Parametric VaR Calculation for a Stock Portfolio

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In this notebook, we calculate the **Value at Risk (VaR)** for a portfolio using the **parametric method**.
We will analyze historical stock data, compute portfolio statistics, and estimate VaR at multiple confidence levels.

Define Analysis Timeframe and Portfolio Stocks

We start by specifying the time range for our analysis and listing the tickers in our portfolio.

In [1]:
```
import numpy as np
import pandas as pd
import datetime as dt
import yfinance as yf
import matplotlib.pyplot as plt
from scipy.stats import norm

# Time horizon for historical data
years_back = 12
end_date = dt.datetime.now()
start_date = end_date - dt.timedelta(days=365*years_back)

# Portfolio tickers (diversified)
tickers = ['AAPL', 'MSFT', 'GOOGL', 'AMZN', 'TSLA']
```

Download Daily Prices and Compute Daily Log Returns

Fetch historical adjusted close prices and calculate **daily logarithmic returns** for each stock.

In [2]:
```
price_data = pd.DataFrame()

for ticker in tickers:
    data = yf.download(ticker, start=start_date, end=end_date)
    price_data[ticker] = data['Close']

# Calculate daily log returns
log_returns = np.log(price_data / price_data.shift(1)).dropna()
```

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

Build Equally Weighted Portfolio and Compute Portfolio Returns

We create a portfolio with **equal weights** and calculate its daily returns.

In [4]:
```
portfolio_value = 600_000
weights = np.array([1/len(tickers)] * len(tickers))

portfolio_returns = (log_returns * weights).sum(axis=1)
```

Compute Rolling X-Day Portfolio Returns

We calculate rolling cumulative returns over a **5-day window** to estimate short-term risk.

In [5]:
```
rolling_days = 5
rolling_returns = portfolio_returns.rolling(window=rolling_days).sum()
```

Calculate Covariance Matrix and Portfolio Volatility

We calculate the annualized covariance matrix and use it to compute the **portfolio standard deviation**.

In [6]:
```
cov_matrix_annual = log_returns.cov() * 252
portfolio_std = np.sqrt(weights.T @ cov_matrix_annual @ weights)
```

Compute Parametric VaR at Multiple Confidence Levels

We calculate the **parametric VaR** for confidence levels of 90%, 95%, and 99%.

In [7]:
```
confidence_levels = [0.90, 0.95, 0.99]
VaR_values = []

for cl in confidence_levels:
    VaR = portfolio_value * (norm.ppf(1 - cl) * portfolio_std * np.sqrt(roll
    VaR_values.append(VaR)
```

Display VaR Results

Print the estimated VaR for each confidence level.

In [8]:
```
print(f'{"Confidence Level":<20} {"Parametric VaR":<20}')
print('-'*40)

for cl, var in zip(confidence_levels, VaR_values):
    print(f'{int(cl*100):>6}%: {"":<8} ${var:>10,.2f}')
```

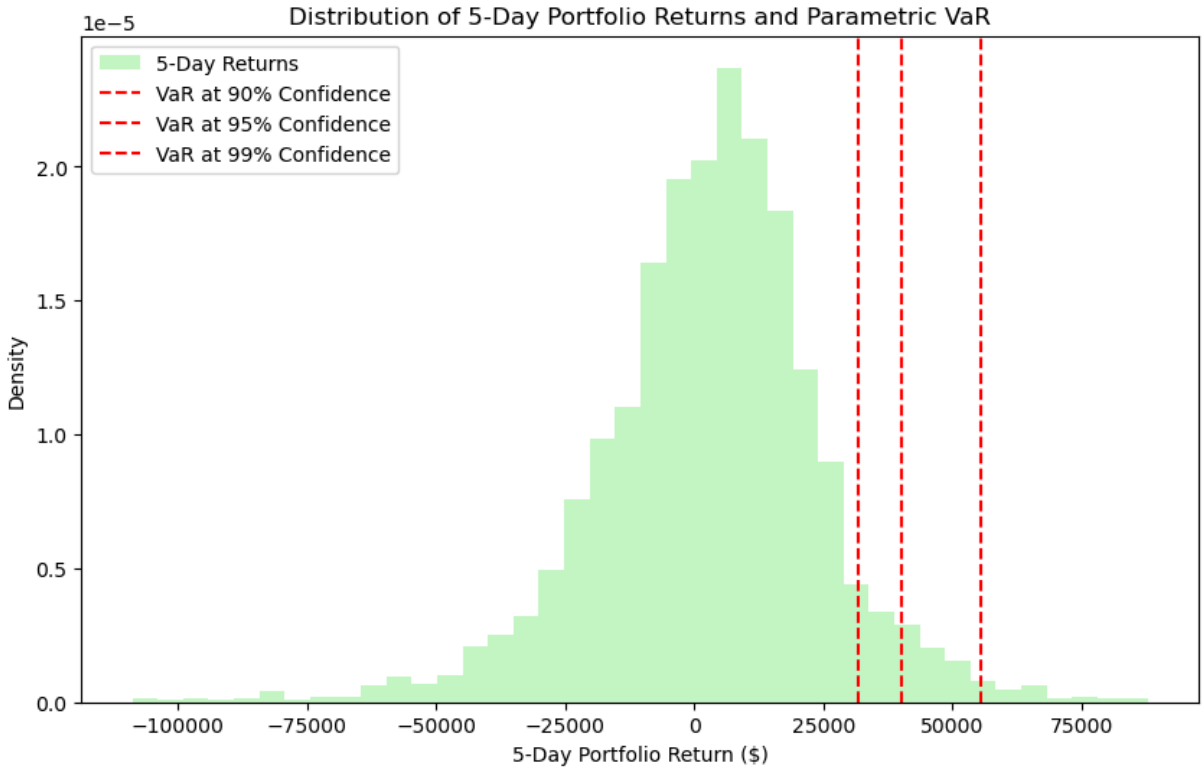
```
Confidence Level     Parametric VaR
----------------------------------------
    90%:          $-31,837.87
    95%:          $-40,079.31
    99%:          $-55,538.87
```

In [9]:
```
# Convert to dollar values
rolling_returns_dollar = rolling_returns * portfolio_value

plt.figure(figsize=(10,6))
plt.hist(rolling_returns_dollar, bins=40, density=True, alpha=0.5, color='li

# Plot vertical lines for VaR at each confidence level
for cl, var in zip(confidence_levels, VaR_values):
    plt.axvline(x=-var, linestyle='--', color='red', label=f'VaR at {int(cl*

plt.xlabel(f'{rolling_days}-Day Portfolio Return ($)')
plt.ylabel('Density')
plt.title(f'Distribution of {rolling_days}-Day Portfolio Returns and Paramet
plt.legend()
plt.show()
```



In [ ]: