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FRE-6991 HW1

Step 1: Download Data from Yahoo Finance

We download the adjusted close prices for the four stocks from 3/01/2024 to 03/01/2025 using the `yfinance` package.

In [3]:
```
import yfinance as yf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# Define the tickers and date range
tickers = ['AAPL', 'XOM', 'PFE', 'ED']
start_date = '2024-03-01'
end_date = '2025-03-01'

# Download adjusted close prices and drop any missing data
data = yf.download(tickers, start=start_date, end=end_date)['Close']
data.dropna(inplace=True)
data.head()
```

```
YF.download() has changed argument auto_adjust default to True
[*********************100%***********************]  4 of 4 completed
```

Out[3]:

Ticker	AAPL	ED	PFE	XOM
Date				
2024-03-01	178.815659	84.080727	25.021681	102.384132
2024-03-04	174.277115	86.129349	24.362968	100.952469
2024-03-05	169.320480	85.994064	24.541761	102.190666
2024-03-06	168.325195	86.825119	25.586290	103.283768
2024-03-07	168.205750	86.912079	25.209885	103.864182

Step 2: Calculate Daily Returns

We compute the daily percentage returns for each stock.

In [5]:
```
daily_returns = data.pct_change().dropna()
daily_returns.head()
```

Out[5]:

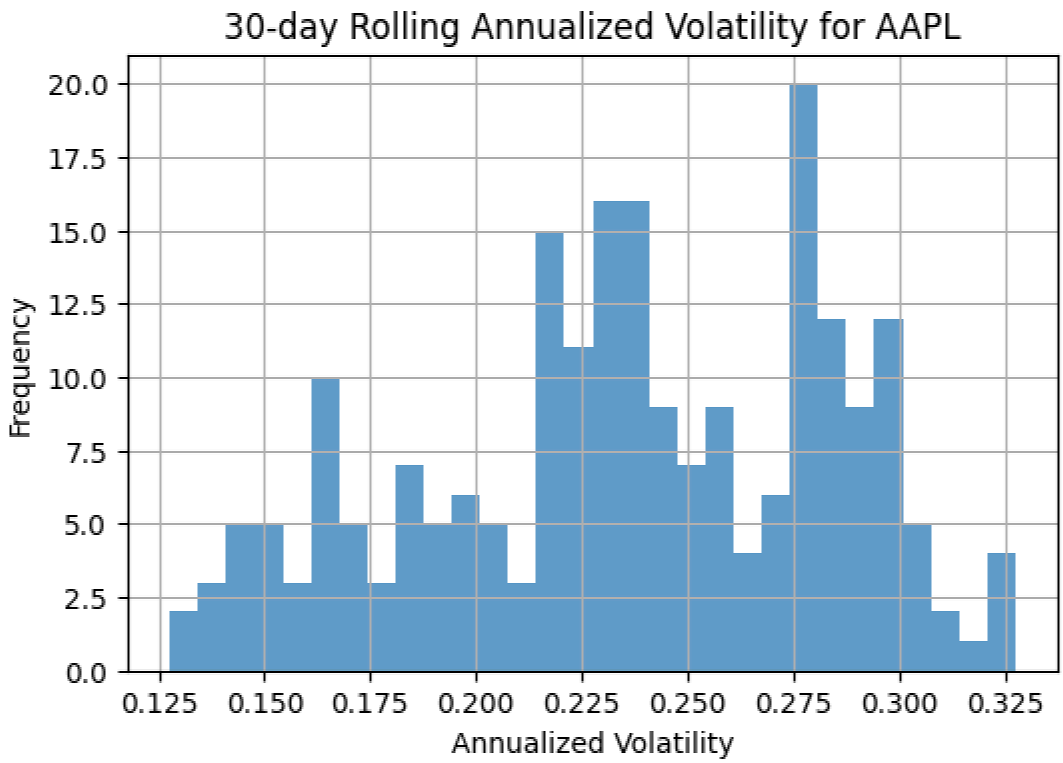
Ticker	AAPL	ED	PFE	XOM
Date				
2024-03-04	-0.025381	0.024365	-0.026326	-0.013983
2024-03-05	-0.028441	-0.001571	0.007339	0.012265
2024-03-06	-0.005878	0.009664	0.042561	0.010697
2024-03-07	-0.000710	0.001002	-0.014711	0.005620
2024-03-08	0.010237	0.002001	0.016051	0.009407

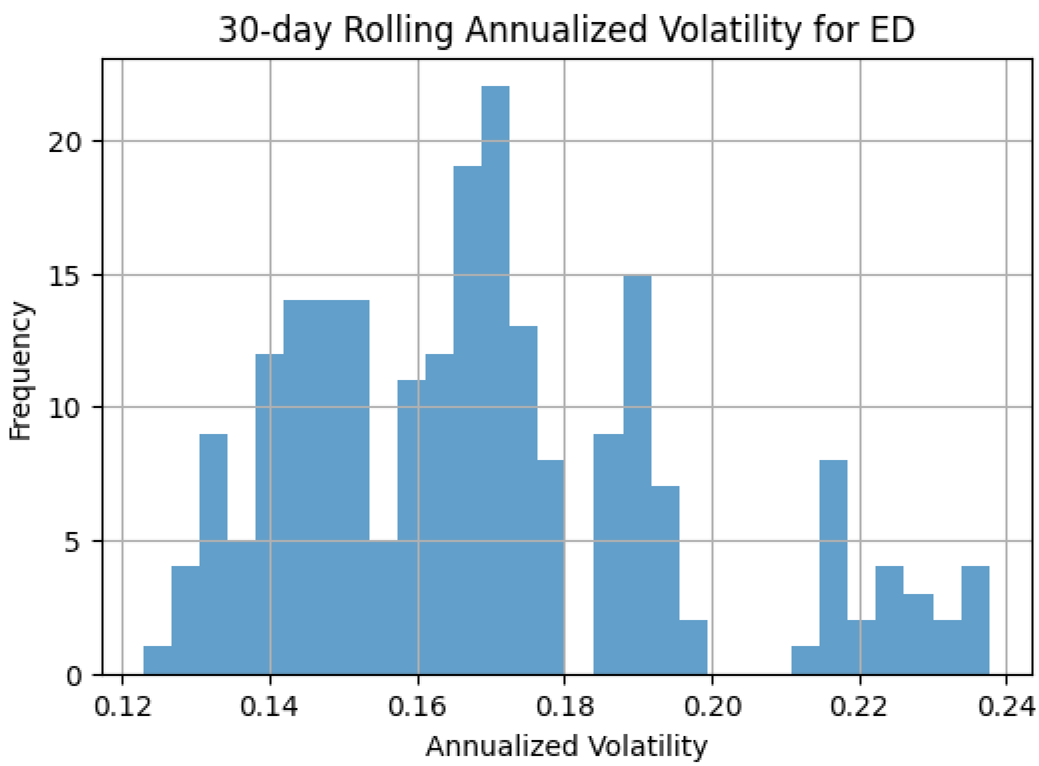
Step 3: Calculate and Plot 30-day Rolling Volatility and Correlation

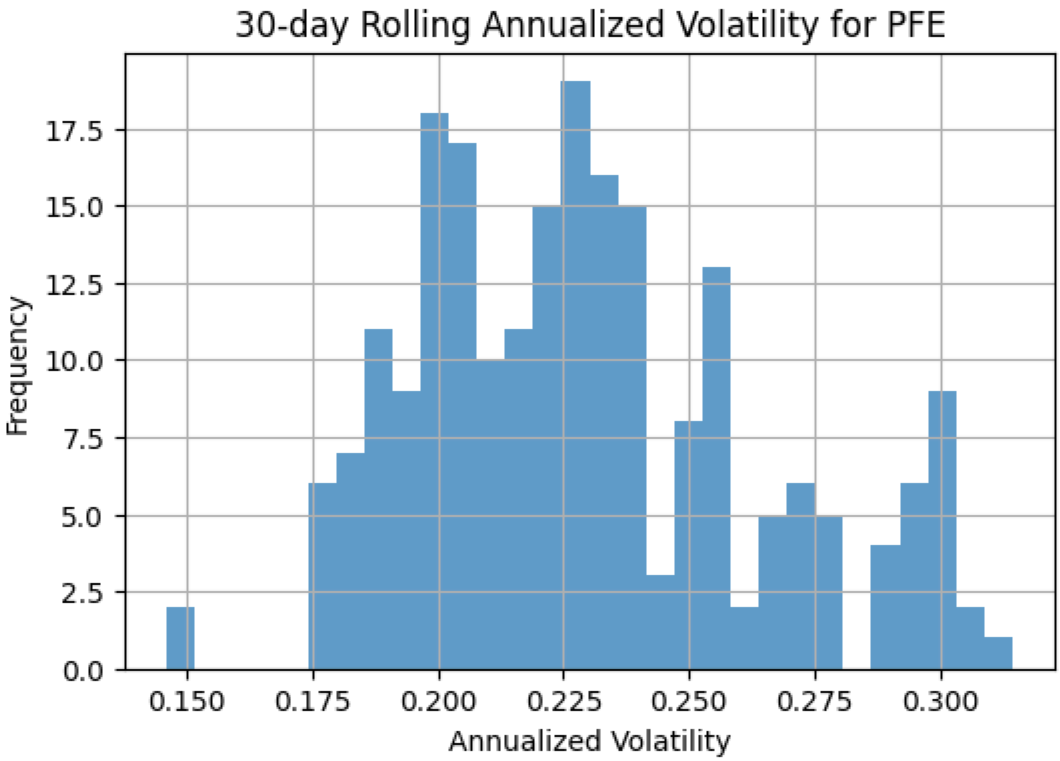
Volatility:

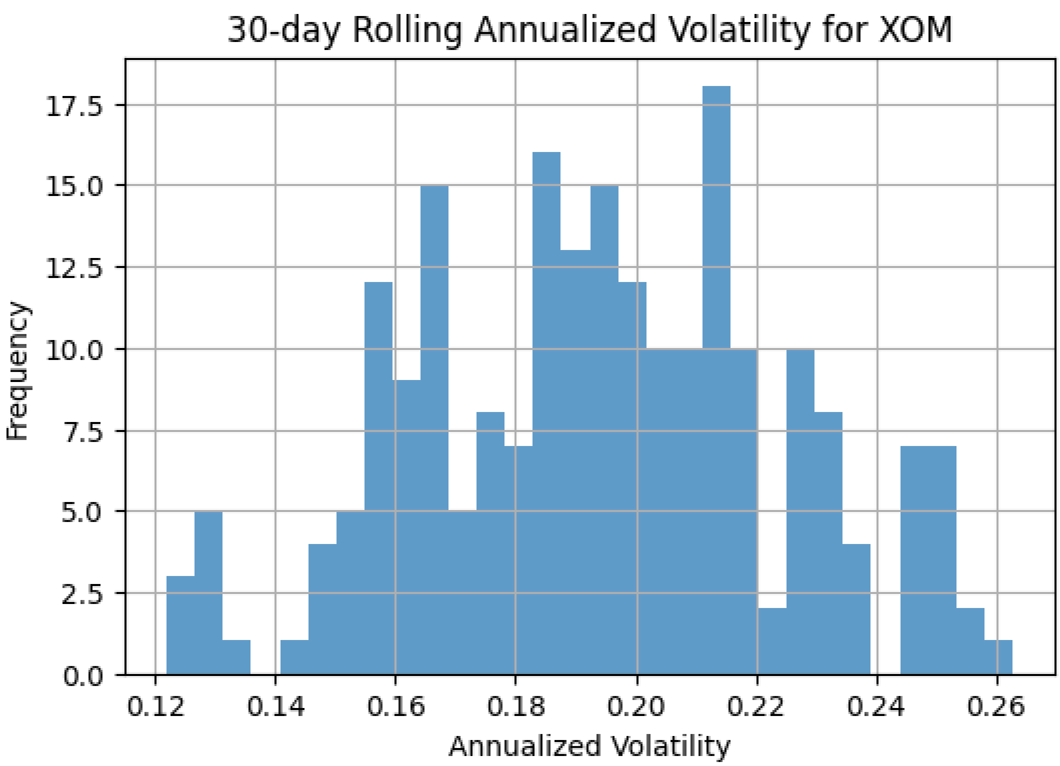
We calculate the rolling standard deviation of daily returns over a 30-day window and annualize it by multiplying by $\sqrt{252}$ (assuming 252 trading days per year).

In [7]:
```
# Rolling 30-day volatility (annualized)
rolling_vol = daily_returns.rolling(window=30).std() * np.sqrt(252)
rolling_vol = rolling_vol.dropna()

# Plot separate histograms for each stock's 30-day rolling annualized volati
for col in rolling_vol.columns:
    plt.figure(figsize=(6, 4))
    plt.hist(rolling_vol[col], bins=30, alpha=0.7)
    plt.title(f'30-day Rolling Annualized Volatility for {col}')
    plt.xlabel('Annualized Volatility')
    plt.ylabel('Frequency')
    plt.grid(True)
    plt.show()
```


30-day Rolling Annualized Volatility for AAPL
Frequency
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0.125
0.150
0.175
0.200
0.225
0.250
0.275
0.300
0.325
Annualized Volatility


30-day Rolling Annualized Volatility for ED
Frequency
20
15
10
5
0
0.12
0.14
0.16
0.18
0.20
0.22
0.24
Annualized Volatility

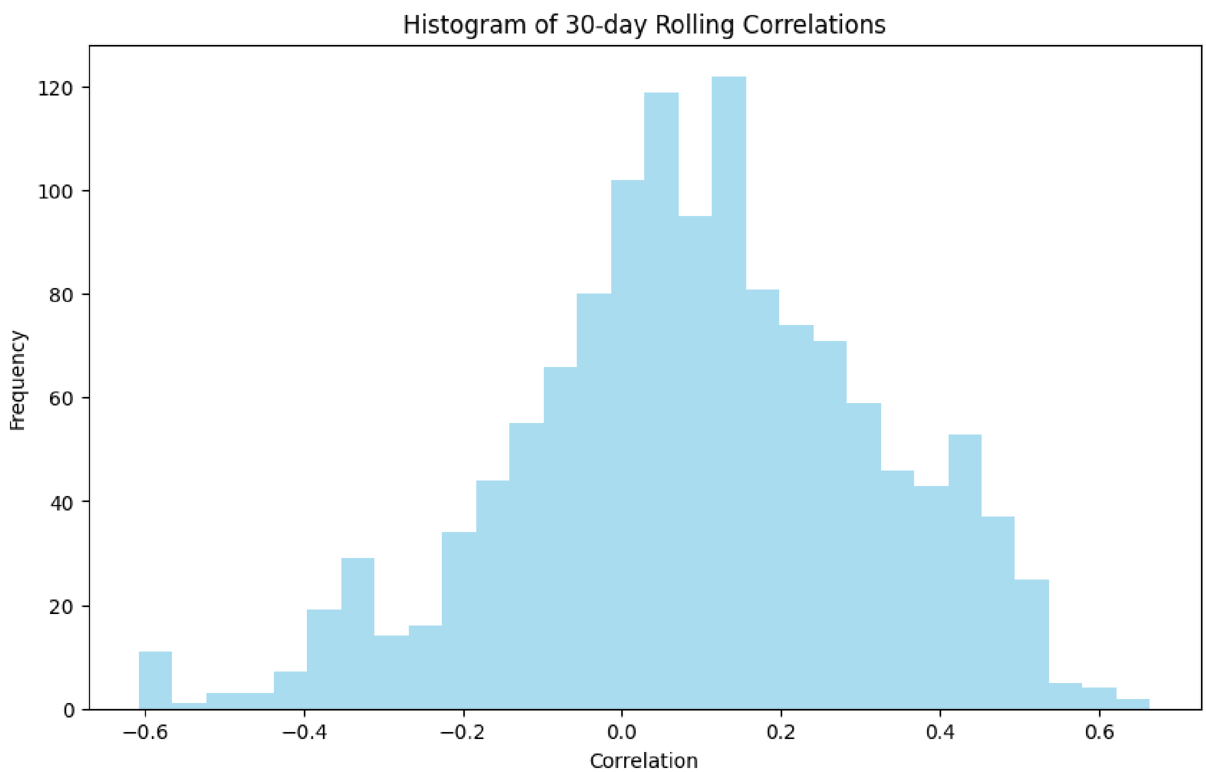




Correlation:
For each 30-day window, we compute the correlation matrix among the stocks and extract the upper triangle values (excluding the diagonal). Then we plot the histogram of these correlation values.

In [9]:
```
# Calculate rolling 30-day correlations.
rolling_corr_list = []
```

```
# Loop over each 30-day window in the daily returns DataFrame
for i in range(29, len(daily_returns)):
    window_data = daily_returns.iloc[i-29:i+1]
    corr_matrix = window_data.corr().values
    # Extract the upper triangle (excluding the diagonal)
    triu_indices = np.triu_indices_from(corr_matrix, k=1)
    rolling_corr_list.extend(corr_matrix[triu_indices])
rolling_corr_array = np.array(rolling_corr_list)

# Plot histogram of the rolling correlations
plt.figure(figsize=(10, 6))
plt.hist(rolling_corr_array, bins=30, alpha=0.7, color='skyblue')
plt.title('Histogram of 30-day Rolling Correlations')
plt.xlabel('Correlation')
plt.ylabel('Frequency')
plt.show()
```



Step 4: Calculate Monthly Returns and Plot the Efficient Frontier

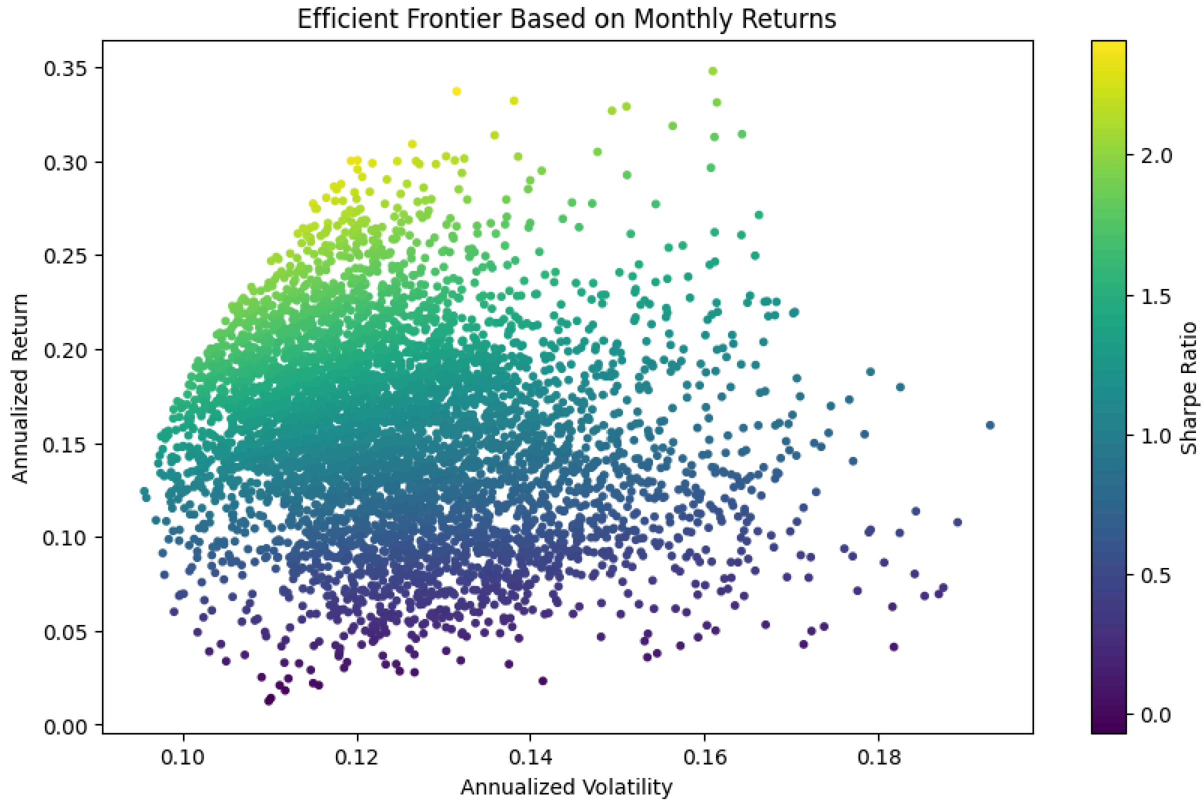
Efficient Frontier:
We simulate a large number of random portfolios. For each portfolio, we calculate:

Annualized Return: Dot product of weights and annualized returns. **Annualized Volatility:** The portfolio standard deviation using the annualized covariance matrix. **Sharpe Ratio:** Using a risk-free rate of 2% (assumed).

Finally, we plot the scatter of portfolio volatilities vs. returns and color the points by their Sharpe ratio.

In [11]:
```
# Resample to monthly data (using the last price of each month)
monthly_prices = data.resample('M').last()
monthly_returns = monthly_prices.pct_change().dropna()

# Annualize the monthly returns and covariance
annual_returns = monthly_returns.mean() * 12
annual_cov = monthly_returns.cov() * 12

# Simulation: Generate random portfolios
num_portfolios = 5000
results = np.zeros((3, num_portfolios))
weights_record = []

for i in range(num_portfolios):
    # Random weights that sum to 1
    weights = np.random.random(len(tickers))
    weights /= np.sum(weights)
    weights_record.append(weights)
    # Portfolio return and volatility calculation
    portfolio_return = np.dot(weights, annual_returns)
    portfolio_volatility = np.sqrt(np.dot(weights.T, np.dot(annual_cov, weig
    results[0, i] = portfolio_volatility
    results[1, i] = portfolio_return
    results[2, i] = (portfolio_return - 0.02) / portfolio_volatility  # Shar

# Plot the efficient frontier
plt.figure(figsize=(10, 6))
plt.scatter(results[0, :], results[1, :], c=results[2, :], cmap='viridis', m
plt.xlabel('Annualized Volatility')
plt.ylabel('Annualized Return')
plt.colorbar(label='Sharpe Ratio')
plt.title('Efficient Frontier Based on Monthly Returns')
plt.show()
```

```
/var/folders/9n/q6k7950n7xg1s3hmhsgf07fh0000gn/T/ipykernel_74301/3342745253.
py:2: FutureWarning: 'M' is deprecated and will be removed in a future versi
on, please use 'ME' instead.
  monthly_prices = data.resample('M').last()
```


Efficient Frontier Based on Monthly Returns
Annualized Return
Annualized Volatility
Sharpe Ratio
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.10
0.12
0.14
0.16
0.18
0.0
0.5
1.0
1.5
2.0

```
In [ ]:
```