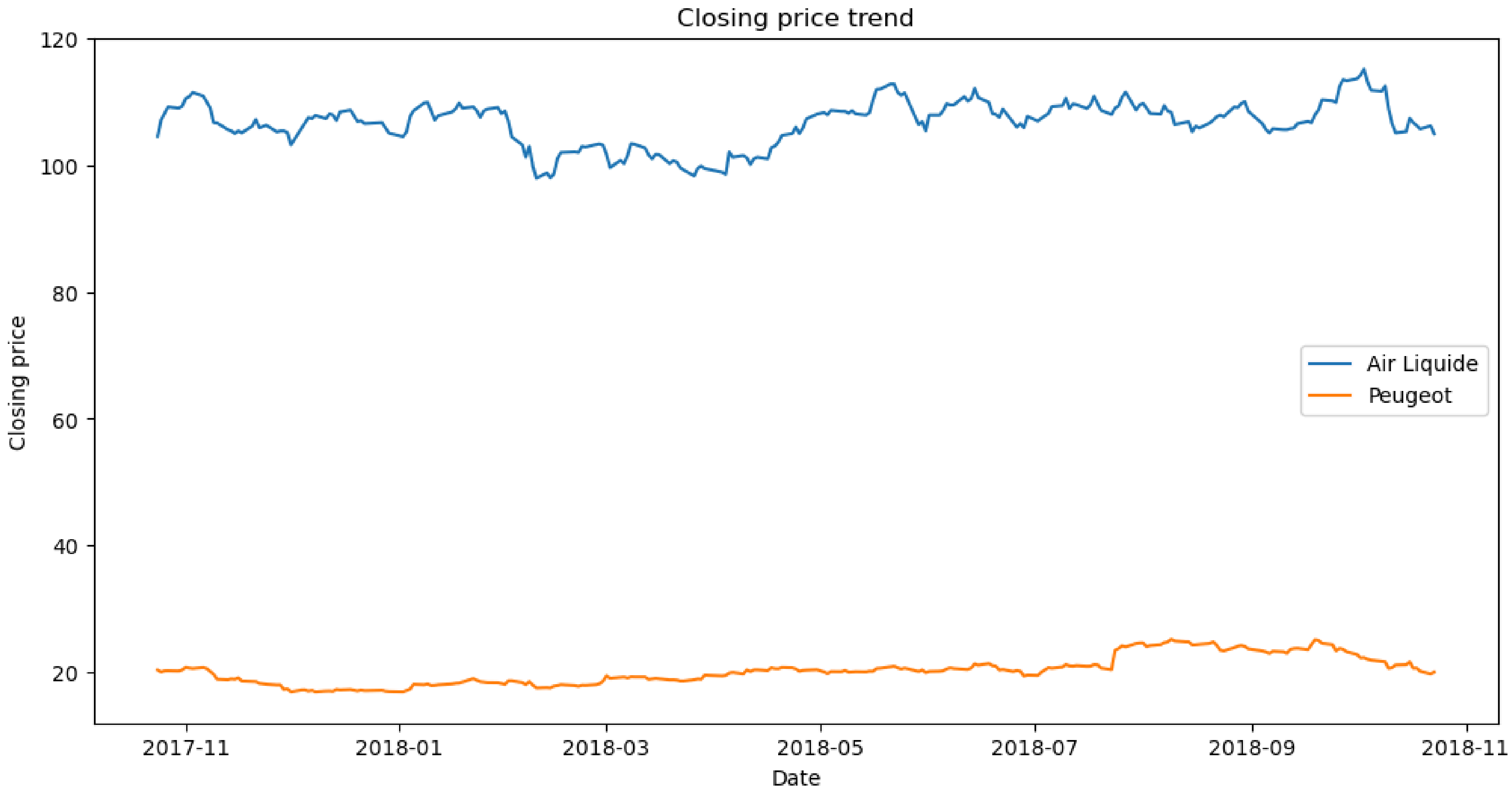
In [ ]:
```
# Update the list of dataframes
updated_list = align_dataframes(str_to_date("Date",updated_list))
df_list = updated_list

# Update the dataframes
air_liquide_stock = df_list[0]
peugeot_stock = df_list[1]
CAC40 = df_list[2]
interest_rate = df_list[3]
```

Question 3.2

Give a short financial analysis of the two stocks by using relevant concepts of the course.

Closing price trend of *Air Liquide* and *Peugeot* stocks:

In [ ]:
```
# Closing price trend
plt.figure(figsize=(12, 6), dpi=100)
plt.plot(air_liquide_stock['Date'], air_liquide_stock['Close'], label='Air Liquide')
plt.plot(peugeot_stock['Date'], peugeot_stock['Close'], label='Peugeot')
plt.title('Closing price trend')
plt.xlabel('Date')
plt.ylabel('Closing price')
plt.legend()
plt.show()
```

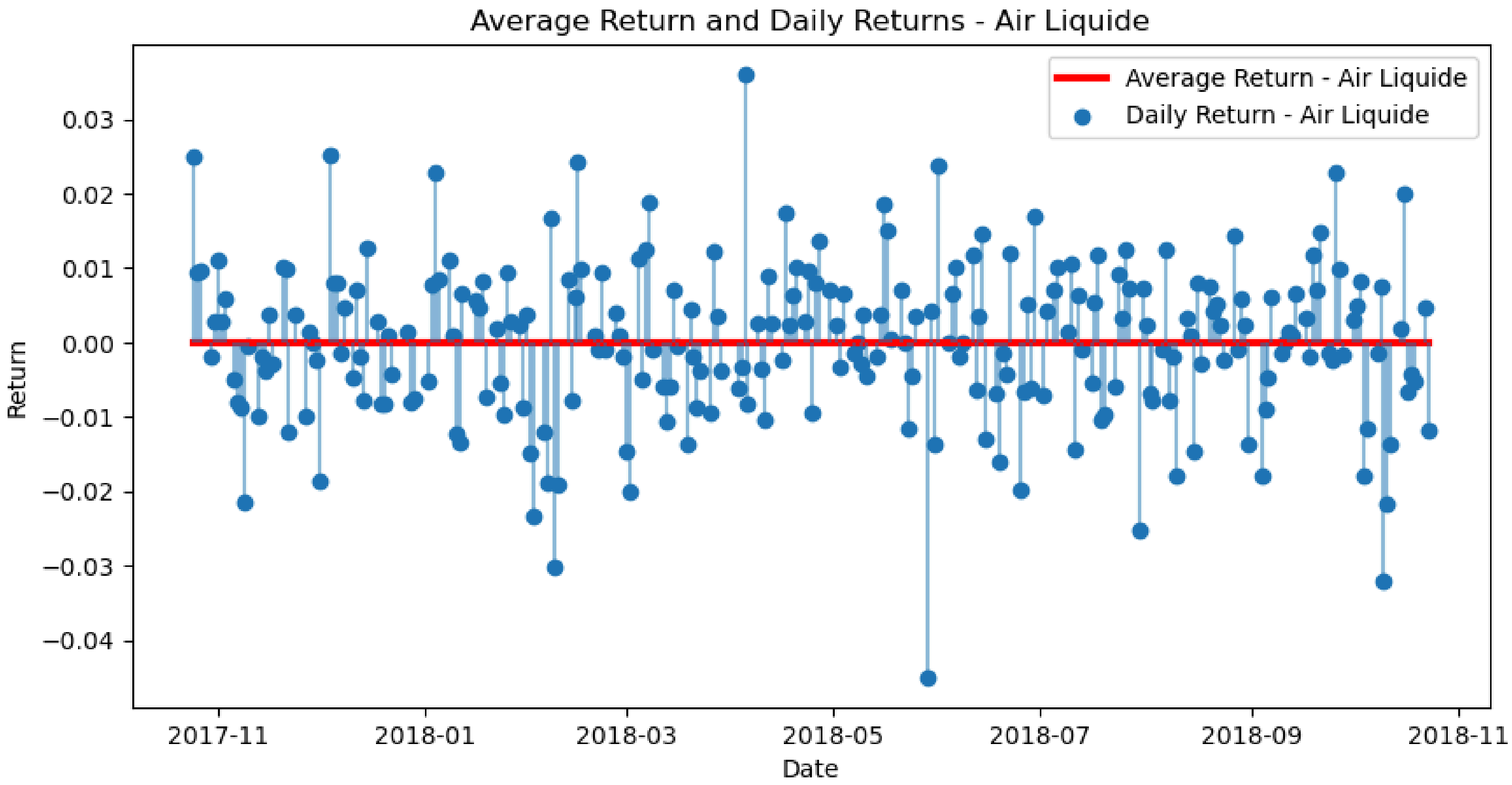


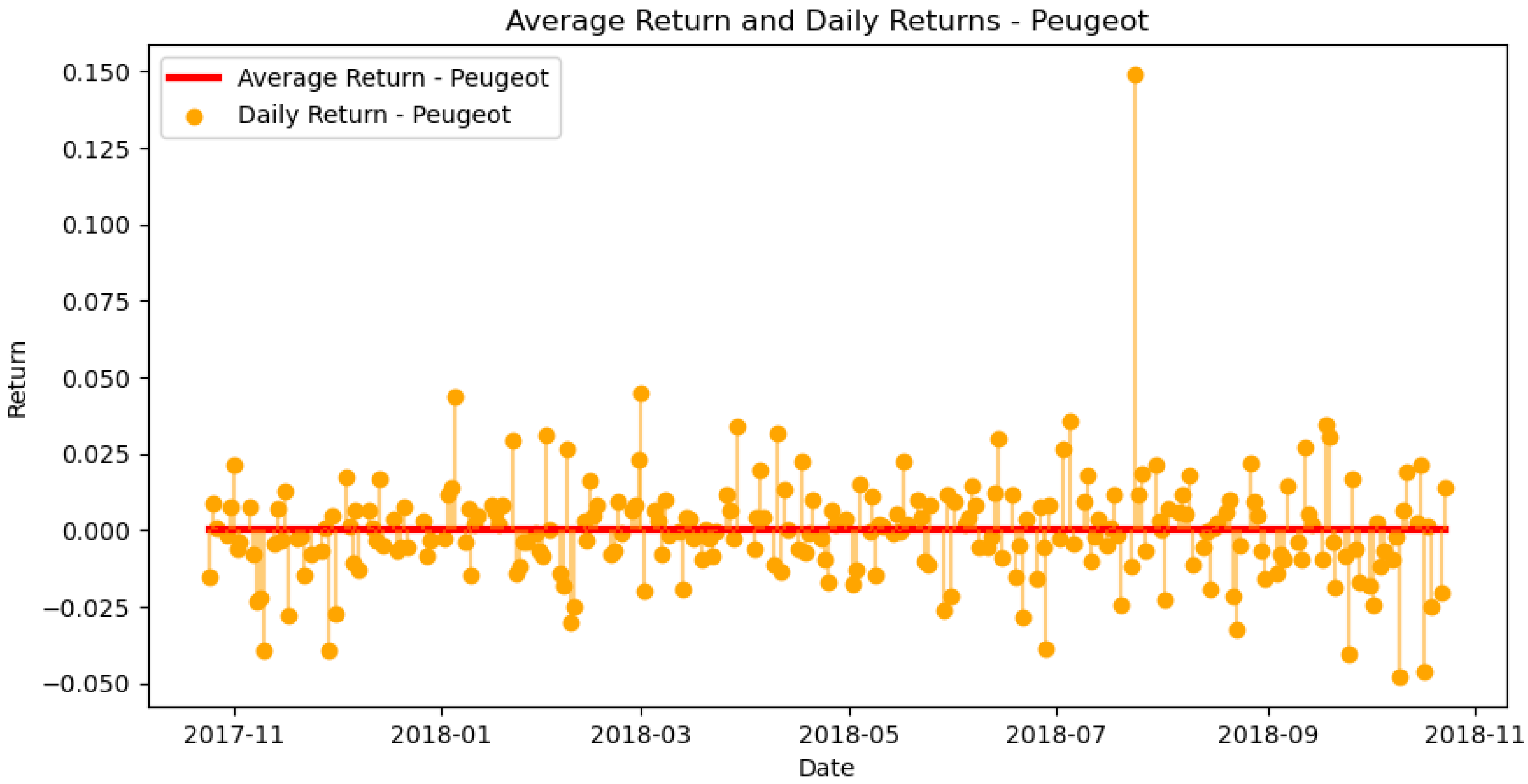
Volatility analysis of *Air Liquide* and *Peugeot* stocks:

In [ ]:
```
# Daily return trend
air_liquide_stock['Daily Return'] = air_liquide_stock['Close'].pct_change()
peugeot_stock['Daily Return'] = peugeot_stock['Close'].pct_change()
CAC40['Daily Return'] = CAC40['Close'].pct_change()
```

In [ ]:
```
# Remove rows with missing 'Date' or 'Daily Return' in air_liquide_stock
air_liquide_stock = air_liquide_stock.dropna(subset=['Date', 'Daily Return'])

# Remove rows with missing 'Date' or 'Daily Return' in peugeot_stock
peugeot_stock = peugeot_stock.dropna(subset=['Date', 'Daily Return'])
```

```
# Plotting the average return line for Air Liquide
plt.figure(figsize=(10, 5), dpi=100)
plt.plot(air_liquide_stock['Date'], [air_liquide_stock['Daily Return'].mean()] * len(air_liquide_stock), label='Average Return - A
plt.scatter(air_liquide_stock['Date'], air_liquide_stock['Daily Return'], label='Daily Return - Air Liquide', marker='o')

# Connect each point with a perpendicular line to the average return line
for x, y in zip(air_liquide_stock['Date'], air_liquide_stock['Daily Return']):
    plt.vlines(x, air_liquide_stock['Daily Return'].mean(), y, alpha=0.5)

plt.title('Average Return and Daily Returns - Air Liquide')
plt.xlabel('Date')
plt.ylabel('Return')
plt.legend()
plt.show()

# Plotting the average return line for Peugeot
plt.figure(figsize=(10, 5), dpi=100)
plt.plot(peugeot_stock['Date'], [peugeot_stock['Daily Return'][1:].mean()] * len(peugeot_stock), label='Average Return - Peugeot'
plt.scatter(peugeot_stock['Date'], peugeot_stock['Daily Return'], label='Daily Return - Peugeot', marker='o', color='orange')

# Connect each point with a perpendicular line to the average return line
for x, y in zip(peugeot_stock['Date'], peugeot_stock['Daily Return']):
    plt.vlines(x, peugeot_stock['Daily Return'].mean(), y, colors='orange', alpha=0.5)

plt.title('Average Return and Daily Returns - Peugeot')
plt.xlabel('Date')
plt.ylabel('Return')
plt.legend()
plt.show()
```


Average Return and Daily Returns - Air Liquide
Average Return - Air Liquide
Daily Return - Air Liquide
0.03
0.02
0.01
0.00
−0.01
−0.02
−0.03
−0.04
Return
2017-11
2018-01
2018-03
2018-05
2018-07
2018-09
2018-11
Date



In [ ]:

```
# Standard deviation of the daily returns
airliquide_std = air_liquide_stock['Daily Return'].std()
peugeot_std = peugeot_stock['Daily Return'].std()

# Standard deviation dataframe
std_df = pd.DataFrame({'Stock': ['Air Liquide', 'Peugeot'], 'Daily Return Standard Deviation': [airliquide_std, peugeot_std]})
std_df = std_df.set_index('Stock', drop=True)

std_df
```

Out[ ]:

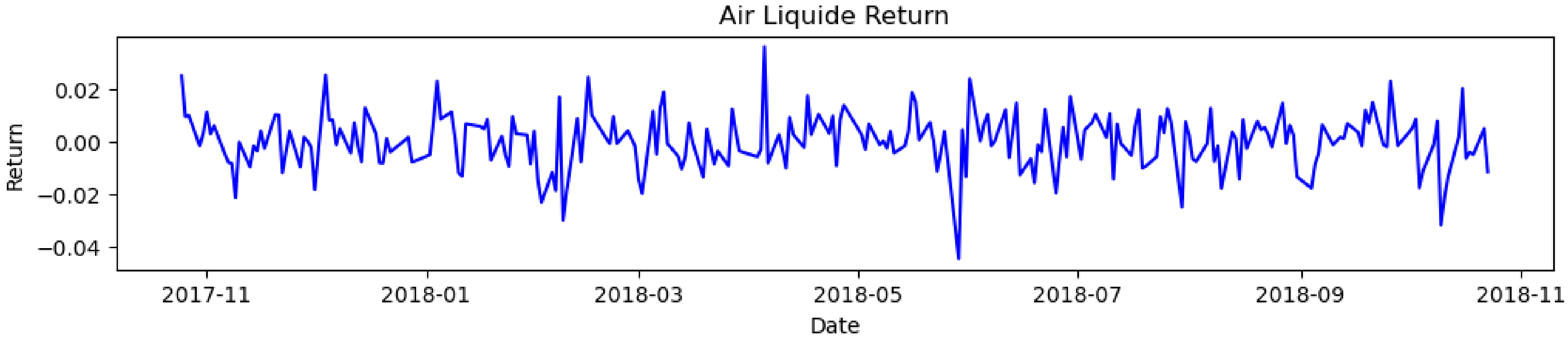
	Daily Return Standard Deviation
Stock	
Air Liquide	0.010580
Peugeot	0.017747

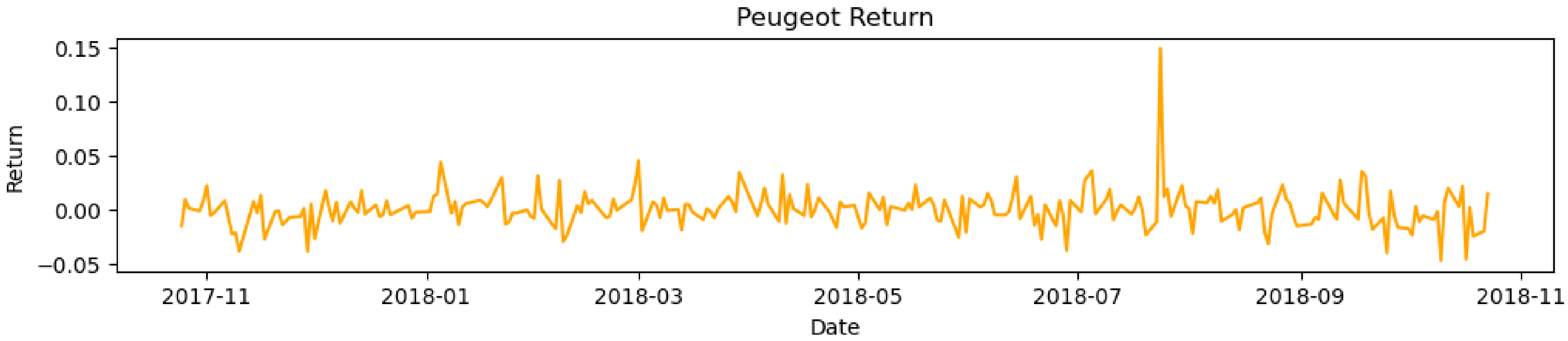
From the dataframe above we can see that the volatility of *Air Liquide* stock is higher than the volatility of *Peugeot* stock.

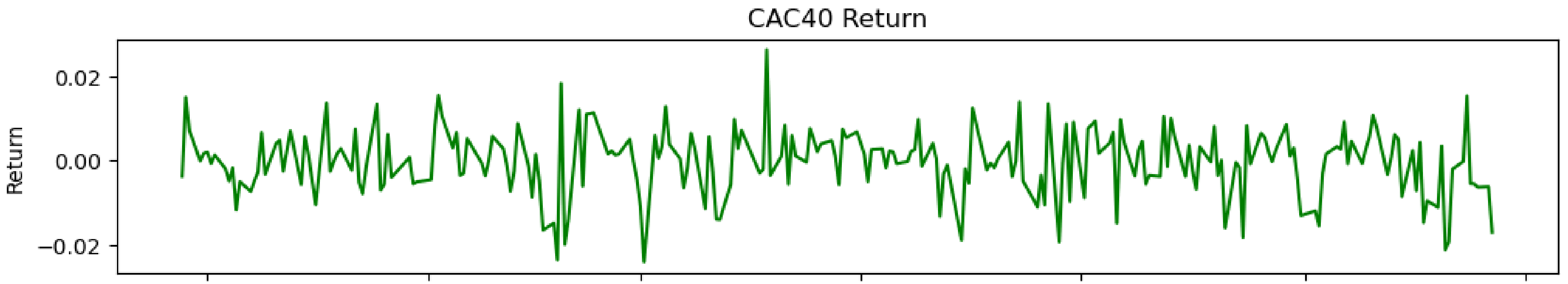
Question 3.3

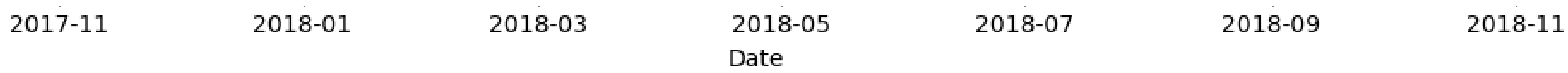
Compute the return for both stocks and for the CAC40 index. Comment on your results.

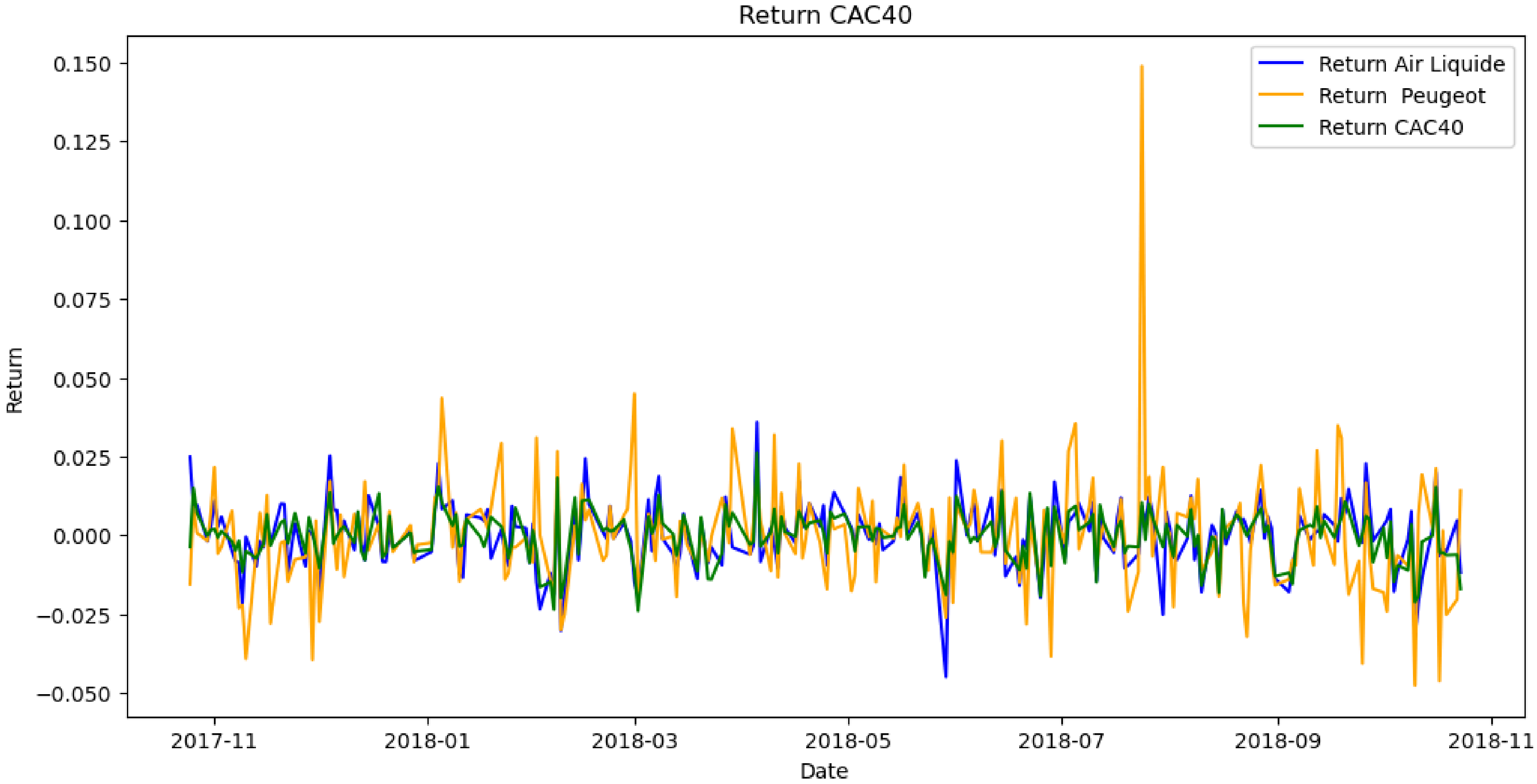
In [ ]:
```
# We computed the returns in the question 3.2

def plot_return(ax, x_axis_data, y_axis_data ,title, color):
    out = ax.plot(x_axis_data, y_axis_data, label=title, color=color)
    ax.set_title(title)
    ax.set_xlabel('Date')
    ax.set_ylabel('Return')
    return out

fig, (ax1, ax2, ax3) = plt.subplots(3, 1, figsize=(12, 10), dpi=100)
fig.subplots_adjust(hspace=1)
plot_return(ax1, air_liquide_stock['Date'], air_liquide_stock['Daily Return'], 'Air Liquide Return', 'blue')
plot_return(ax2, peugeot_stock['Date'], peugeot_stock['Daily Return'], 'Peugeot Return', 'orange')
plot_return(ax3, CAC40['Date'], CAC40['Daily Return'], 'CAC40 Return', 'green')


fig, ax = plt.subplots(figsize=(12, 6), dpi=100)
plot_return(ax, air_liquide_stock['Date'], air_liquide_stock['Daily Return'], 'Return Air Liquide', "blue")
plot_return(ax, peugeot_stock['Date'], peugeot_stock['Daily Return'], 'Return  Peugeot', 'orange')
plot_return(ax, CAC40['Date'], CAC40['Daily Return'], 'Return CAC40', 'green')
ax.legend()
plt.show()
```


Air Liquide Return
Return
0.02
0.00
−0.02
−0.04
2017-11
2018-01
2018-03
2018-05
2018-07
2018-09
2018-11
Date


Peugeot Return
Return
0.15
0.10
0.05
0.00
−0.05
2017-11
2018-01
2018-03
2018-05
2018-07
2018-09
2018-11
Date


CAC40 Return
Return
0.02
0.00
−0.02





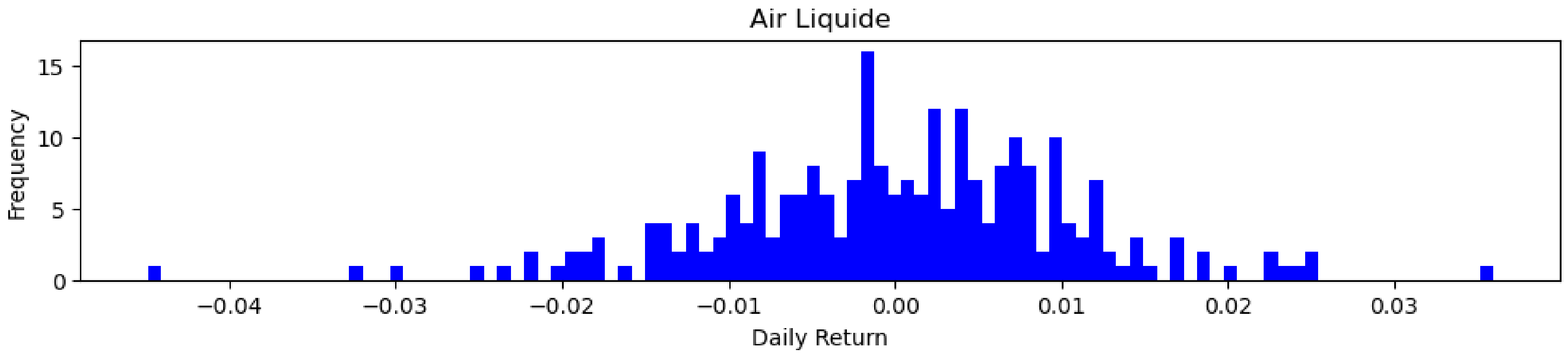
We can highlight some aspects of this chart. Firstly, all three lines are very close, with some trends occurring simultaneously in all of them, which might indicate a macro effect on all stocks and the index. For instance, around 2018-06, we observe a significant dip in all of the stocks and the index, which might have been caused by some factor affecting all of them. Additionally, we can clearly see that the curves overlap, indicating a similar behavior among them. The most distinctive one is the Peugeot curve. In this case, we have the highest global peak, but also the most distinct local valleys and peaks for the series, suggesting that this stock might be more volatile than the others.

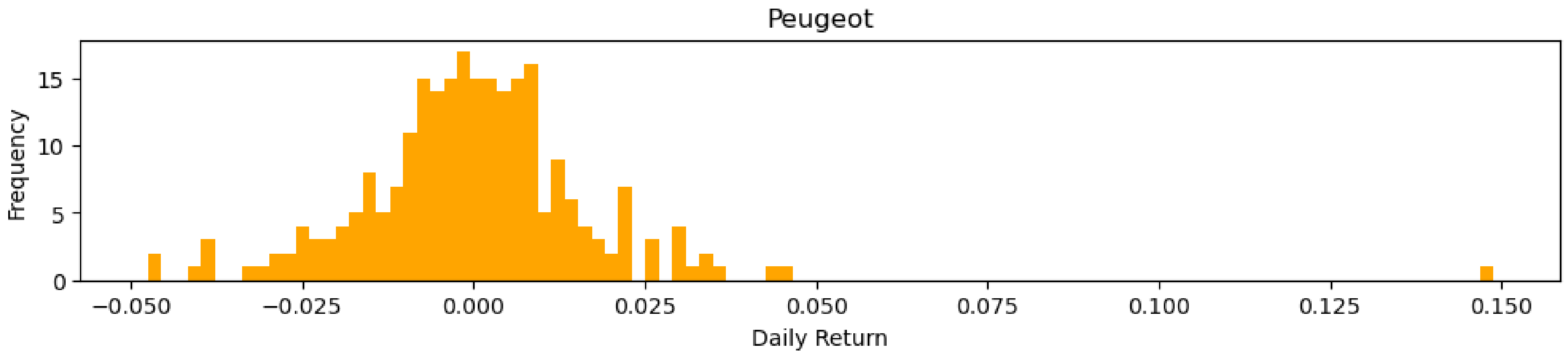
Question 3.4

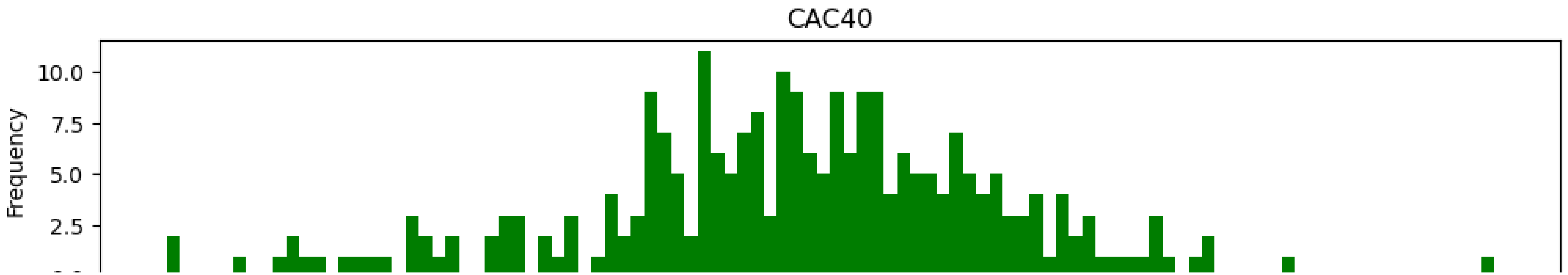
Compute the coefficients of Kurtosis and of asymmetry of the 3 series of `Question 3.3`. Plot the histograms and comment on your results.

In [ ]:
```
# Compute the Kurtosis of each serie:
airliquide_kurtosis = air_liquide_stock['Daily Return'].kurtosis()
peugeot_kurtosis = peugeot_stock['Daily Return'].kurtosis()
CAC40_kurtosis = CAC40['Daily Return'].kurtosis()

print(f'Air Liquide kurtosis: {airliquide_kurtosis}')
print(f'Peugeot kurtosis: {peugeot_kurtosis}')
print(f'CAC40 kurtosis: {CAC40_kurtosis}')
print('')

# Compute the asymmetry of each serie:
airliquide_skew = air_liquide_stock['Daily Return'].skew()
peugeot_skew = peugeot_stock['Daily Return'].skew()
CAC40_skew = CAC40['Daily Return'].skew()

print(f'Air Liquide skew: {airliquide_skew}')
print(f'Peugeot skew: {peugeot_skew}')
print(f'CAC40 skew: {CAC40_skew}')

# Plot the histograms of the daily returns
def plot_histogram(data, title, ax, color):
    ax.hist(data['Daily Return'], bins=100, label=title, color=color)
    ax.set_title(title)
    ax.set_xlabel('Daily Return')
    ax.set_ylabel('Frequency')

fig, (ax1, ax2, ax3) = plt.subplots(3, 1, figsize=(12, 10), dpi=100)
fig.subplots_adjust(hspace=1)

plot_histogram(air_liquide_stock, 'Air Liquide', ax1, 'blue')
plot_histogram(peugeot_stock, 'Peugeot', ax2, 'orange')
plot_histogram(CAC40, 'CAC40', ax3, 'green')

plt.show()
```

```
Air Liquide kurtosis: 1.5436828227054535
Peugeot kurtosis: 19.479876263450755
CAC40 kurtosis: 0.7000638041951324

Air Liquide skew: -0.32333524527574187
Peugeot skew: 2.2741133050672624
CAC40 skew: -0.34798069388850855
```


Air Liquide
Frequency
Daily Return
15
10
5
0
−0.04
−0.03
−0.02
−0.01
0.00
0.01
0.02
0.03


Peugeot
Frequency
Daily Return
15
10
5
0
−0.050
−0.025
0.000
0.025
0.050
0.075
0.100
0.125
0.150


CAC40
Frequency
10.0
7.5
5.0
2.5

When examining the kurtosis, it's evident that all of them exhibit a positive coefficient, indicating a leptokurtic curve characterized by higher peaks and heavier tails compared to the normal distribution. However, the Peugeot's coefficient stands out as the largest, suggesting that it adheres more closely to this pattern, a fact corroborated by the histograms.

Additionally, by analyzing the asymmetry, we can discern whether the distribution's tail inclines more towards the right (positive values) or the left (negative values), as demonstrated in the histograms.

Question 3.5

Compute the standard errors of the return for both stocks for the full period and then for 3 sub-periods of equal size. Is volatility constant?

In [ ]:
```
from scipy.stats import levene

# Standard error of the full period (stardard deviation of the sample)
se_airliquide = air_liquide_stock['Daily Return'].std() / np.sqrt(len(air_liquide_stock['Daily Return']))
se_peugeot = peugeot_stock['Daily Return'].std() / np.sqrt(len(peugeot_stock['Daily Return']))

print(f'Air Liquide standard error: {se_airliquide}')
print(f'Peugeot standard error: {se_peugeot}\n')

# Divide the data into 3 subperiods of equal length
subperiods_airliquide = np.array_split(air_liquide_stock['Daily Return'], 3)
subperiods_peugeot = np.array_split(peugeot_stock['Daily Return'], 3)

# Standard error of each subperiod
se_subperiods_airliquide = [subperiod.std() for subperiod in subperiods_airliquide]
se_subperiods_peugeot = [subperiod.std() for subperiod in subperiods_peugeot]

print("Standard Error of Subperiods:")
for i in range(3):
    print(f"Subperiod {i+1}:")
    print(f"    Air Liquide: {se_subperiods_airliquide[i]:.4f}")
    print(f"    Peugeot: {se_subperiods_peugeot[i]:.4f}")
    print()

# Levene test for the homogeneity of variances (volatility) of the 3 subperiods
statistic, p_value = levene(*subperiods_airliquide)

alpha = 0.01
```

```
# Check if the p-value is less than the significance level
if p_value < alpha:
    print("The volatity are constant among the subperiods (reject the null hypothesis)")
else:
    print("The volatity is NOT constant among the subperiods (fail to reject the null hypothesis)")
```

```
Air Liquide standard error: 0.0006718119820775511
Peugeot standard error: 0.0011269503374705051

Standard Error of Subperiods:
Subperiod 1:
    Air Liquide: 0.0107
    Peugeot: 0.0143

Subperiod 2:
    Air Liquide: 0.0110
    Peugeot: 0.0133

Subperiod 3:
    Air Liquide: 0.0101
    Peugeot: 0.0239

The volatity is NOT constant among the subperiods (fail to reject the null hypothesis)
```

Question 3.6

Compute the correlation between each stock and the CAC40. Comment on your results.

In [ ]:

```
# Correlation between each stock and the CAC40
airliquide_CAC40_corr = air_liquide_stock['Daily Return'].corr(CAC40['Daily Return'])
peugeot_CAC40_corr = peugeot_stock['Daily Return'].corr(CAC40['Daily Return'])

# Pearson correlation between each stock and the CAC40
airliquide_CAC40_corr_pearson = air_liquide_stock['Daily Return'].corr(CAC40['Daily Return'], method='pearson')
peugeot_CAC40_corr_pearson = peugeot_stock['Daily Return'].corr(CAC40['Daily Return'], method='pearson')

if airliquide_CAC40_corr_pearson > 0.5:
    print(f"The Pearson correlation between Air Liquide and CAC40 is {airliquide_CAC40_corr_pearson}, which indicates a strong po
elif airliquide_CAC40_corr_pearson < -0.5:
    print(f"The Pearson correlation between Air Liquide and CAC40 is {airliquide_CAC40_corr_pearson}, which indicates a strong ne
else:
    print(f"The Pearson correlation between Air Liquide and CAC40 is {airliquide_CAC40_corr_pearson}, which indicates a weak corr

if peugeot_CAC40_corr_pearson > 0.5:
    print(f"The Pearson correlation between Peugeot and CAC40 is {peugeot_CAC40_corr_pearson}, which indicates a strong positive
```

```
elif peugeot_CAC40_corr_pearson < -0.5:
    print(f"The Pearson correlation between Peugeot and CAC40 is {peugeot_CAC40_corr_pearson}, which indicates a strong negative
else:
    print(f"The Pearson correlation between Peugeot and CAC40 is {peugeot_CAC40_corr_pearson}, which indicates a weak correlation
```

```
The Pearson correlation between Air Liquide and CAC40 is 0.8190382535877568, which indicates a strong positive correlation
The Pearson correlation between Peugeot and CAC40 is 0.47110156112767565, which indicates a weak correlation
```

The analysis of the correlation between the daily returns of Air Liquide's shares and the CAC40 index reveals a strong positive correlation, with a Pearson coefficient of approximately 0.82. This indicates that, historically, Air Liquide's shares tend to move in a similar direction to the CAC40 index. This high level of correlation may suggest that Air Liquide, as one of the components of the index, has a significant impact on it or vice versa, and that the macroeconomic or market factors influencing the CAC40 also have a similar impact on Air Liquide. For investors, this could mean that investing in Air Liquide might be a way to gain exposure to the general trends of the French market, given its alignment with the movements of the CAC40 index.

On the other hand, the correlation between the daily returns of Peugeot's shares and the CAC40 index is lower, with a Pearson coefficient of approximately 0.47. Although positive, this correlation indicates a less direct relationship between the movements of Peugeot's stock prices and the CAC40 index. This may suggest that, while Peugeot is influenced by the general economic conditions affecting the French market, there are specific factors related to the automotive sector or the company itself that may influence its performance more significantly than the broader market trends. For investors, this might indicate that Peugeot offers diversification opportunities within a portfolio seeking both exposure to general market trends and specific sectors with potentially different dynamics from the index as a whole.

Question 3.7

Compute the returns of a portfolio in which both stocks have an equal weight. Compute the average return and the standard deviation over the whole sample period. Comment on your results.

In [ ]:
```
average_return_peugeot = peugeot_stock['Daily Return'].mean()
std_peugeot = peugeot_stock['Daily Return'].std()
average_return_airliquide = air_liquide_stock['Daily Return'].mean()
std_airliquide = air_liquide_stock['Daily Return'].std()

# The return of the portfolio is the average of the returns of the two stocks
portfolio_return = (air_liquide_stock['Daily Return'] + peugeot_stock['Daily Return']) / 2

# The standard deviation and the average return of the portfolio
average_return_portfolio = portfolio_return.mean()
std_portfolio = portfolio_return.std()

# Dataframe with the data of the stocks and the portfolio
data = {
    'Stock': ['Air Liquide', 'Peugeot', 'Portfolio'],
    'Average Return': [average_return_airliquide, average_return_peugeot, average_return_portfolio],
```

```
    'Standard Deviation': [std_airliquide, std_peugeot, std_portfolio]
}
df_returns_std = pd.DataFrame(data)
df_returns_std
```

Out[ ]:

	Stock	Average Return	Standard Deviation
0	Air Liquide	0.000071	0.010580
1	Peugeot	0.000085	0.017747
2	Portfolio	0.000078	0.011887

From the results we can see that when we mix both stocks in the portfolio we can minimize the risk, but also the return, compared to when we have only one stock. This can guide ones strategy to mix different stocks on a portfolio so it be less risky.

Question 3.8

Consider a portfolio with one stock and the risk-free interest rate (you can choose the stock out of the two that are available). What is the optimal portfolio allocation between these two assets for an investor with a utility function presented in the course and $A = 1.5$?

We will consider the stock Air Liquide and the risk-free interest rate. The optimal portfolio allocation $\omega^\star$ between two assets is obtained by solving the utility's maximization problem:

$$\underset{\omega}{max}\, U = \omega\mathbb{E}(r_A) + (1-\omega)r_f - \frac{A}{2}\omega^2\sigma_A^2,$$

where:

- ω is the percentage allocated to the asset A;
- r_A and r_f are the daily returns associated to the asset A and the risk-free interest rate, respectively;
- $A = 1.5$ is the risk aversion coefficient and σ_A^2 is the variance of the asset A.

To that, we solve the utility problem with the following equation:

$$\frac{\partial U}{\partial \omega} = 0 \iff \mathbb{E}(r_A) - r_f - A\omega\sigma_A^2 = 0 \iff \omega^\star = \frac{\mathbb{E}(r_A) - r_f}{A\sigma_A^2}.$$

We considered the asset A to be the *Air Liquide* stock and the risk-free interest rate to be the 5-week interest rate from the US Treasury, taken from this website.

In [ ]:
```
A = 1.5
days_in_year = 252

# We chose the Air Liquide stock to compose the portfolio
expected_return_airliquide = air_liquide_stock['Daily Return'].mean()
std_airliquide = air_liquide_stock['Daily Return'].std()

# The risk-free rate is the T-bills 13-weeks interest rate from the US Treasury,
# which is in anual values in the dataset. We transform it to daily values
rf = (((1+interest_rate['Adj Close'])**(1/252) - 1)/100).mean()

# Weight of the Air Liquide stock in the portfolio
w = (expected_return_airliquide - rf) / (A * std_airliquide ** 2)

print(f"The weight of the Air Liquide stock in the portfolio is {w:.4f}")
```

```
The weight of the Air Liquide stock in the portfolio is 0.1890
```

In [ ]:
```
anual_return_airliquide = (1+air_liquide_stock['Daily Return'].mean()) ** days_in_year - 1
annual_std_airliquide = air_liquide_stock['Daily Return'].std() * np.sqrt(days_in_year)

rf = interest_rate['Adj Close'].mean() / 100

w = (anual_return_airliquide - rf) / (A * annual_std_airliquide ** 2)
w
```

Out[ ]:
```
0.021318337281923706
```

Question 3.9

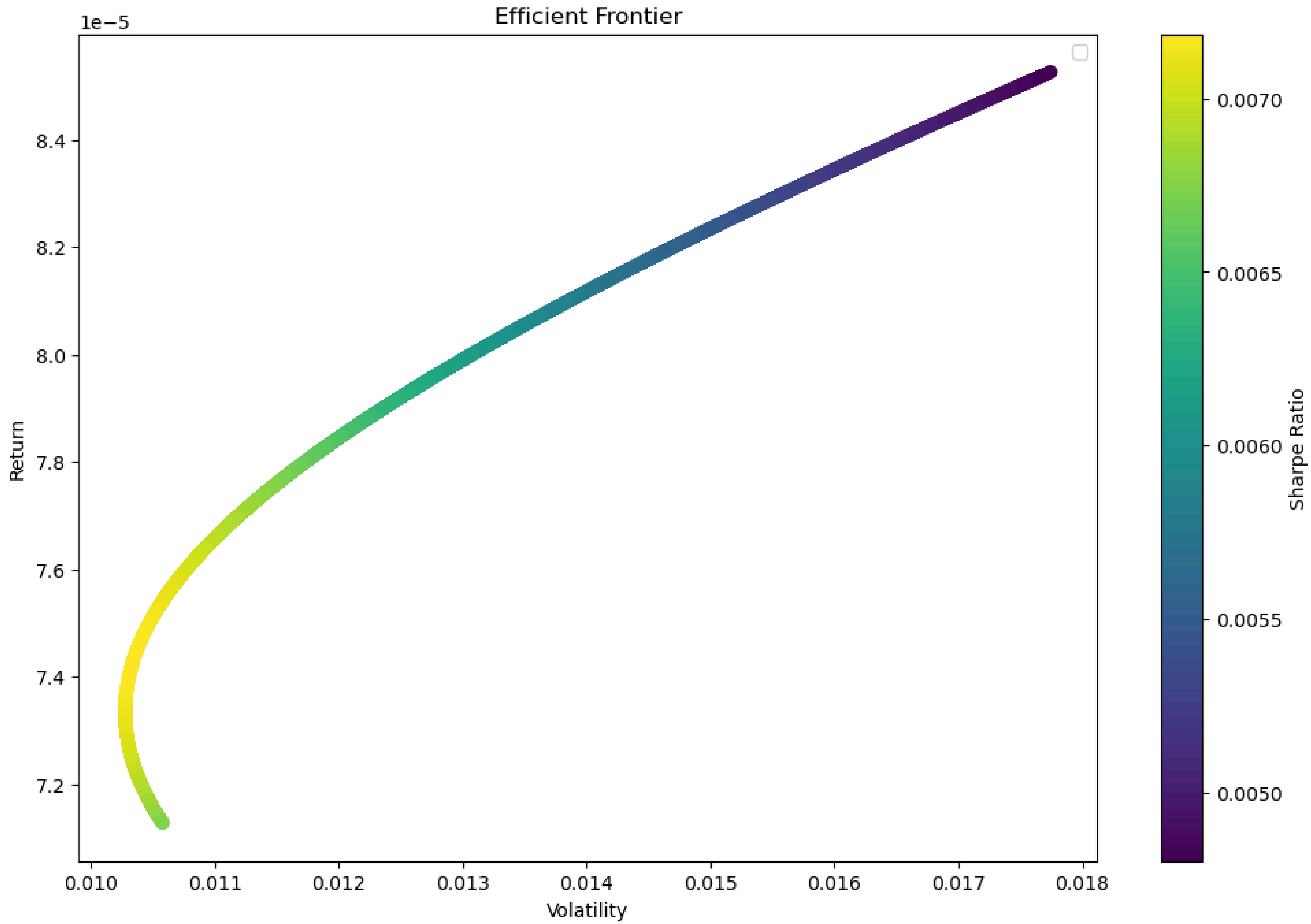
Consider the following 3 portfolios: portfolio 1 has stock 1 as the only component; portfolio 2 has stock 2 as the only component; portfolio 3 is the portfolio of `Question 3.7`. These are the only portfolio available to investors. Draw the efficient frontier. Which portfolio are inefficient?

We first plot the Efficient Frontier itself.

In [ ]:
```
# Combination of the daily returns into one DataFrame
df = pd.concat([air_liquide_stock['Daily Return'], peugeot_stock['Daily Return']], axis=1)
df.columns = ['Air Liquide', 'Peugeot']

# Drop any rows with missing values
df = df.dropna()

# Mean returns and the covariance matrix of returns
mean_returns = df.mean()
```

```python
cov_matrix = df.cov()

# Number of portfolios to simulate
num_portfolios = 10000

# Initialization of the arrays to store the portfolio weights, returns and volatilities
weights_array = np.zeros((num_portfolios, len(df.columns)))
returns_array = np.zeros(num_portfolios)
volatility_array = np.zeros(num_portfolios)

# Simulation of the portfolios
for i in range(num_portfolios):
    weights = np.random.random(len(df.columns))
    weights /= np.sum(weights)
    returns = np.dot(weights, mean_returns)
    volatility = np.sqrt(np.dot(weights.T, np.dot(cov_matrix, weights)))
    weights_array[i, :] = weights
    returns_array[i] = returns
    volatility_array[i] = volatility

# Efficient frontier plot
plt.figure(figsize=(12, 8), dpi=100)
plt.scatter(volatility_array, returns_array, c=returns_array/volatility_array, marker='o')
plt.colorbar(label='Sharpe Ratio')
plt.xlabel('Volatility')
plt.ylabel('Return')
plt.title('Efficient Frontier')

plt.legend()
plt.show()
```

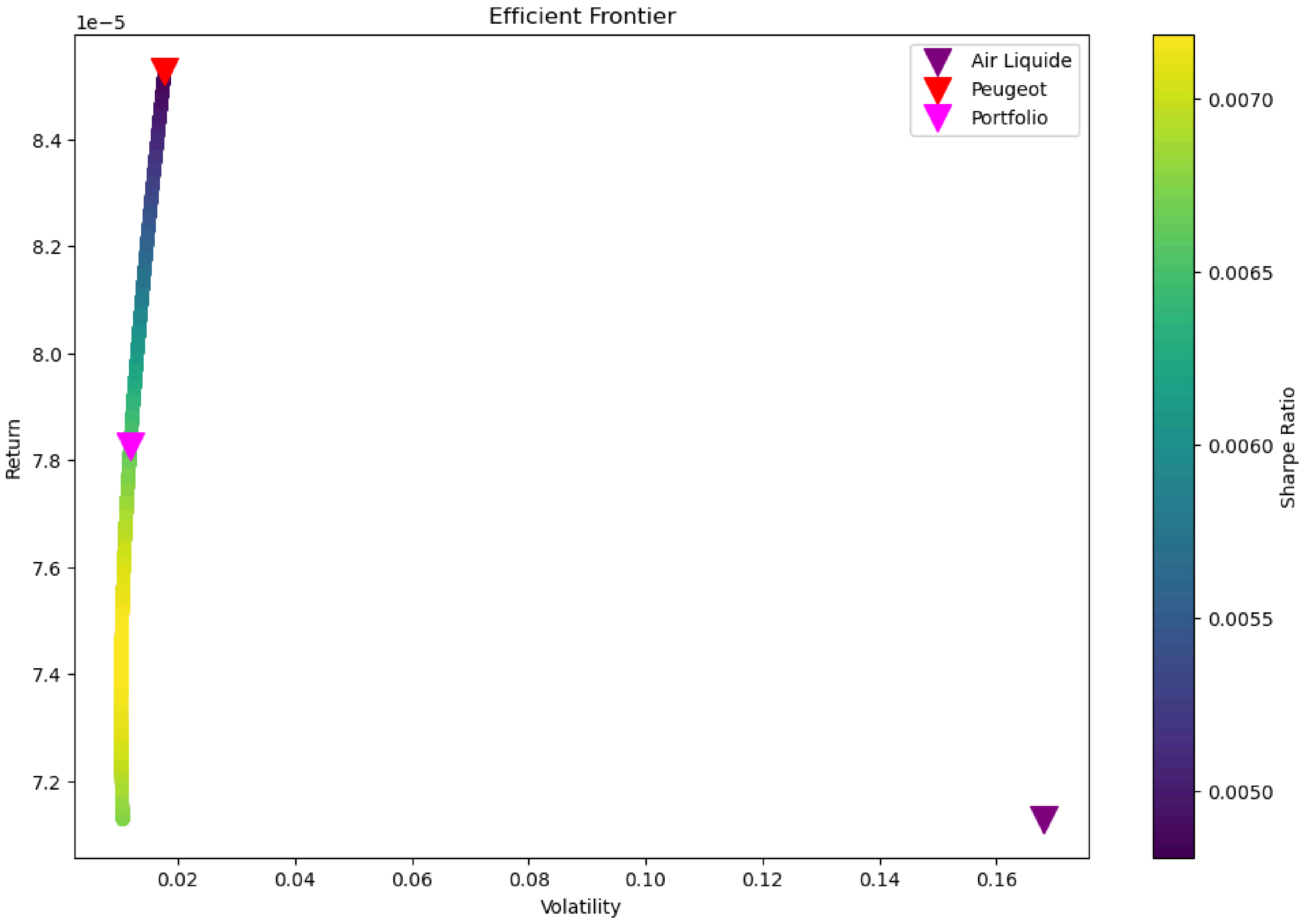
```
No artists with labels found to put in legend.  Note that artists whose label start with an underscore are ignored when legend()
is called with no argument.
```



Then, we plot both the Efficient Frontier and the three portfolios points.

In [ ]:
```
# Combination of the daily returns into one DataFrame
df = pd.concat([air_liquide_stock['Daily Return'], peugeot_stock['Daily Return']], axis=1)
```

```python
df.columns = ['Air Liquide', 'Peugeot']

# Drop any rows with missing values
df = df.dropna()

# Mean returns and the covariance matrix of returns
mean_returns = df.mean()
cov_matrix = df.cov()

# Number of portfolios to simulate
num_portfolios = 10000

# Initialization of the arrays to store the portfolio weights, returns and volatilities
weights_array = np.zeros((num_portfolios, len(df.columns)))
returns_array = np.zeros(num_portfolios)
volatility_array = np.zeros(num_portfolios)

# Simulation of the portfolios
for i in range(num_portfolios):
    weights = np.random.random(len(df.columns))
    weights /= np.sum(weights)
    returns = np.dot(weights, mean_returns)
    volatility = np.sqrt(np.dot(weights.T, np.dot(cov_matrix, weights)))
    weights_array[i, :] = weights
    returns_array[i] = returns
    volatility_array[i] = volatility

# Efficient frontier plot
plt.figure(figsize=(12, 8), dpi=100)
plt.scatter(volatility_array, returns_array, c=returns_array/volatility_array, marker='o')
plt.colorbar(label='Sharpe Ratio')
plt.xlabel('Volatility')
plt.ylabel('Return')
plt.title('Efficient Frontier')

# Plotting the additional points
airliquide_avg = air_liquide_stock['Daily Return'].mean()
peugeot_avg = peugeot_stock['Daily Return'].mean()
plt.scatter(annual_std_airliquide, airliquide_avg, color='purple', label='Air Liquide', marker='v', s=200)
plt.scatter(peugeot_std, peugeot_avg, color='red', label='Peugeot', marker='v', s=200)
plt.scatter(std_portfolio, average_return_portfolio, color='magenta', label='Portfolio', marker='v', s=200)

plt.legend()
plt.show()
```



From the plot above, we conclude that the portfolio and the Peugeot stock are efficient, whereas the Air Liquide stock is inefficient. This is because the Air Liquide stock is located below the efficient frontier, meaning that it has a lower return for a given level of risk compared to the portfolio and the

Peugeot stock. On the other hand, the portfolio and the Peugeot stock are located on the efficient frontier, indicating that they offer the highest return for a given level of risk, making them efficient investments.

Question 3.10

Consider the portfolio of `Question 3.7`. Compute the Sharpe ratio, the Sortino ratio, the Sterling ratio. Why are there differences between these ratios?

In [ ]:
```
# Average return of the portfolio
portfolio_return = (0.5 * air_liquide_stock['Daily Return']) + (0.5 * peugeot_stock['Daily Return'])
average_return_portfolio = portfolio_return.mean()

# Standard deviation of the portfolio
std_portfolio = portfolio_return.std()

# Setting the risk-free rate
risk_free_rate = 0.02

# Sharpe ratio
sharpe_ratio = (average_return_portfolio - risk_free_rate) / std_portfolio

# Sortino ratio
downside_returns = portfolio_return[portfolio_return < 0]
downside_std = downside_returns.std()
sortino_ratio = (average_return_portfolio - risk_free_rate) / downside_std

# Sterling ratio
sterling_ratio = average_return_portfolio / downside_std

# Dataframe with the ratios
ratios = {
    'Ratio': ['Sharpe ratio', 'Sortino ratio', 'Sterling ratio'],
    'Value': [sharpe_ratio, sortino_ratio, sterling_ratio]
}
ratios_df = pd.DataFrame(ratios)
ratios_df = ratios_df.reset_index(drop=True)

ratios_df
```

Out[ ]:

	Ratio	Value
0	Sharpe ratio	-1.675891
1	Sortino ratio	-2.591047
2	Sterling ratio	0.010179

The negative values for Sharpe and Sortino ratios indicate performance below the risk-free rate, suggesting the portfolio isn't adequately compensating for the risks taken. The small positive value of the Sterling Ratio shows the portfolio's average return is nearly at the level of its downside risk, which could be seen as unsatisfactory in terms of compensation for specific risks. These outcomes suggest a need to reassess investment choices or risk mitigation strategies.

Question 3.11

Compute the empirical VaR at 1% for the same portfolio. Compute the 1st percentile of the normal distribution with mean and variance corresponding respectively to the empirical mean and to the empirical variance. Comment on your results.

In [ ]:

```
# Empirical Value at Risk (VaR) at 1% for the portfolio
var_1 = np.percentile(portfolio_return, 1)

# Empirical mean and variance of the daily returns of the portfolio
empirical_mean = np.mean(portfolio_return)
empirical_variance = np.var(portfolio_return)

# First percentile of the standard normal distribution
first_percentile = norm.ppf(0.01, loc=empirical_mean, scale=np.sqrt(empirical_variance))

print(f"Value at Risk (VaR) at 1% for the portfolio: {var_1:.4f}")
print(f"First percentile of the standard normal distribution: {first_percentile:.4f}")
```

```
Value at Risk (VaR) at 1% for the portfolio: -0.0283
First percentile of the standard normal distribution: -0.0275
```

The empirical Value at Risk (VaR) at 1% for the portfolio is -0.0283, or -2.83%, indicates that, under normal market conditions, there is only a 1% chance that the portfolio will lose more than 2.83% of its value in one day.

The empirical VaR at -2.83% versus the normal distribution-based VaR at -2.75% highlights the following insight: financial markets' returns often deviate from normality, exhibiting fat tails or skewness, which can lead to underestimations of risk. This slight discrepancy suggests that real-world portfolio return distributions might have heavier tails, implying a potentially higher risk of extreme losses than predicted by models assuming normal distribution, making the empirical VaR a more conservative and, perhaps, more realistic measure of risk.

Question 3.12

Compute the VaR using resampling with 1000 observations. Compute the 1% VaR on the simulated data set. Comment on your results.

In [ ]:
```python
# VaR using resampling with 1000 observations
var_1_resampling = np.percentile(np.random.choice(portfolio_return, 1000), 1)

print(f"Value at Risk (VaR) at 1% for the portfolio using resampling: {var_1_resampling:.4f}")
```

```
Value at Risk (VaR) at 1% for the portfolio using resampling: -0.0264
```

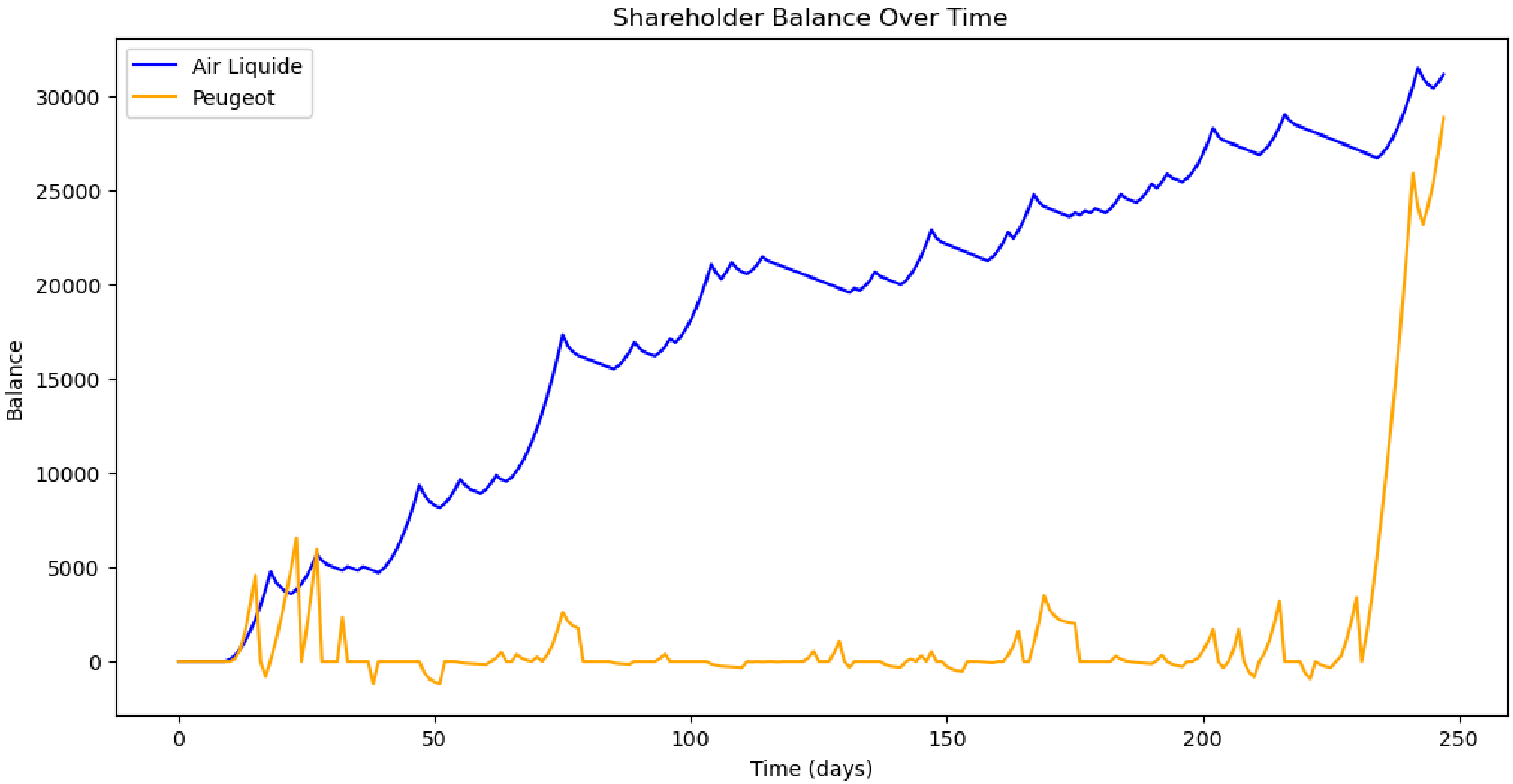
The differences in the 1% Value at Risk (VaR) calculations across various methods - empirical (-2.83%), based on the normal distribution assumption (-2.75%), and through resampling with 1000 observations (-2.64%) - underscore the sensitivity of risk estimates to the chosen statistical approach. The slight variation in results reflects the inherent limitations and assumptions within each method, particularly the assumption of normality in financial returns and how it may not adequately capture the real-world distributions of returns characterized by fat tails and skewness. The resampling method, by leveraging the empirical distribution without assuming a predefined shape, potentially offers a more nuanced estimation of VaR, highlighting the critical need for selecting a method that aligns with the actual risk profile and distribution characteristics of portfolio returns.

Question 4

Run an automated trading algorithm using any method you want (moving averages, candlesticks, patterns, ML, ...) over the sample period. You can only have 3 positions: buy/sell, short/cover, do nothing. You cannot use derivative products. Can you beat the market?

In [ ]:
```python
# Average of the last 3 days for each stock
airliquide_avg = air_liquide_stock['Daily Return'].rolling(window=3).mean()
peugeot_avg = peugeot_stock['Daily Return'].rolling(window=3).mean()

# Initialization of the variables for tracking positions and balance
airliquide_position = 0
peugeot_position = 0
airliquide_balance = [0] * len(air_liquide_stock)  # Initial balance with list of zeros
peugeot_balance = [0] * len(peugeot_stock)  # Initial balance with list of zeros

# Iteration over the rows of the dataframes
for i in range(3, len(air_liquide_stock)):

    # Check if the average is positive for Air Liquide stock
    if airliquide_avg[i] > 0:
        # Sell the stock if already bought
```

```
        if airliquide_position > 0:
            delta_pos = airliquide_position // 2
            airliquide_position -= delta_pos
            airliquide_balance[i] = airliquide_balance[i-1] - airliquide_position * air_liquide_stock['Close'][i]
    elif airliquide_avg[i] < 0:
        airliquide_position += 1
        airliquide_balance[i] = airliquide_balance[i-1] + air_liquide_stock['Close'][i] * airliquide_position # Subtract the buyi

    # Check if the average is positive for Peugeot stock
    if peugeot_avg[i] > 0.005:
        # Sell the stock if already bought
        if peugeot_position > 0:
            delta_pos = peugeot_position // 2
            peugeot_position -= delta_pos
            peugeot_balance[i] = peugeot_balance[i-1] - peugeot_position * peugeot_stock['Close'][i]  # Add the selling price to
    elif peugeot_avg[i] < - 0.005:
        peugeot_position += int(1000 * abs(peugeot_avg[i]))
        peugeot_balance[i] = peugeot_balance[i-1] + peugeot_stock['Close'][i] * peugeot_position  # Subtract the buying price fro

# Plot the balance over time for each stock
plt.figure(figsize=(12, 6), dpi=100)
plt.plot(airliquide_balance, label='Air Liquide', color='blue')
plt.plot(peugeot_balance, label='Peugeot', color='orange')
plt.title('Shareholder Balance Over Time')
plt.xlabel('Time (days)')
plt.ylabel('Balance')
plt.legend()
plt.show()

# Portfolio at the end
print(f"Portfolio at the end:")
print(f"{airliquide_position} Air liquide stocks in {len(air_liquide_stock) - 3} days")
print(f"{peugeot_position} Peugeot stocks in {len(peugeot_stock) - 3} days")
```




```
Portfolio at the end:
4 Air liquide stocks in 245 days
94 Peugeot stocks in 245 days
```