



# BLACK-LITTERMAN MODEL WITH FACTOR PRACTICE TO THEORY

WEEK I: ALGORITHMIC TRADING &  
MEAN-VARIANCE PORTFOLIO IN PRACTICE

Pasin Marupanthorn, Ph.D, CQF

25<sup>th</sup> Jaunary 2025





# Lecturer Biography

Who am I?

Pasin Marupanthorn, Ph.D., CQF

## Experience

- Quantitative Researcher/Trader
- Senior Advisor - Groundup Academy - Thailand
- Quantitative Researcher/Trader - ResilientML - Australia
- Quantitative Researcher - QRSLab - United Kingdom
- Graduate Researcher in Analysis & Probability Research Group - Maxwell Institute of Mathematical Science - United Kingdom
- Lecturer - RMUTSB



# Lecturer Biography

Who am I?

## Education

- Ph.D. Actuarial Mathematics & Statistics - Heriot-Watt University, UK
- Certificate in Quantitative Finance - CQF Institute
- M.Sc. Financial Engineering - WorldQuant University, US
- M.Sc. Mathematical Modelling - University of Birmingham, UK
- M.Sc. Mathematics - Thammasat University
- B.Sc. Applied Mathematics with Physics - Thammasat University

**Areas of Expertise** Financial Mathematics, Actuarial Mathematics, Stochastic Modelling & Statistical Machine Learning



# Lecturer Biography

Collaboration

*Industry Project Collaboration*

*Research Collaboration*

*Co-supervise Ph.D. students in Financial Mathematics and Actuarial Mathematics in collaboration with labs from the UK, US, France, Australia, or Japan.*

<https://quantfilab.github.io/pmarupanthorn/>





# A Guideline for Three Weeks

## Lecture Series

### Black-Litterman Model with Factor: Practice to Theory

Week 1 *Algorithmic Trading & Mean-Variance Portfolio in Practice* - 25<sup>th</sup>  
January 2025 - Practice Focus

Week 2 *Black-Litterman Model & Investor View with Factors in Practice* - 8<sup>th</sup>  
February 2025 - Practice Focus

Week 3 *Advanced Mathematics behind Back-Litterman Model & other  
Bayesian Approach Portfolios* - 22<sup>nd</sup> March 2025 - Theory Focus



*Markowitz Portfolio Theory*  $\equiv$  *Modern Portfolio Theory*  $\equiv$  *Mean-Variance Portfolio Theory*

These terms are not exactly identical, but for the purpose of this lecture, I will assume they are equivalent.



# Section

## 1 Motivation

- ▶ Motivation
- ▶ Algorithmic Trading
- ▶ Brief Story of Modern Portfolio Theory
- ▶ Background on Financial Mathematics
- ▶ Mean-Variance Portfolio



# Introduction to Investment

## 1 Motivation

- **What is Investment?** Allocating resources (money, time) into assets or projects to generate future returns.
- **Why Do We Invest?** To grow wealth, achieve financial goals, hedge against inflation, and manage risk.
- **Why Is Investment Important to Companies?** - Provides capital for growth and innovation. - Enhances market valuation and competitiveness.



# Investment in the Financial Market

## 1 Motivation

- **Liquidity:**
  - Financial markets like stocks and bonds offer high liquidity, allowing investors to buy and sell assets quickly.
  - Other markets, such as real estate, often require more time to execute transactions.
- **Diversification:**
  - Wide range of assets, including stocks, bonds, ETFs, and derivatives, enables effective risk management.
  - Other markets may lack the variety needed for proper diversification.
- **Accessibility:**
  - Financial markets are accessible to both retail and institutional investors through online platforms.
  - Other markets, like private equity, often have higher entry barriers.



# Why Should You Study Investment?

## 1 Motivation

- Salary Insights:** Median salary for investment analysts: \$90,000+ annually (varies by region and experience).
- Global Opportunities:** The financial market operates worldwide, offering careers in major financial hubs.
- Job Security:** Investment professionals are in demand across economic cycles, especially in wealth management and risk advisory.
- Personal Finance Benefits:** Gain the knowledge to manage your own wealth effectively.



### Entry-Level Quantitative Researcher

New York, United States · 1 year ago

\$150K/yr - \$200K/yr On-site Full-time



### Quantitative Researcher – Digital Assets

New York City Metropolitan Area · 2 weeks ago · Over 100 people clicked apply

\$125K/yr - \$250K/yr + Bonus Hybrid Full-time



### Quantitative Researcher - Full-Time Campus Hire

New York, United States · Reposted 2 weeks ago · Over 100 people clicked apply

\$200K/yr - \$220K/yr Hybrid Full-time



# The Quant Era in Investment

## 1 Motivation

- The rise of data-driven and algorithmic investment strategies.
- Heavily relies on quantitative models, machine learning, and big data.
- Prominent players: Renaissance Technologies, Two Sigma, Citadel.



Some Quant Firms



## Quant Funds' Share of Trading Soars

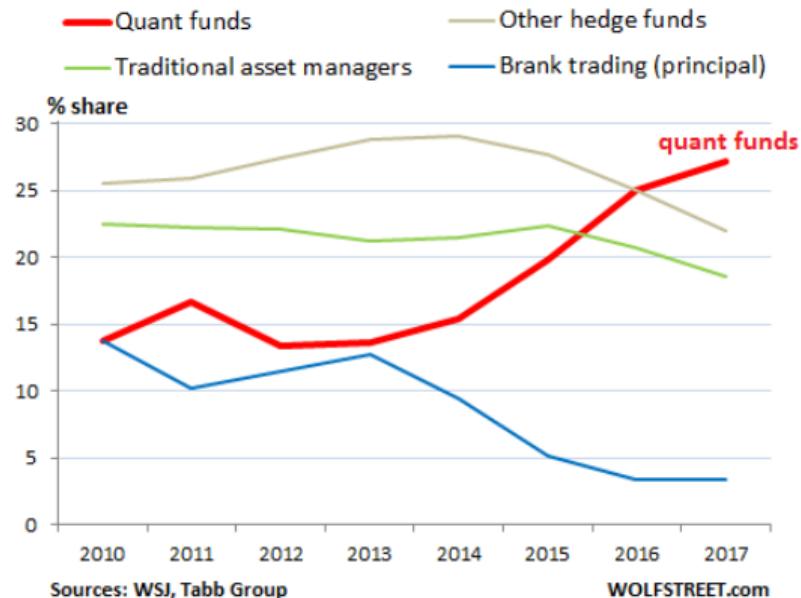


Figure: Quant Cap



# Jim Simons: The King of Quant

## 1 Motivation

- Founder of **Renaissance Technologies**, one of the most successful hedge funds in history.
- A former mathematician specializing in geometry and topology.
- Known as the "Quant King" for pioneering quantitative investment strategies.
- *Medallion Fund*, a highly profitable fund averaging 40% annual returns after fees.
- Proved the power of mathematics and science in financial markets.



Jim Simons, Founder of Renaissance Technologies, 1938 - 2024



# Thai's Quant Community: QuantCorner

## 1 Motivation



<https://www.facebook.com/quantcornerthailand/>



## Section

### 2 Algorithmic Trading

- ▶ Motivation
- ▶ Algorithmic Trading
- ▶ Brief Story of Modern Portfolio Theory
- ▶ Background on Financial Mathematics
- ▶ Mean-Variance Portfolio



# Asset Classes

## 2 Algorithmic Trading

### Classification by Time Value

- **Spot Markets:** Involve immediate settlement and delivery of assets.
- **Derivatives Markets:** Include contracts based on future value, such as options, futures, and swaps.

### Classification by Market Type

- **Equity:** Shares and stock-related securities.
- **Rates:** Bonds, interest rates, and fixed income products.
- **Commodities:** Physical goods like gold, oil, and agricultural products.
- **Carbon and Green Assets:** Emission trading credits and sustainable financial products.
- **Cryptocurrency:** Digital assets such as Bitcoin, Ethereum, and altcoins.



# Steps in Demo and Paper Trading

## 2 Algorithmic Trading

- 1. Choose a Platform:** Select a trading platform offering demo or paper trading.
- 2. Set Up a Virtual Account:** Create an account and allocate virtual funds for practice.
- 3. Learn Market Basics:** Understand trading instruments, market conditions, and strategies.
- 4. Test Strategies:** Apply trading strategies and evaluate performance without financial risk.
- 5. Analyze Performance:** Review trades, refine strategies, and measure metrics like profit, loss, and drawdown.



# Interface for Algorithmic Trading

## 2 Algorithmic Trading

A platform or API used to automate trading strategies and allows traders to connect to financial markets programmatically.

### Key Features:

- **Order Placement:** Send market, limit, or stop orders directly to the market.
- **Market Data Access:** Real-time and historical data for analysis and strategy development.
- **Strategy Execution:** Run automated trading algorithms based on predefined rules.
- **Risk Management:** Automate stop-loss, take-profit, and position sizing.



# Interface for Algorithmic Trading

## 2 Algorithmic Trading

### Type of Interfaces:

- **Direct APIs:** Interactive Brokers API, Alpaca, Binance API.
- **Platforms APIs:** MetaTrader, QuantConnect, TradingView, Interactive Brokers TWS API.



# Free Data Sources

## 2 Algorithmic Trading

### Daily Data

- Yahoo Finance
- Investing.com
- Provider; SETTrade,

Intraday Data usually from Specific Provider

- Crypto: Binance, Deripit,
- Equity: Globlex (Thai), IBKR (US)
- Exchange & Metral; All broker linked to MT4 and MT5



# Free Data Sources

## 2 Algorithmic Trading

### Daily Data: General Availability

- **Yahoo Finance:** Comprehensive financial data for global markets.
- **Investing.com:** Real-time data and market analysis tools.
- **SETTrade:** Thai stock market data provided by the Stock Exchange of Thailand (SET).



## Intraday Data: Specific Providers

- **Cryptocurrency:**
  - Binance: Leading global crypto exchange with detailed intraday data.
  - Deribit: Specializing in cryptocurrency derivatives and options.
- **Equity Markets:**
  - Globlex: Thai brokerage offering real-time stock data.
  - IBKR (Interactive Brokers): U.S.-based broker providing real-time equity and options data.
- **Forex and Commodities:**
  - All brokers linked to MT4 and MT5: Includes forex, metals, and other financial instruments.



## Section

### 3 Brief Story of Modern Portfolio Theory

- ▶ Motivation
- ▶ Algorithmic Trading
- ▶ Brief Story of Modern Portfolio Theory
- ▶ Background on Financial Mathematics
- ▶ Mean-Variance Portfolio



# Investment Before Modern Portfolio Theory, 1930s

## 3 Brief Story of Modern Portfolio Theory

- **Rule of Thumb:** Investments were often based on intuition, experience, or simple heuristics rather than mathematical models.
- **Focus on Individual Assets:** Investors analyzed and selected assets based on their standalone performance without considering diversification.
- **Lack of Risk Quantification:** Risk was subjectively assessed, with no formal framework to measure or manage it systematically.
- **Popular Strategies:**
  - Investing in blue-chip stocks for stability.
  - Real estate and tangible assets were favored for long-term growth.
  - Dividend yields and fixed-income securities were prioritized for income generation.

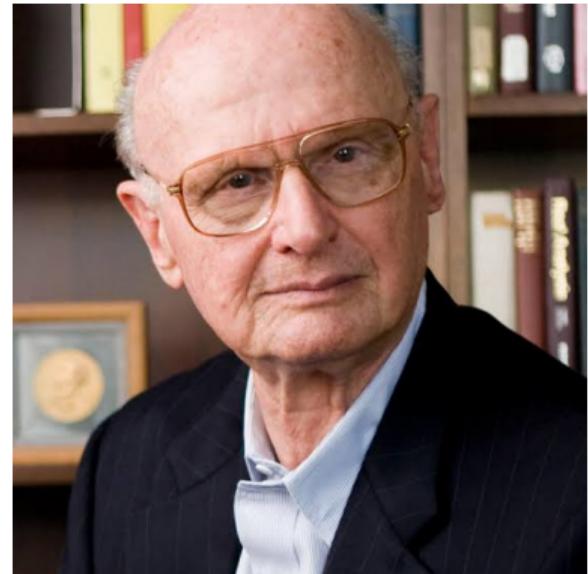


# Harry Markowitz: The Pioneer of Modern Portfolio Theory

## 3 Brief Story of Modern Portfolio Theory

### Who is Harry Markowitz?

- An American economist and pioneer in quantitative finance.
- Introduced **Modern Portfolio Theory (MPT)** in 1952 through his paper *Portfolio Selection*.
- Awarded the **Nobel Prize in Economic Sciences** in 1990.



Harry Markowitz (1927–2023)



# How Markowitz Revolutionized Investment

## 3 Brief Story of Modern Portfolio Theory

### Key Innovations:

- **Diversification Principle:** Emphasized reducing risk by investing in multiple assets.
- **Efficient Frontier:** Proposed the set of portfolios that provide the highest return for a given risk level.
- **Risk-Return Optimization:** Introduced variance (or standard deviation) as a measure of portfolio risk.

### Impact on Investment:

- Shifted from intuition-based investing to data-driven portfolio construction.
- Popularized diversification to reduce unsystematic risk.
- Laid the foundation for modern investment strategies used globally.



*Don't Put All Your Eggs in One Basket.*



Figure: Diversification

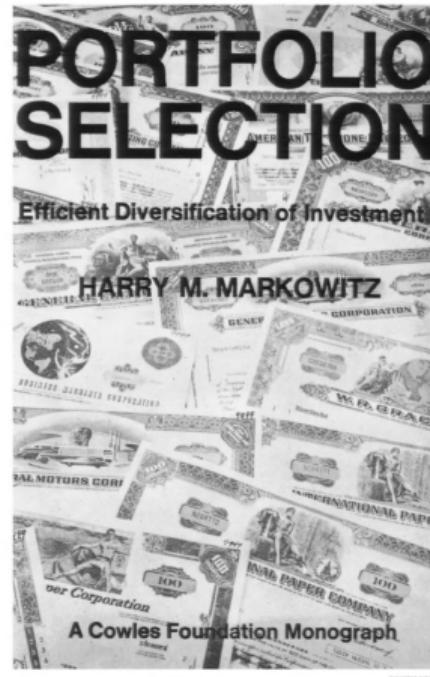


# Portfolio Selection: Efficient Diversification of Investments

## 3 Brief Story of Modern Portfolio Theory

By Harry Markowitz:

- The foundational text introducing **Modern Portfolio Theory (MPT)**.
- Focused on:
  - Risk-return tradeoff.
  - The principle of diversification.
  - Developing the efficient frontier.



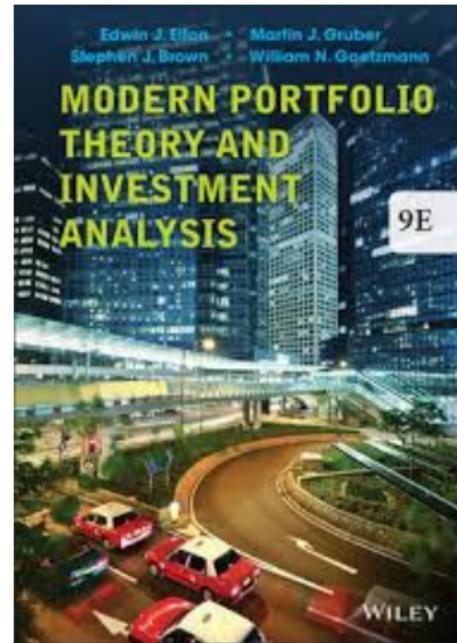


# Modern Portfolio Theory and Investment Analysis

## 3 Brief Story of Modern Portfolio Theory

By Edwin J. Elton, Martin J. Gruber,  
Stephen J. Brown, and William N.  
Goetzmann:

- A comprehensive guide covering:
  - Theory and practical applications of Modern Portfolio Theory.
  - Risk-adjusted returns and portfolio performance.
  - Real-world examples and case studies.
- Widely used in academic and professional finance courses.



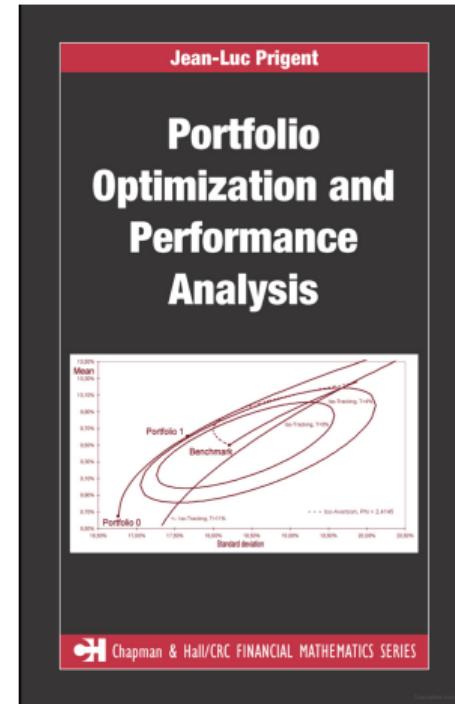


# Portfolio Optimization and Performance Analysis

## 3 Brief Story of Modern Portfolio Theory

By Stephen G. Kellison:

- Covers foundational principles in portfolio optimization.
- Focuses on:
  - Analyzing portfolio performance.
  - Optimizing asset allocation for better returns.
  - Practical insights for risk management.
- Suitable for students and professionals.



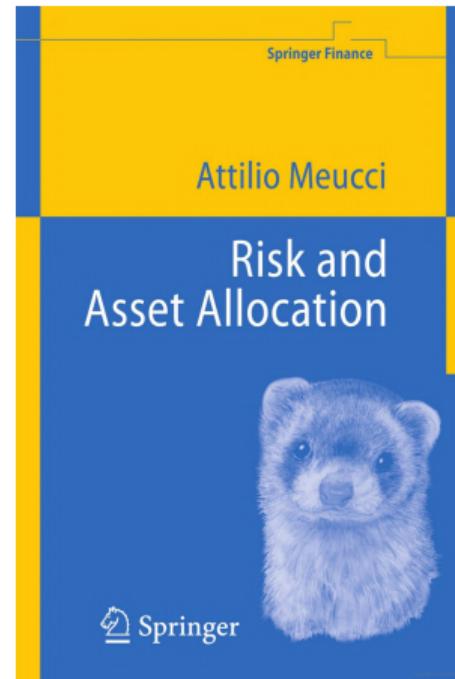


# Risk and Asset Allocation

## 3 Brief Story of Modern Portfolio Theory

By Bernhard Pfaff:

- Focuses on advanced mathematical models for portfolio construction.
- Key topics include:
  - Risk management frameworks.
  - The Black-Litterman Model for portfolio optimization.
  - Advanced quantitative techniques for asset allocation.
- Designed for advanced practitioners and researchers.





# Section

## 4 Background on Financial Mathematics

- ▶ Motivation
- ▶ Algorithmic Trading
- ▶ Brief Story of Modern Portfolio Theory
- ▶ Background on Financial Mathematics
- ▶ Mean-Variance Portfolio



## 4 Background on Financial Mathematics

### Section 4.1

## Stationary of Time Series



# Stationary Time Series Process

## 4 Background on Financial Mathematics

A time series  $\{X_t\}$  is **strictly stationary** if the joint distribution of  $(X_{t_1}, X_{t_2}, \dots, X_{t_k})$  is the same as that of  $(X_{t_1+h}, X_{t_2+h}, \dots, X_{t_k+h})$  for all  $t_1, t_2, \dots, t_k, h$ , and  $k$ . A **weakly stationary** (or second-order stationary) time series satisfies the following conditions:

- **Constant Mean:**

$$\mathbb{E}[X_t] = \mu \quad \text{for all } t.$$

- **Constant Variance:**

$$\text{Var}(X_t) = \mathbb{E}[(X_t - \mu)^2] = \sigma^2 \quad \text{for all } t.$$

- **Time-Invariant Autocovariance:**

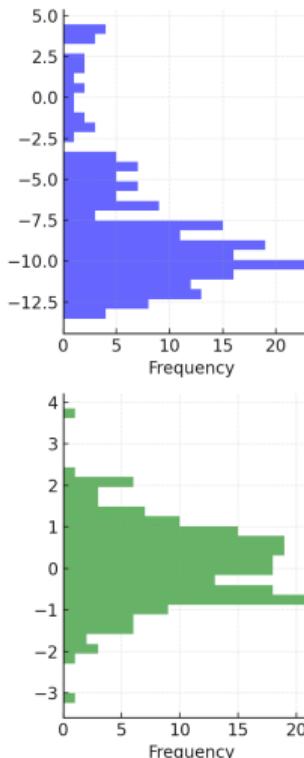
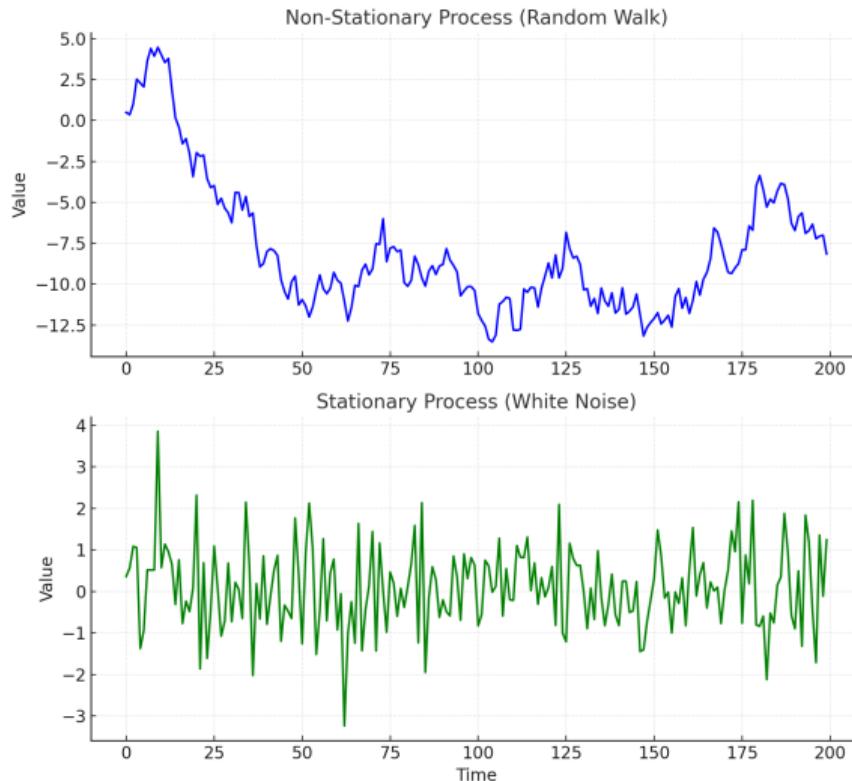
$$\text{Cov}(X_t, X_{t+h}) = \mathbb{E}[(X_t - \mu)(X_{t+h} - \mu)] = \gamma(h),$$

where  $\gamma(h)$  depends only on the lag  $h$ , not on  $t$ .



# Stationary Time Series Process

## 4 Background on Financial Mathematics





## 4 Background on Financial Mathematics

### Section 4.2

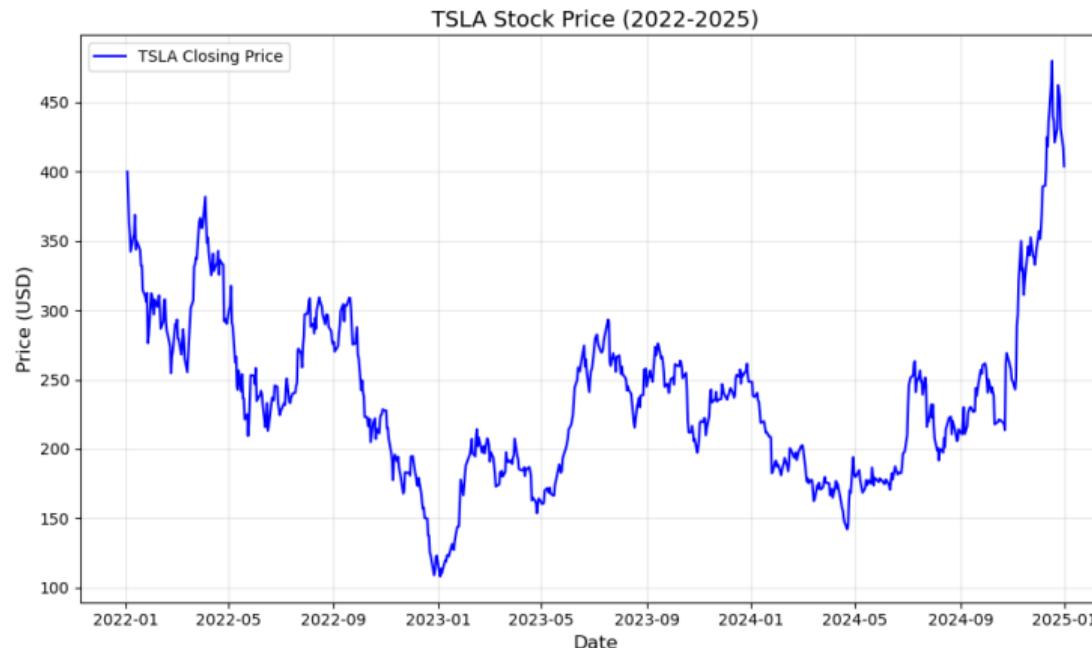
## Price and Return Processes



# Price Processes in Finance: Non-Stationary Nature

## 4 Background on Financial Mathematics

Common in finance, as asset prices evolve unpredictably and depend on external factors like market trends and macroeconomic conditions.





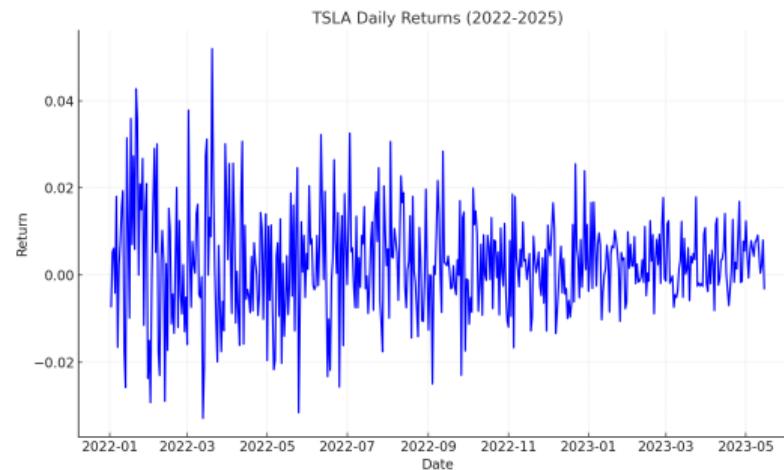
# Return Process and Near Stationarity

## 4 Background on Financial Mathematics

- Let  $P_t$  denote the price of an asset at time  $t$ .
- The **logarithmic return** is given by:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln(P_{t-1}),$$

where  $R_t$ : Return at time  $t$  and  $P_t$ : Asset price at time  $t$ .





## 4 Background on Financial Mathematics

### Section 4.3

# Financial Data & Stylized Fact



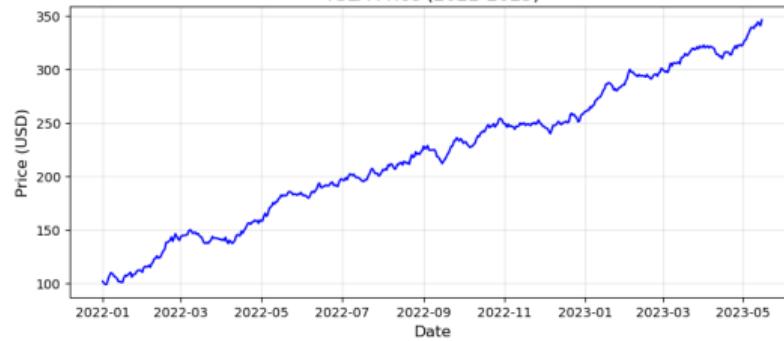
# Stylized Facts of Financial Data

## 4 Background on Financial Mathematics

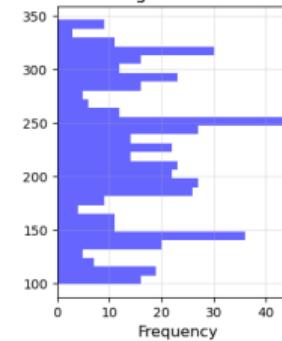
- **Heavy Tails:** The distribution of returns often has fatter tails than the normal distribution, meaning extreme events (outliers) occur more frequently.
- **Volatility Clustering:** High volatility tends to be followed by high volatility, and low volatility follows low volatility, indicating periods of market calm and turbulence.
- **Leverage Effect:** Negative returns tend to increase volatility more than positive returns of the same magnitude.
- **Autocorrelation:** Returns often exhibit short-term autocorrelation, meaning past returns may influence future returns, although this is weak over long periods.
- **Non-Stationarity:** Asset prices are often non-stationary, meaning their statistical properties, such as mean and variance, change over time.



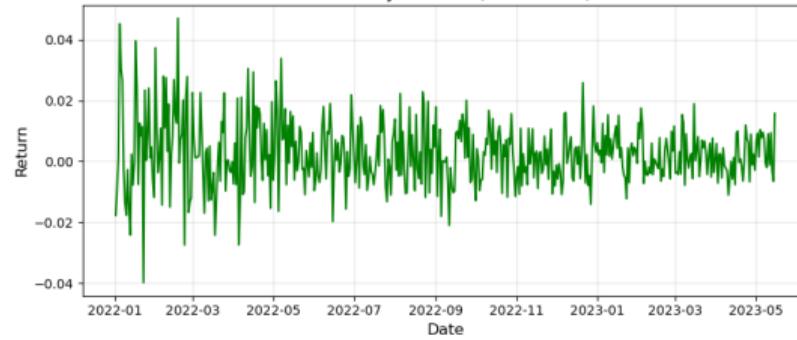
TSLA Price (2022-2025)



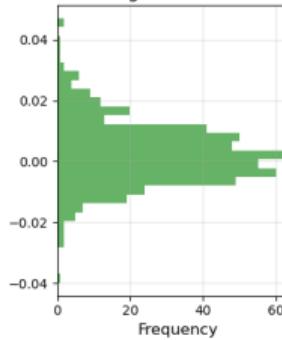
Histogram of Prices



TSLA Daily Returns (2022-2025)



Histogram of Returns





# Section

## 5 Mean-Variance Portfolio

- ▶ Motivation
- ▶ Algorithmic Trading
- ▶ Brief Story of Modern Portfolio Theory
- ▶ Background on Financial Mathematics
- ▶ Mean-Variance Portfolio



## 5 Mean-Variance Portfolio

Section 5.1

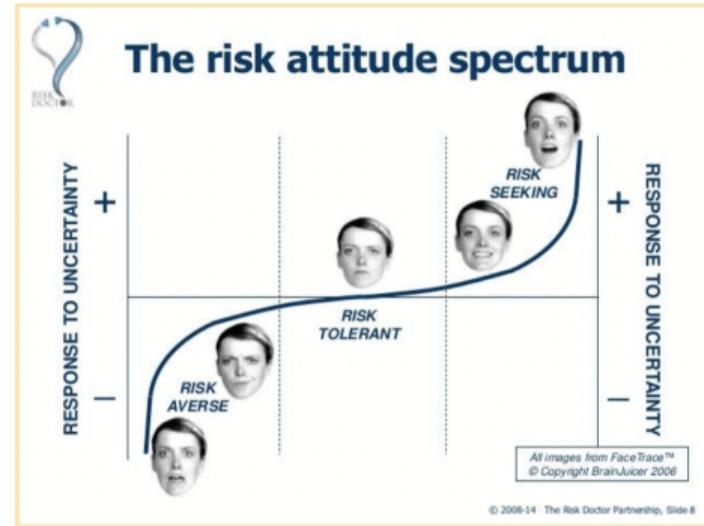
# Mean-Variance Portfolio



# Risk-Averse vs. Risk-Seeking vs. Risk-Neutral Investors

## 5 Mean-Variance Portfolio

- Risk-Averse Investors prefer lower risk and are willing to sacrifice some return to avoid uncertainty.
- Risk-Seeking Investors prefer higher risk, even if it means a lower expected return.
- Risk-Neutral Investors are indifferent to risk and base decisions solely on expected return.



Risk



# Definition of a Portfolio in Mathematical Notation

## 5 Mean-Variance Portfolio

### What is a Portfolio?

- A portfolio is a collection of financial assets, such as stocks, bonds, or other securities, represented by their weights.
- The weights represent the proportion of total investment allocated to each asset.



# Definition of a Portfolio in Mathematical Notation

## 5 Mean-Variance Portfolio

### Mathematical Representation:

- Let  $n$  be the number of assets in the portfolio.
- The portfolio is represented as a vector of weights:

$$\mathbf{w} = [w_1 \quad w_2 \quad \cdots \quad w_n]^T,$$

where  $w_i$  is the proportion of total capital allocated to asset  $i$ .

- The total weight must satisfy the following constraints:

$$\sum_{i=1}^n w_i = 1, \quad (\text{fully invested portfolio}).$$



# Portfolio Return and Variance

## 5 Mean-Variance Portfolio

### Expected Return of the Portfolio:

- If  $\mu$  is the vector of expected returns of the assets, the portfolio's expected return is:

$$\mu_p = \mathbf{w}^T \mu = \sum_{i=1}^n w_i \mu_i.$$

### Portfolio Variance:

- If  $\Sigma$  is the covariance matrix of asset returns, the portfolio variance is:

$$\sigma_p^2 = \mathbf{w}^T \Sigma \mathbf{w}.$$



# Introduction to Mean-Variance Portfolio

## 5 Mean-Variance Portfolio

- The goal is to construct an optimal portfolio by balancing:
  - **Expected Return ( $\mu$ ):** Defined as:

$$\mu_p = \mathbf{w}^T \boldsymbol{\mu},$$

where:

- $\mu_p$ : Portfolio expected return.
- $\mathbf{w}$ : Vector of portfolio weights  $(w_1, w_2, \dots, w_n)$ .
- $\boldsymbol{\mu}$ : Vector of individual asset expected returns.
- **Volatility ( $\sigma$ ):** Defined as the square root of portfolio variance:

$$\sigma_p = \sqrt{\mathbf{w}^T \boldsymbol{\Sigma} \mathbf{w}},$$

where  $\boldsymbol{\Sigma}$  is the covariance matrix of asset returns.



# Risk-Return Trade-Off: Maximizing Return

## 5 Mean-Variance Portfolio

- Investors aim to achieve the highest return ( $\mu_p$ ) for a specific level of risk ( $\sigma_{\text{target}}$ ).
- Optimization Problem:

$$\max_{\mathbf{w}} \mathbf{w}^T \boldsymbol{\mu},$$

subject to:

$$\mathbf{w}^T \boldsymbol{\Sigma} \mathbf{w} \leq \sigma_{\text{target}}^2, \quad \sum_{i=1}^n w_i = 1.$$

- Constraints:
  - $\mathbf{w}^T \boldsymbol{\Sigma} \mathbf{w}$ : Ensures portfolio risk is below the target.
  - $\sum_{i=1}^n w_i = 1$ : Fully invested portfolio.
- Investors with a low-risk tolerance choose a lower  $\sigma_{\text{target}}$ .
- This approach finds portfolios on the efficient frontier corresponding to a fixed risk level.



# Maximizing Return for a Given Risk

## 5 Mean-Variance Portfolio

**Analytical Solution:**

$$\mathbf{w} = \frac{\Sigma^{-1}(\mu - \lambda \mathbf{1})}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}},$$

where:

- $\mathbf{w}$ : Vector of portfolio weights.
- $\mu$ : Vector of expected returns.
- $\Sigma$ : Covariance matrix of asset returns.
- $\lambda$ : Determined by the risk constraint  $\sigma_{\text{target}}^2$ .



# Risk-Return Trade-Off: Minimizing Risk

## 5 Mean-Variance Portfolio

- Investors aim to achieve the lowest possible risk ( $\sigma_p^2$ ) for a desired return ( $\mu_{\text{target}}$ ).
- Optimization Problem:

$$\min_{\mathbf{w}} \mathbf{w}^T \Sigma \mathbf{w},$$

subject to:

$$\mathbf{w}^T \boldsymbol{\mu} = \mu_{\text{target}}, \quad \sum_{i=1}^n w_i = 1.$$

- Constraints:
  - $\mathbf{w}^T \boldsymbol{\mu}$ : Ensures the portfolio meets the desired return.
  - $\sum_{i=1}^n w_i = 1$ : Fully invested portfolio.
- This approach identifies the minimum-risk portfolio for a specific return level on the efficient frontier.



# Minimizing Risk for a Desired Return

## 5 Mean-Variance Portfolio

Analytical Solution:

$$\mathbf{w} = \Sigma^{-1}(\mathbf{A}\boldsymbol{\mu} + \mathbf{B}\mathbf{1}),$$

where:

$$\mathbf{A} = \frac{\mu_{\text{target}}(\mathbf{1}^T \Sigma^{-1} \mathbf{1}) - (\mathbf{1}^T \Sigma^{-1} \boldsymbol{\mu})}{D},$$

$$\mathbf{B} = \frac{(\boldsymbol{\mu}^T \Sigma^{-1} \boldsymbol{\mu}) - \mu_{\text{target}}(\mathbf{1}^T \Sigma^{-1} \boldsymbol{\mu})}{D},$$

and:

$$D = (\boldsymbol{\mu}^T \Sigma^{-1} \boldsymbol{\mu})(\mathbf{1}^T \Sigma^{-1} \mathbf{1}) - (\mathbf{1}^T \Sigma^{-1} \boldsymbol{\mu})^2.$$

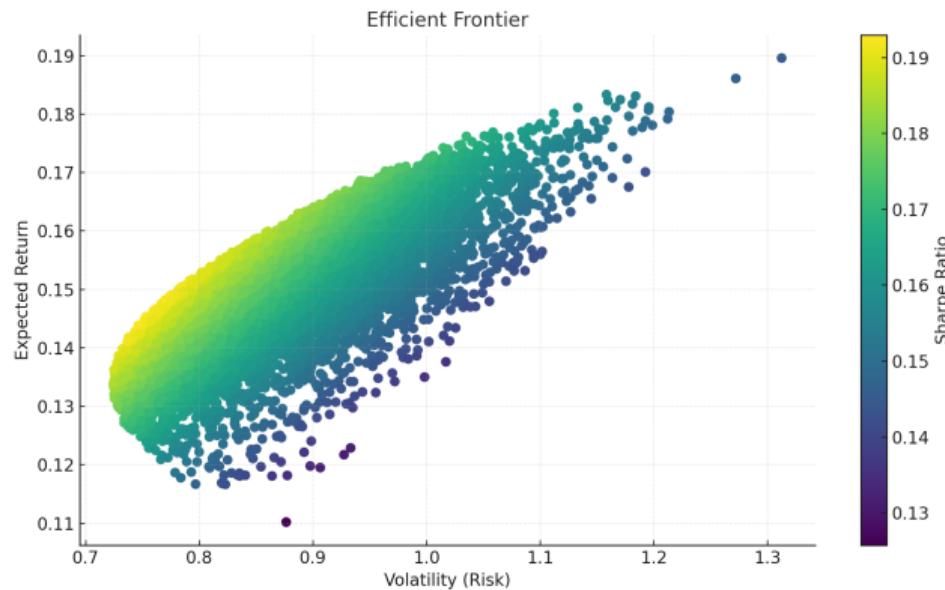


# Efficient Frontier

## 5 Mean-Variance Portfolio

### What is the Efficient Frontier?

- A graphical representation of optimal portfolios that maximize return for a given risk or minimize risk for a given return.
- Portfolios on the frontier are efficient, while portfolios below it are suboptimal.





# Efficient Frontier

## 5 Mean-Variance Portfolio

- Each portfolio on the frontier satisfies:

$$\sigma_p^2 = \mathbf{w}^T \Sigma \mathbf{w}, \quad \mu_p = \mathbf{w}^T \boldsymbol{\mu}.$$

- The shape of the frontier is a parabola in risk-return space due to the quadratic nature of variance.
- The frontier's upper portion represents portfolios that dominate in both return and risk.



# Minimum Variance Portfolio

## 5 Mean-Variance Portfolio

**Objective:**

$$\min_{\mathbf{w}} \mathbf{w}^T \Sigma \mathbf{w},$$

subject to:

$$\sum_{i=1}^n w_i = 1.$$

**Analytical Solution:**

- The weights for the minimum variance portfolio are:

$$\mathbf{w} = \frac{\Sigma^{-1} \mathbf{1}}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}},$$

where  $\Sigma$  is the covariance matrix of asset returns,  $\mathbf{1}$  is the vector of ones of size  $n$  (number of assets).



# Maximum Sharpe Ratio Portfolio

## 5 Mean-Variance Portfolio

**Objective:**

$$\max_{\mathbf{w}} \frac{\mathbf{w}^T \boldsymbol{\mu} - r_f}{\sqrt{\mathbf{w}^T \boldsymbol{\Sigma} \mathbf{w}}},$$

subject to:

$$\sum_{i=1}^n w_i = 1.$$

**Analytical Solution:**

- The weights for the maximum Sharpe ratio portfolio are:

$$\mathbf{w} = \frac{\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - r_f \mathbf{1})}{\mathbf{1}^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - r_f \mathbf{1})},$$

where  $\boldsymbol{\mu}$ : is the vector of expected returns and  $r_f$  is the risk-free



# Efficient Portfolio: Convex Combination of Portfolios

## 5 Mean-Variance Portfolio

### Theory: Efficient Portfolio Combination

- Any portfolio on the **efficient frontier** is a linear combination of:
  - The **Minimum Variance Portfolio** ( $\mathbf{w}_{\min}$ ), which minimizes risk.
  - The **Maximum Sharpe Ratio Portfolio** ( $\mathbf{w}_{\max}$ ), which maximizes return per unit of risk.

### Mathematical Representation:

- The weights of an efficient portfolio are given by:

$$\mathbf{w}_{\text{efficient}} = \alpha \mathbf{w}_{\min} + (1 - \alpha) \mathbf{w}_{\max},$$

where:

- $\alpha$ : The proportion of the portfolio allocated to the minimum variance portfolio.
- $1 - \alpha$ : The proportion allocated to the maximum Sharpe ratio portfolio.
- The value of  $\alpha$  depends on the investor's risk preference or return target.



# Efficient Portfolio Weights

## 5 Mean-Variance Portfolio

Given the target expected return,  $\alpha$  convex combination parameter, calculated as:

$$\alpha = \frac{\mu_{\max} - \mu_{\text{target}}}{\mu_{\max} - \mu_{\min}},$$

where:

- $\mu_{\max}$ : Expected return of the maximum return portfolio.
- $\mu_{\min}$ : Expected return of the minimum variance portfolio.
- $\mu_{\text{target}}$ : Target expected return.



# Assumptions of the Mean-Variance Portfolio Model

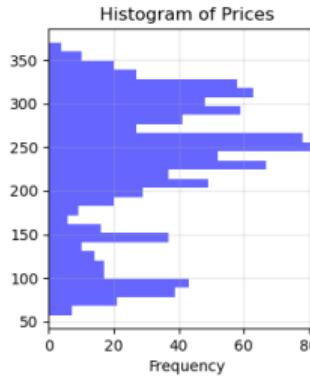
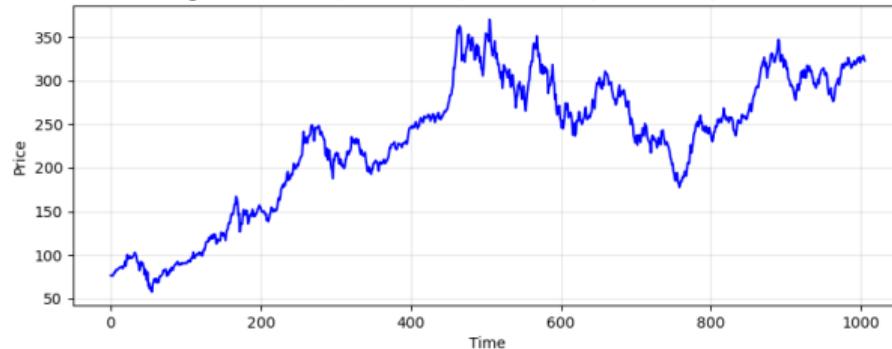
## 5 Mean-Variance Portfolio

- **Asset Returns are Normally Distributed:**
  - The returns of assets are assumed to follow a normal distribution.
  - This ensures that the mean and variance fully describe the distribution of returns.
- **Investors are Rational and Risk-Averse:**
  - Investors prefer higher returns for a given level of risk.
  - They aim to maximize utility, which is a function of return and risk.
- **Stationarity of Returns:**
  - The statistical properties (mean, variance, and covariance) of returns are assumed to remain constant over time.

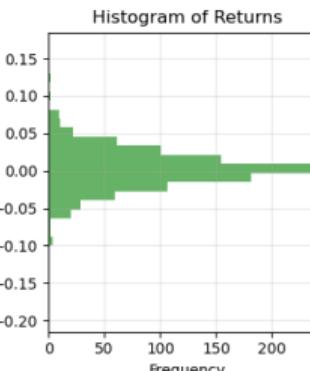
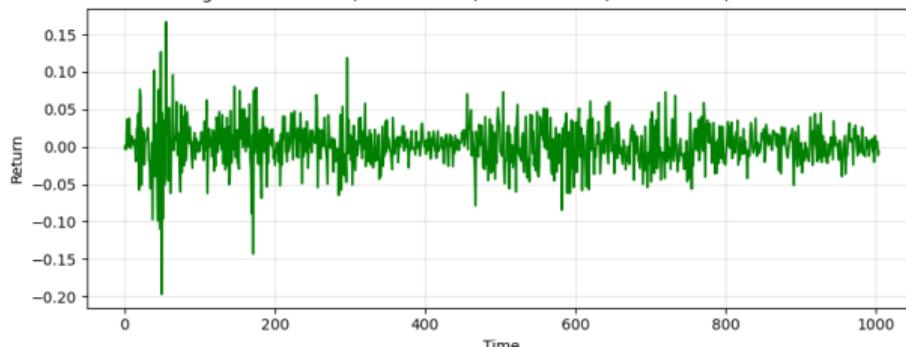


# Example: Max Sharpe 5 Mean-Variance Portfolio

Price Process: Max Return Portfolio  
Expected Return: 0.0024, Volatility: 0.0301, Sharpe Ratio: 0.0780  
Weights: AAPL=0.39, MSFT=-0.46, GOOGL=0.05, AMZN=0.47, TSLA=0.54



Return Process: Max Return Portfolio  
Expected Return: 0.0024, Volatility: 0.0301, Sharpe Ratio: 0.0780  
Weights: AAPL=0.39, MSFT=-0.46, GOOGL=0.05, AMZN=0.47, TSLA=0.54

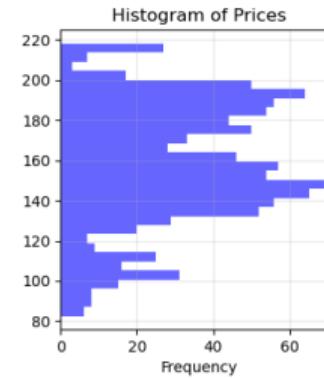
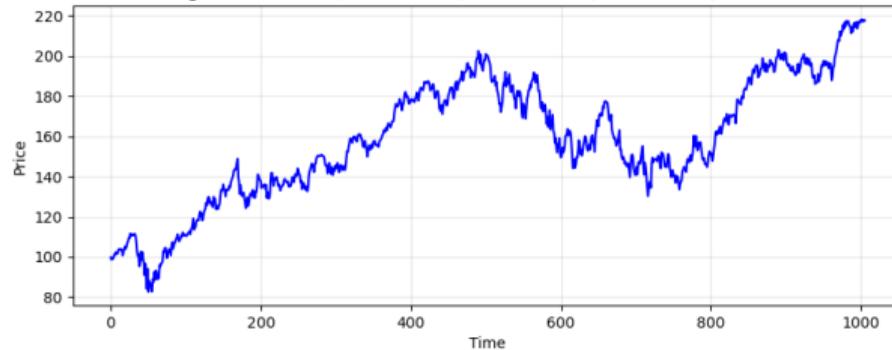




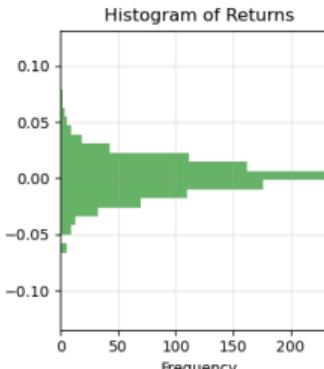
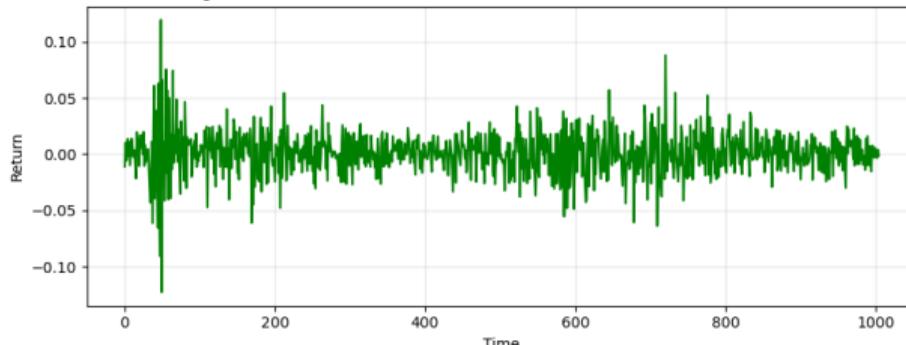
# Example: Min Var

## 5 Mean-Variance Portfolio

Price Process: Min Risk Portfolio  
Expected Return: 0.0009, Volatility: 0.0188, Sharpe Ratio: 0.0488  
Weights: AAPL=0.39, MSFT=-0.46, GOOGL=0.05, AMZN=0.47, TSLA=0.54



Return Process: Min Risk Portfolio  
Expected Return: 0.0009, Volatility: 0.0188, Sharpe Ratio: 0.0488  
Weights: AAPL=0.39, MSFT=-0.46, GOOGL=0.05, AMZN=0.47, TSLA=0.54





## 5 Mean-Variance Portfolio

### Section 5.2

## Case Study I: Small US Equity Portfolio



# Portfolio Analysis of 5 Stocks (Part 1)

## 5 Mean-Variance Portfolio

### Selected Assets:

- The portfolio consists of 5 leading US technology and automotive stocks:
  - **AAPL**: Apple Inc.
  - **MSFT**: Microsoft Corporation
  - **GOOGL**: Alphabet Inc. (Google)
  - **AMZN**: Amazon.com Inc.
  - **TSLA**: Tesla, Inc.

### Data Source:

- Historical stock data retrieved using Yahoo Finance API.
- Time period: **January 1, 2020 – December 31, 2023.**



# Portfolio Analysis of 5 Stocks (Part 2)

## 5 Mean-Variance Portfolio

### Portfolio Construction:

- Daily adjusted closing prices are used to calculate returns.
- The covariance matrix of returns is computed for risk assessment.
- Portfolio weights are optimized to achieve the target of the daily expected return of 1% with minimum volatility.



# Validating Covariance

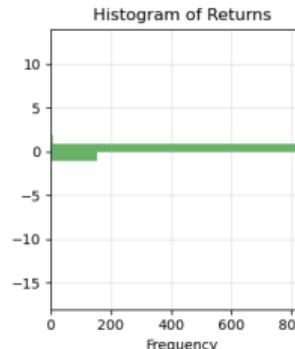
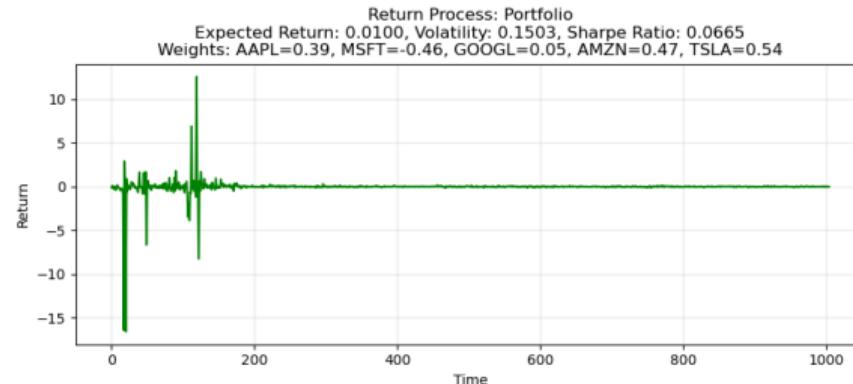
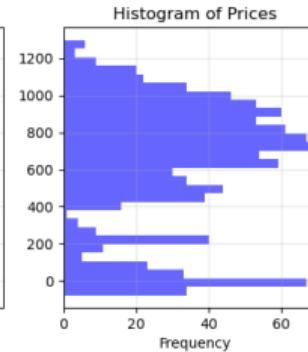
## 5 Mean-Variance Portfolio





# Results

## 5 Mean-Variance Portfolio





# Warning

## 5 Mean-Variance Portfolio

*If this were valid, everyone would be a billionaire.*

- You cannot determine the optimal weights until empirical data is obtained - it is data-dependent and not currency-dependent.
- If investing in the stock market, odd lots and fractional shares may affect your results, especially with a small budget.

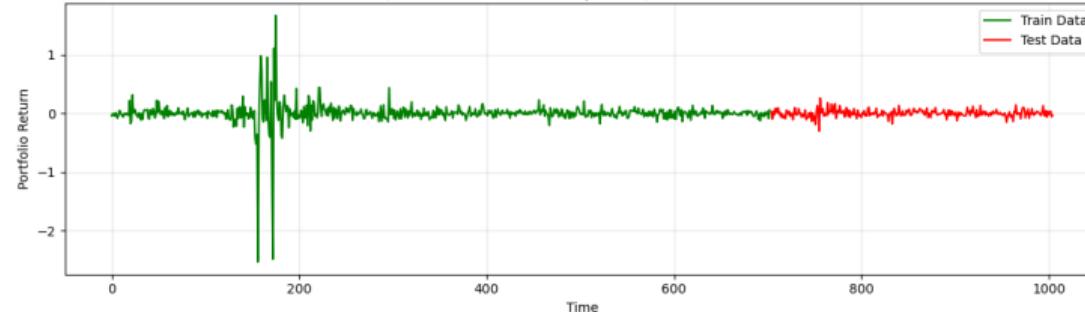


# Frame Title

## 5 Mean-Variance Portfolio



Portfolio Returns with Train-Test Split  
Train:  $\mu=0.0019, \sigma=0.1943$  | Test:  $\mu=0.0014, \sigma=0.0605$





# Methods for Non-Stationary Covariance Matrix

## 5 Mean-Variance Portfolio

### 1. Rebalancing:

- Regularly update portfolio weights based on the latest covariance estimates.
- Choose a rebalancing frequency (e.g., daily, monthly) based on market dynamics.

### 2. Predicted Covariance Structure:

- Use machine learning models (e.g., GARCH, LSTM) to forecast the covariance matrix.
- Incorporate macroeconomic factors or market indicators into predictions.

### 3. Rolling Windows:

- Estimate the covariance matrix using a rolling window of historical data.
- Adjust the window size to balance stability and responsiveness.



# Effect of Rounding Estimate Weight

## 5 Mean-Variance Portfolio

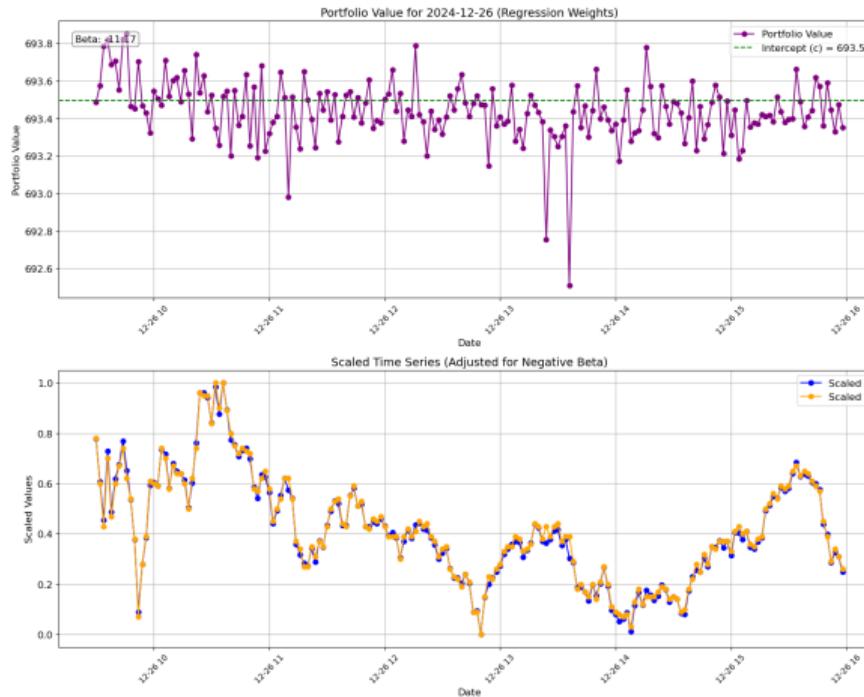


Figure: Estimate Weight



# Effect of Rounding Estimate Weight

## 5 Mean-Variance Portfolio

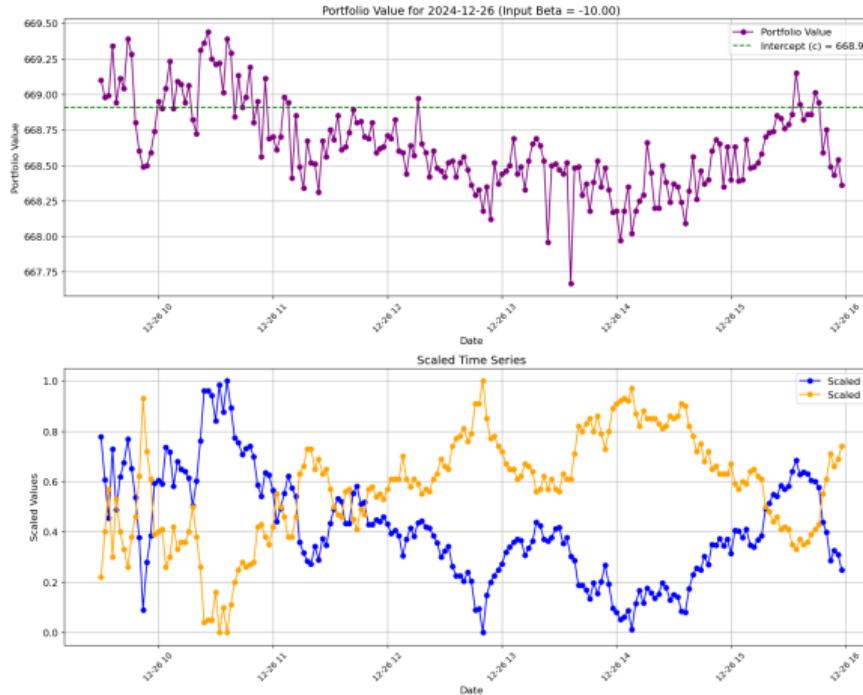


Figure: Rounded Weight



## 5 Mean-Variance Portfolio

### Section 5.3

# Case Study II: Medium-Size US Equity Portfolio



# Portfolio of Assets

## 5 Mean-Variance Portfolio

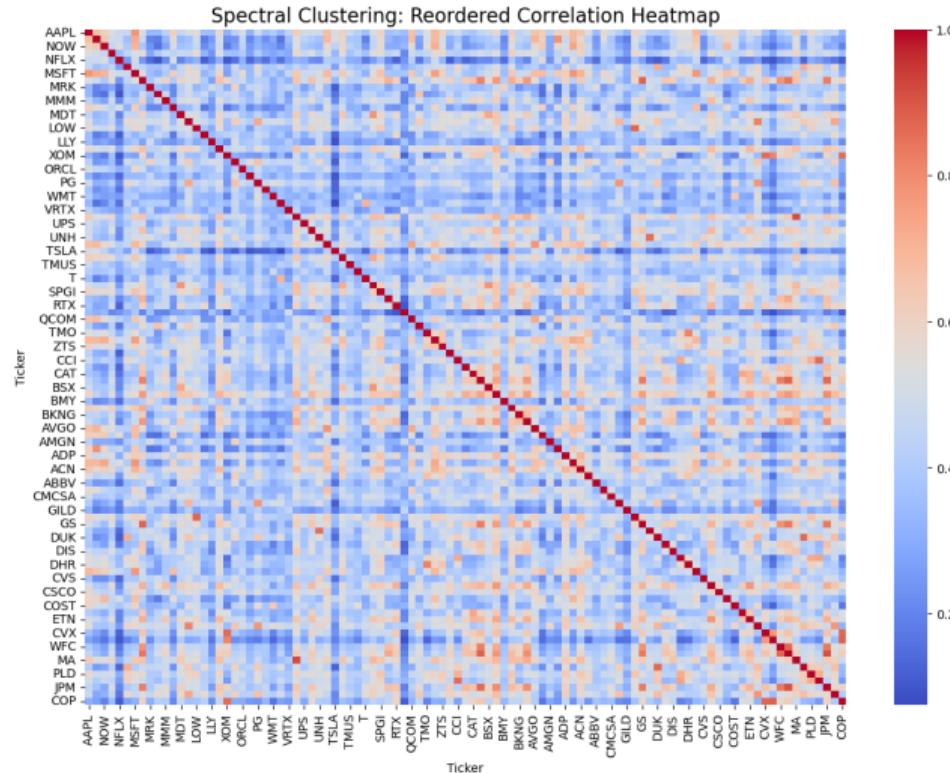
The portfolio consists of 100 US stocks from diverse sectors, including:

- Technology: AAPL, MSFT, AMZN, GOOGL, META
- Consumer Goods: KO, PEP, PG, WMT
- Healthcare: JNJ, PFE, ABBV, MRK, LLY
- Finance: JPM, BAC, GS, MA, MS
- Energy: XOM, CVX, COP, NEE



# Correlation Matrix fo Asset Return

## 5 Mean-Variance Portfolio





# Problem: Condition Number of Covariance Matrix

## 5 Mean-Variance Portfolio

- A **high condition number** implies that  $\Sigma$  is nearly singular or ill-conditioned.
- This means that the matrix has eigenvalues with large disparities.
- It can lead to numerical instability when performing operations such as inversion.

### Analysis for $\Sigma$ :

- **Computed Condition Number:** 887.30.
- **Implication:**
  - The covariance matrix is moderately ill-conditioned.
  - Some assets in the portfolio have highly correlated returns, resulting in a lack of diversification.
  - Numerical methods (e.g., portfolio optimization) may require regularization to ensure stability.



# Methods to Address Singularity of Covariance Matrix (Part 1)

## 5 Mean-Variance Portfolio

### Regularization:

- Add a small constant  $\lambda I$  to the diagonal of the covariance matrix:

$$\Sigma_{\text{regularized}} = \Sigma + \lambda I$$

- Ensures numerical stability and invertibility.

### Dimensionality Reduction:

- Use Principal Component Analysis (PCA) to reduce the dimensionality of the dataset.
- Retain the principal components that explain the majority of the variance.



# Methods to Address Singularity of Covariance Matrix (Part 2)

## 5 Mean-Variance Portfolio

### Shrinkage Estimators:

- Use methods like Ledoit-Wolf shrinkage to estimate a more robust covariance matrix.
- Combines the sample covariance matrix with a structured estimator (e.g., identity matrix).

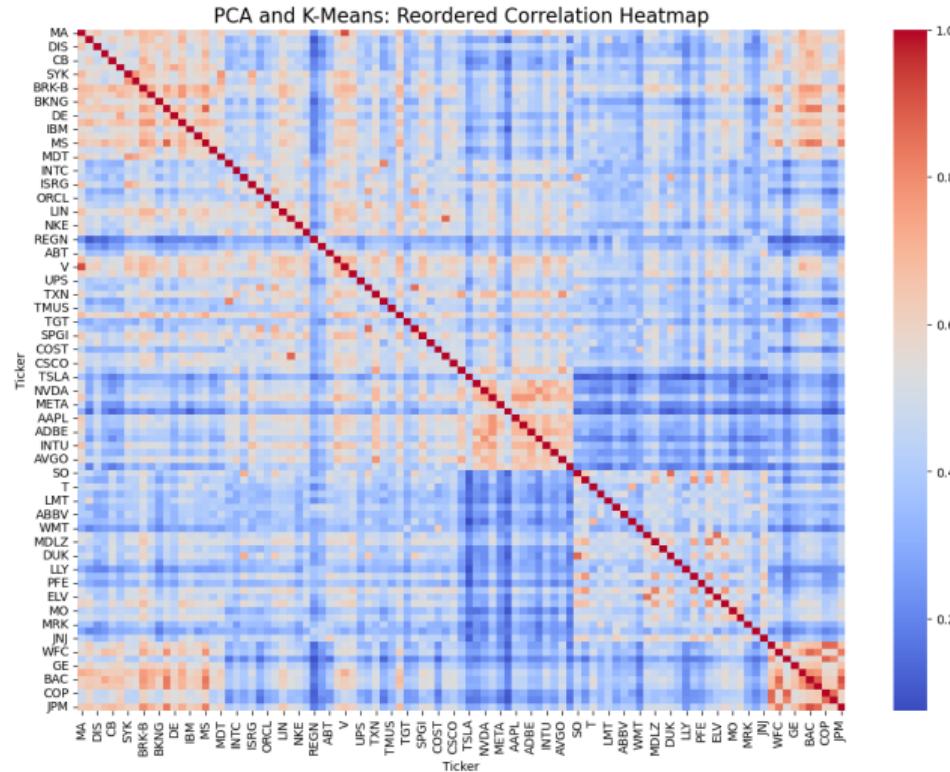
### Asset Selection:

- Reduce the number of assets in the portfolio.
- Remove assets with near-perfect correlations or redundant information.



# Asset Selection by Clustering

## 5 Mean-Variance Portfolio





# *Q&A*

Thank you for your attention