Data Driven Methods in Finance:

Practical Application: Performance Assessment, Backtesting, and Performance Attribution

Fall 2023: IEOR 4576

Naftali Cohen

Performance Measurement and Attribution

- **Role of Performance Measurement:**
  - Key in understanding portfolio returns and their alignment with set standards.
  - Ensures accurate and transparent reporting of portfolio results.
  - Crucial for evaluating portfolio manager’s skill vs. luck, and assessing overall risk.
  - Facilitates marketing and public comparison of portfolio performance.
- **Importance of Performance Attribution:**
  - Breaks down overall results into specific contributing factors.
  - Helps identify primary causes of outperforming or underperforming the benchmark.
  - Essential for assessing the efficacy of the factor model and investment strategy.

Beardstown Ladies

Add languages

Article Talk Read Edit source View history

From Wikipedia, the free encyclopedia

The **Beardstown Ladies** is a group of 16 women in their 70s who formed an investment club, formally known as the **Beardstown Business and Professional Women's Investment Club**, in Beardstown, Illinois, in 1983 in a church basement. The club got media attention after it authored a book, published in 1995, titled *The Beardstown Ladies' Common-Sense Investment Guide: How We Beat the Stock Market - And How You Can Too*, which claimed that the club has produced annual returns of 23.4% since inception. The club authored additional books, including *The Beardstown Ladies' Stitch-In-Time Guide to Growing Your Nest Egg: Step-by-Step Planning for a Comfortable Financial Future* in January 1996 and *The Beardstown Ladies' Pocketbook Guide to Picking Stocks* in April 1998.[1] The ladies gained speaking tours and became minor celebrities.[2]

In March 1998, Shane Tritsch published an article in *Chicago* titled *Bull Marketing: Debunking the Myth of the Beardstown Ladies and Their Spectacular Stock Market Gains*. The article noted that the club included a disclaimer in its books that the published returns included fees that were charged to members.[3][4]

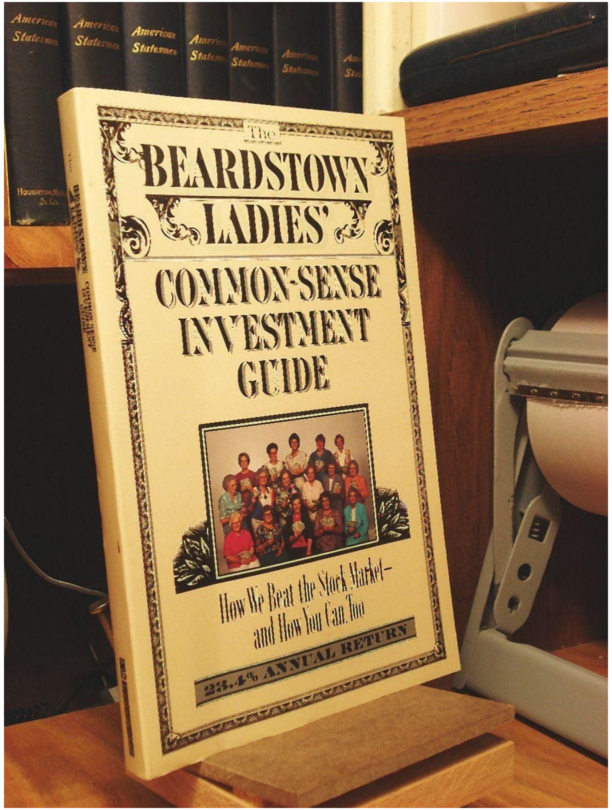
After an audit by PricewaterhouseCoopers, the club noted that it had made a computer formula error in calculating its returns, and its actual annual returns were 9.1%, which were below those of the S&P 500 Index during the same time period.[5] The club issued an apology and a disclaimer on all of its books, but by that time, it had sold over 1.1 million.[6]

This revelation led to a class action lawsuit against publisher Hyperion, a division of The Walt Disney Company, which settled the case by offering to swap the Beardstown Ladies books for other Hyperion books.[1]

The experience provided many with a lesson on the importance of vetting investment claims.[7]

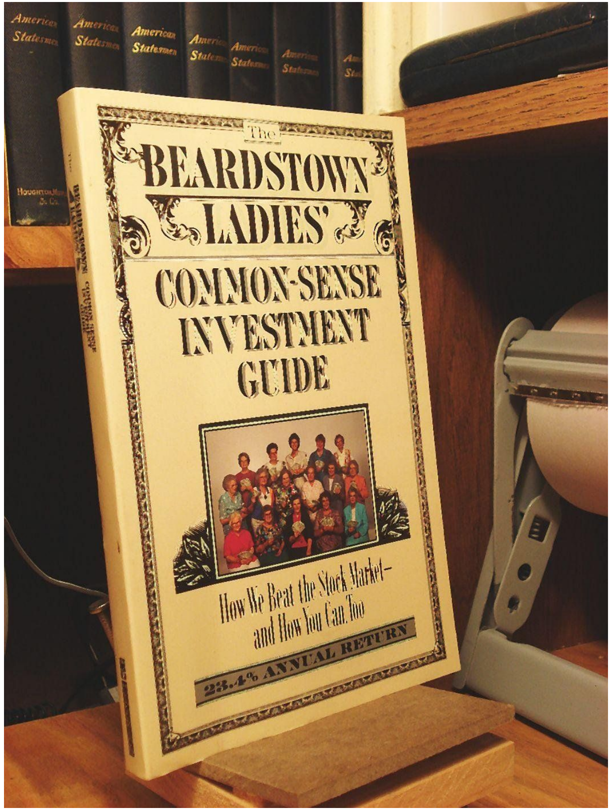
In 2010, a member of the club stated that only 4 or 5 of the original members remained in the club; the rest had died.[8]

In 2016, the club was still active, with over $400,000 invested and 75% of the members being descendents of the original club members.[9]



Performance Measurement and Attribution

- **The Beardstown Ladies Case Study:**
  - Highlights the significance of accurate portfolio return calculation.
  - Demonstrates the risks of misleading performance reporting due to calculation errors.
- **Practical Challenges in Performance Measurement:**
  - Navigating between focusing solely on bottom-line returns vs. comprehensive analysis.
  - Balancing portfolio building with thorough performance analysis.
  - Attracting skilled professionals to the performance analysis sector.



Performance Measurement: Returns

- **Importance of Accurate Return Calculation:**
  - Essential for evaluating both actual and hypothetical (paper) portfolio performances.
  - Used in backtesting strategies and assessing portfolio manager's success.
- **Calculating Stock Returns:**
  - Price returns based on closing prices and dividends.
  - Adjustments for dividends vary depending on data frequency (monthly or daily).
  - Corporate actions (bankruptcy, acquisitions, stock splits) may complicate calculations.
- **Portfolio Return Computation:**
  - Weighted sum of individual stock returns, using beginning-period weights.
  - Adjusting portfolio weights over time for price changes.

$$r_{i,t,t+k} = \frac{p_{i,t+k}}{p_{i,t}} - 1$$

$$r_{i,t,t+k} = \frac{p_{i,t+k} + d_{i,t,t+k}}{p_{i,t}} - 1$$

$$r_{P,t,t+k} = \sum_{i=1}^{N} w_{i,t}^{P} r_{i,t,t+k}$$

$$w_{i,t+k}^{P} = \frac{w_{i,t}^{P}\left(1 + r_{i,t,t+k}\right)}{\sum_{j=1}^{N} w_{j,t}^{P}\left(1 + r_{j,t,t+k}\right)}$$

Performance Measurement: w/ Cash Flows

- **Handling Cash Flows in Return Calculations:**
  - Crucial for actual portfolios with customer investments or withdrawals.
  - Need to isolate effects of cash flows to accurately measure portfolio manager's performance.
- **Performance Measurement without Cash Flows:**
  - Assumes no buys or sells during the measurement period.
  - Suitable for hypothetical portfolios without real customer transactions.
- **Practical Challenges and Mistakes:**
  - Beardstown ladies' case underscores importance of removing cash flow effects.
  - Performance analysts must ensure accuracy in return calculations for credibility.
- **Outcomes and Implications:**
  - Reliable return measurement forms the basis for portfolio evaluation.
  - Enables identification of true drivers of portfolio performance (e.g., stock-picking skills).

Performance Measurement: w/ Cash Flows

- **Impact of Cash Flows:**
  - Cash inflows/outflows significantly affect accurate return calculations.
  - Allocation decisions (cash reserves, stock purchases, futures) influence portfolio performance.
  - Time-weighted return (TWR) crucial for minimizing cash flow impact on returns.
- **Portfolio X Example with Cash Inflow:**
  - Initial value (day t-1): $100,000.
  - Day t (after market open): $30,000 customer cash inflow; funds immediately invested proportionately in portfolio stocks.
  - Actual weighted return for day t: 5%.
  - EOD market value: $136,269.23
  - Simple return calculation: Overestimates at 36.27%.
  - Dietz method: More accurate daily return of 5.45%.

$$r_{t,t+1}^{\text{Dietz}} = \frac{V_{t+1} - V_t - C_{t+1}}{V_t + 0.5C_{t+1}}$$

- **Considerations for TWR Calculation:**
  - Dietz method may be less precise with large daily returns or substantial cash flows.
  - Important for performance analysts to choose appropriate methods for return calculation.

Performance Measurement: w/ Cash Flows

- **Longer Period Return Calculations:**
  - Geometric linking of daily returns for monthly or yearly periods.
  - Example: Monthly/yearly return calculated by multiplying daily returns.

$$r_{t,t+k} = \prod_{s=0}^{k-1}\left(1 + r_{t+s,t+1+s}\right) - 1$$

- **Annualizing Returns:**
  - Applicable for portfolios with at least one year of data.
  - Geometrically linked return raised to the power of (365/total days) minus 1.
  - Example: A 2-year, 10-day portfolio with 26% linked return (D = 365, k= # days portfolio exists) annualizes to 1.26^(365/740)-1=12.07%.

$$r^{\text{annualized}} = \left(1 + r_{t,t+k}\right)^{\frac{D}{k}} - 1$$

Performance Measurement: Risk

- Significance of Measuring Risk:
  - Balances high returns with volatility concerns.
  - Key for portfolio stability and client retention.
  - Essential alongside return to evaluate investment performance.
- Risk Measurement Metrics:
  - Standard Deviation: Reflects deviation of returns from the average.
  - Semi-Standard Deviation: Focuses on downside risk, more relevant when returns are skewed.
  - Other metrics: Variance, Tracking Error, Value at Risk (VaR), Correlation, Covariance, and Beta.
- Standard Deviation in Practice:
  - Measures variability of portfolio returns around the mean.
  - More effective with normally distributed returns.
  - Estimated using historical data.

$$\hat{\sigma}_P = \sqrt{\hat{V}(r_P)} = \sqrt{\frac{\sum_{t=1}^{T}\left(r_{P,t} - \overline{r}_P\right)^2}{T-1}}$$

$$\hat{\sigma}_P^{DR} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}[\min(r_{P,t} - k),0]^2}$$

Performance Measurement: Tracking Error

- **Concept and Relevance:**
  - Tracking error quantifies deviation of portfolio returns from a benchmark return.
  - Crucial for index managers aiming for minimal deviation and quantitative managers seeking controlled risk relative to benchmark.
- **Implications for Different Portfolio Managers:**
  - Index managers aim for a tracking error close to 0, considering factors like transaction costs and dividend reinvestment.
  - Quantitative managers utilize tracking error to balance higher returns against benchmark risk, often under specific constraints (e.g., ex-ante tracking error below 5%).

$$TE = \hat{\sigma}_x = \sqrt{\hat{\sigma}_x^2} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(x_t - \bar{x})^2}$$

where $x_t = r_{P,t} - r_{B,t}$ and $\bar{x} = \frac{1}{T}\sum_{t=1}^{T} x_t$.

Performance Measurement: CAPM Beta

- **Role of Beta (β) in CAPM:**
  - Measures portfolio risk relative to the market (typically the S&P 500).
  - A β of 1 implies portfolio moves in sync with the market.
  - β > 1 indicates amplified market returns; β < 1 indicates muted market reactions.
  - β = 0 suggests no correlation with the market.
- **Methods to Calculate Portfolio β:**
  - Weighted average of individual stock betas.
  - Linear regression of portfolio returns against market returns.

Performance Measurement: CAPM Beta

- **Practical Insights on Beta Measurement:**
  - Stability: Larger number of stocks in a portfolio tends to stabilize β over time.
  - Mean Regression: Extreme β values often regress towards 1.
  - Providers' Consistency: Similar β values across different data providers.
  - Historical Data Horizon: Typically based on monthly data over 3-5 years; limited for stocks with shorter histories.
  - Adjusted Beta: Combines measured β with market β for more accurate reflection ($\beta_{adj} = a\beta + (1 - a)1$).
  - Slope Discrepancy: Actual returns vs. β often differ from theoretical predictions.
  - Limitations: β alone may not fully explain stock returns.
- **Implications for Portfolio Managers:**
  - β is a key tool for assessing relative market risk.
  - Adjustments and alternative measures might be necessary for a more accurate risk profile.
  - Essential for strategic decision-making and risk management in portfolio construction.

Performance Measurement: VaR

- **Concept of VaR (Value-at-Risk):**
  - Measures the maximum expected loss over a set period within a specified confidence interval.
  - Widely used for assessing risk in banks and individual trading positions.
  - Particularly relevant for short-term risk assessment.
- **Calculating VaR with Normal Distribution:**
  - Requires estimated portfolio mean and standard deviation.
  - Critical values determined from standard normal table (e.g., 1.65 for 95% confidence).

$$\text{VaR}_t = V_t\,(\hat{\mu}_P - k\hat{\sigma}_P)$$

- **Practical Example:**
  - Portfolio Value: $100 million. Annualized Mean: 10%, Standard Deviation: 20%.
  - $\text{VaR}_t = 100{,}000{,}000(0.10 - 1.96 \cdot 0.20) = -29{,}200{,}000$
  - 97.5% Confidence Level VaR: $29.2 million annual loss.
  - We can be 97.5% confident that, in a given year, the worst loss that the portfolio could suffer is $29,200,000.
  - Users of VaR often prefer to have a VaR measure over a shorter period of time, such as one day or one week, so that they can understand a bank's exposure over a short period of time.

Performance Measurement: Cov/ Corr

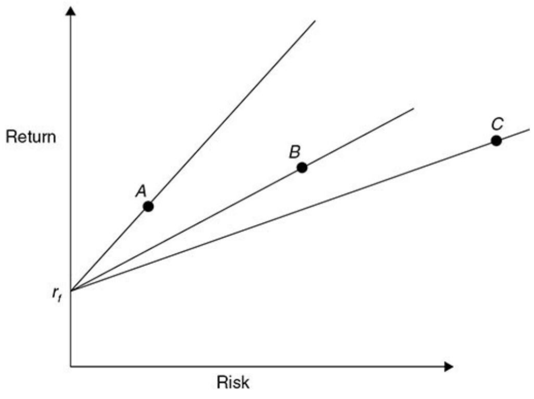
- **Role in Risk Assessment:**
  - Measures portfolio's risk in relation to a major index.
  - Indicates diversification benefits of combining portfolios.
- **Calculating Covariance:**
  - Uses portfolio and index returns.
- **Calculating Correlation:**
  - Derived from covariance and standard deviations of portfolio and index.
  - Always ranges between −1 and 1.
- **Interpreting Correlation Values:**
  - Correlation of 1: Portfolio and index returns move identically.
  - Correlation of −1: Portfolio and index returns move in opposite directions.
  - Correlation near 0: Low relationship between portfolio and index returns.
- **Implications for Portfolio Strategy:**
  - Essential for understanding market alignment and risk exposure.
  - Assists in strategic decisions regarding portfolio diversification.
  - Useful for evaluating the portfolio's behavior under different market conditions.

$$\hat{C}(r_P, r_I) = \frac{1}{T}\sum_{t=1}^{T}(r_{P,t} - \bar{r}_P)(r_{I,t} - \bar{r}_I)$$

$$\hat{\rho}(r_P, r_I) = \frac{\hat{C}(r_P, r_I)}{\hat{\sigma}_P \hat{\sigma}_I}$$

Performance Measurement: Risk Adjusted

- **Beyond Raw Returns:**
  - Emphasizes that evaluating investment performance solely on returns is incomplete.
  - Risk context crucial for a comprehensive assessment.
- **Case of Three Portfolio Managers:**
  - Manager A: Lowest return but possibly lowest risk.
  - Manager B: Middle ground in both return and risk.
  - Manager C: Highest return but also highest risk.
  - Illustrates that high returns may accompany high risks.
- **Sharpe Ratio: A Key Metric:**
  - Most prominent measure of risk-adjusted returns.
  - Helps compare portfolio performances on a risk-adjusted basis.
- **Implications for Investors and Portfolio Managers:**
  - Necessitates looking at returns in the context of the risks taken to achieve them.
  - Enables more accurate comparison of portfolio managers.
  - Highlights the value of balancing returns with risk in portfolio management.



Performance Measurement: Sharpe/ IR

- **Origin of the Sharpe Ratio:**
  - Developed by Nobel Laureate William F. Sharpe as part of the CAPM framework.
  - Measures excess return (over risk-free) per unit of risk.
- **Practical Application:**
  - Provides a basis for comparing portfolios on a risk-adjusted basis.
  - Value is relative; higher Sharpe Ratio indicates better risk-adjusted performance.
- **Information Ratio (IR) Concept:**
  - Tailored for portfolios managed against a benchmark.
  - Measures excess return (over a benchmark) per unit of residual risk.
- **Implications for Portfolio Managers:**
  - Index managers aim for an IR of 0 (no deviation from the benchmark).
  - Active managers seek higher IR, indicating outperformance of the benchmark with considered risk.
  - Useful for evaluating manager performance on a risk-adjusted basis compared to a specific benchmark.

$$SR = \frac{\overline{r}_P - \overline{r}_f}{\hat{\sigma}_P}$$

$$IR = \frac{\hat{\alpha}^B}{\hat{\omega}}$$

Performance Measurement: Practical Issues

Months Required to Verify a Portfolio Manager's α and Information Ratio

	Benchmark's Sharpe Ratio (SR_B)						
IR	0	0.1	0.25	0.5	0.75	0.9	1
0.25	64	65	68	80	99	115	126
0.5	$\boxed{18}$	19	19	22	27	31	34
0.6	14	14	15	17	20	23	25
0.7	11	11	12	13	16	18	19
0.8	9	9	10	11	13	14	16
0.9	8	8	8	9	11	12	13
1	7	7	8	8	10	11	11

Note: *IR* signifies the portfolio manager's information ratio, *SR* is the benchmark's Sharpe ratio.

Simplification (for small SR): t = a/std(a) → (sqrt(T)â/std(â)) ⇒ t = sqrt(T)IR ⇒ T = $(t/IR)^2$.
Example: T=$(2/0.5)^2$ =16. For a more general case, one can show: t = IR/sqrt(1/T+SR^2/(T-1))

Assuming a benchmark such as the S&P 500, one could estimate the Sharpe ratio at about 0.25. Thus, for a portfolio manager with an information ratio of 0.5, it takes at least 22 monthly returns to determine whether or not he or she had a significantly positive α or not.

Performance Attribution: Classic Approach

- **Purpose**: Performance attribution is essential for dissecting a portfolio's return into distinct components, offering critical insights into the sources of gains and the efficacy of the stock selection process.
- **Customization**: It must be tailored to fit the specific investment approach of a portfolio manager's department, as different processes require different attribution systems.
- **Classical vs. Quantitative Systems**: While simple systems exist for traditional qualitative equity portfolio managers, creating an appropriate system for a quantitative manager is more complex.

Classical Attribution Method

- Developed By: Brinson, Beebower, and Hood (1986).
- **Key Categories:**

  Security-Selection Effect: The portion of excess return over a benchmark attributable to stock-picking skills.

  Sector-Allocation Effect: Reflects the effectiveness of allocating equity among different stock sectors.

Performance Attribution: Classic Approach

- **Allocation Effect (AE):**
  - Computed using sector returns of the benchmark but assigned portfolio weights.
  - Represents excess return due to sector allocation.
- **Security-Selection Effect (SSE):**
  - Difference between actual portfolio return and the portfolio return with benchmark sector returns.
  - Attributable to differential returns within each sector due to stock selection.
- **$r_p - r_B$ = AE + SSE**

Per sector j

$$r_P = \sum_{i=1}^{N} w_i^P r_i \qquad w_j^P = \sum_{i \in S_j} w_{i,j}^P \qquad r_{P,j} = \frac{1}{w_j^P} \sum_{i \in S_j} w_{i,j}^P r_i \qquad AE = \sum_j w_j^P r_{B,j} - r_B$$

$$r_B = \sum_{i=1}^{N} w_i^B r_i \qquad w_j^B = \sum_{i \in S_j} w_{i,j}^B \qquad r_{B,j} = \frac{1}{w_j^B} \sum_{i \in S_j} w_{i,j}^B r_i \qquad SSE = r_P - \sum_j w_j^P r_{B,j}$$

Performance Attribution: Numerical Approach

Return Decomposition	
Source	**Value**
$\hat{\alpha}_P$	$\sum_{i=1}^{N} \tilde{w}_i \hat{\alpha}_i$
Name of factor 1	$\sum_{i=1}^{N} \tilde{w}_i \hat{\beta}_{i1} f_1$
Name of factor 2	$\sum_{i=1}^{N} \tilde{w}_i \hat{\beta}_{i2} f_2$
…	…
Name of factor K	$\sum_{i=1}^{N} \tilde{w}_i \hat{\beta}_{iK} f_K$

Risk Decomposition	
Source	**Value**
Name of factor 1	$\left(\sum_{i=1}^{N} \tilde{w}_i \hat{\beta}_{i1}\right)^2 \hat{V}(f_1)$
Name of factor 2	$\left(\sum_{i=1}^{N} \tilde{w}_i \hat{\beta}_{i2}\right)^2 \hat{V}(f_2)$
…	…
Name of factor K	$\left(\sum_{i=1}^{N} \tilde{w}_i \hat{\beta}_{iK}\right)^2 \hat{V}(f_k)$
$\hat{\omega}_P$	$\left(\sum_{i=1}^{N} \tilde{w}_i\right)^2 \hat{V}(\epsilon_i)$
Adjustment for factor correlation	$2\sum_{k=1}^{K}\sum_{l=k+1}^{K}\left(\sum_i \tilde{w}_i \hat{\beta}_{ik}\right)\left(\sum_j \tilde{w}_j \hat{\beta}_{jl}\right)\hat{C}(f_k, f_l)$

						Exposure on		
Ticker	r_i	w_i^P	w_i^B	x_i	$\hat{\alpha}_i^{MF}$	Name of Factor 1	…	Name of Factor K
ABC								

						Return on			
Ticker	r_i	w_i^P	w_i^B	x_i	$\hat{\alpha}_i$	Name of Factor 1	…	Name of Factor K	MR
ABC									

Backtesting

Using historical data to test performance of hypothetical portfolios. Essential for evaluating new investment ideas:

- **Key Decisions in Backtesting:**
  - Selection of historical data set and software.
  - Time period and data frequency.
  - Investment universe and benchmark selection.
  - Choice of factors in the stock return model.
  - Stock return and risk model selection.
  - Rebalancing frequency.
  - Portfolio construction approach.
  - Performance result presentation.

- **Data and Software Choices**:
  - Data from 1981-2020, including fundamental, price and return, analyst forecasts, social-issue, and macroeconomic data.
  - Main databases: Standard & Poor's Compustat, CRSP, IBES, MSCI-KLD, and Bloomberg.
  - Data management and model estimation using Python.
  - Portfolio optimization and related processes using CVXPY.

Backtesting: Data Collection and Management

- **Long-Term Data Collection**: Data was collected from 1981 to 2020, ensuring a sufficient historical range for testing strategies. For datasets starting later (e.g., analyst data from 1993, social-issue data from 1991), the earliest available data was used.
- **Data Frequency Harmonization**: With varying data frequencies (daily, monthly, quarterly, and annual), all data was standardized to a monthly format. This involved aggregating daily data and adjusting quarterly and annual data to reflect in the month they ended.
- **Inclusion Criteria for Stocks**: A total of 14,945 stocks were included based on specific criteria:
    - Inclusion in both CRSP and Compustat databases.
    - Ranking in the top 3,000 in market capitalization at any point in the sample period.
    - Availability of essential financial data and monthly returns.

Backtesting: Data Collection and Management

- **Data Set Construction**: Steps for constructing the database included:
  - Selection of common stocks from CRSP.
  - Identification of primary share class based on market capitalization.
  - Verification of availability of key financial metrics and monthly returns.
- **Data Integration and Matching**:
  - Merging different databases posed challenges due to changing and recycled identifiers like CUSIP numbers and tickers.
  - Utilized existing mappings like CRSP ID to Compustat ID, and manually verified ambiguous matches.
  - Ensured accurate matching despite identifier changes over time.
- **Dealing with Data Variability and Coverage**:
  - Acknowledged that coverage varied across databases, affecting the percentage of stocks matched in each database.
  - Adapted to the limitations of data availability (e.g., MSCI-KLD data only up to 2018, SEC odd-lot volume data from 2012 to 2020).

Backtesting: Data Collection and Management

Number of Companies in the Historical Data Set

Period	Compustat-CRSP	IBES	Percent	MSCI-KLD	Percent	SEC	Percent
Dec 1990	4,714	2,835	60.14	0	0.00	0	0.00
Dec 1995	5,820	4,021	69.09	640	11.00	0	0.00
Dec 2000	5,501	4,084	74.24	636	11.56	0	0.00
Dec 2005	4,566	3,612	79.11	2,814	61.63	0	0.00
Dec 2010	3,999	3,299	82.50	2,804	70.12	0	0.00
Dec 2015	3,920	3,386	86.38	2,218	56.58	3,468	88.47
Dec 2020	3,459	2,870	82.97	0	0.00	3,031	87.63
Entire Period	4,647.92	3,519.46	75.72	1,747.14	37.59	3,342.31	71.91

Selected Summary Statistics of the Historical Data Set

Factor	Period	Nobs	Average	SD	Min	Max
Earnings-to-price (E/P)	Dec 1990	2,984	−0.016	1.034	−36.686	5.699
	Dec 2000	2,985	0.013	0.317	−9.378	2.986
	Dec 2010	2,992	0.017	0.157	−2.218	2.123
	Dec 2020	2,992	−0.053	0.395	−10.499	1.479
	All	1,071,502	−0.003	0.680	−157.647	50.937
Log of market capitalization (LOGSIZE)	Dec 1990	3,000	5.001	1.749	2.541	11.075
	Dec 2000	3,000	6.755	1.580	4.626	13.071
	Dec 2010	3,000	7.057	1.581	4.669	12.818
	Dec 2020	3,000	7.631	1.823	4.628	14.629
	All	1,083,000	6.822	1.657	2.541	14.629
Inventory turnover (IT)	Dec 1990	2,310	16.040	77.889	0.041	2,456.714
	Dec 2000	2,111	31.086	149.758	0.050	4,550.412
	Dec 2010	2,196	20.960	127.651	0.013	5,268.000
	Dec 2020	2,122	35.232	318.606	0.009	9,095.750
	All	788,702	30.778	555.739	0.000	128,118.000
Net profit margin (NPM)	Dec 1990	2,984	−1.319	43.218	−2,177.000	131.882
	Dec 2000	2,985	−1.239	26.978	−1,114.882	175.189
	Dec 2010	2,992	−1.365	42.813	−2,062.226	571.027
	Dec 2020	2,992	−7.070	99.338	−3,128.667	1,248.432
	All	1,071,502	−3.709	329.731	−1.544e+05	1,562.764

Backtesting: Time Period and Structure in Backtesting

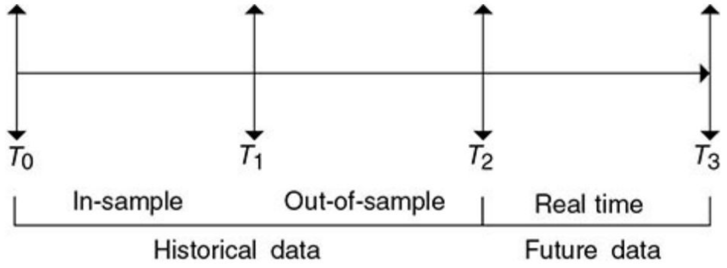
- **Backtesting vs. Real-time Testing**: Backtesting uses historical data for immediate strategy evaluation, while real-time testing applies strategies to current data and observes outcomes over years.
- **Structure of Backtesting**:
  - Three Segments of Data:
    - In-Sample Data (T0 to T1): Early segment for initial testing.
    - Out-of-Sample Data (T1 to T2): Later segment for validating model performance.
    - Future Data (T2 to T3): For real-time testing and forward analysis.
- **Sequential Testing and Data Mining**:
  - Involves testing multiple models, modifying factors each time.
  - In-sample data is used for creating models; out-of-sample data for testing final model to avoid data mining.
- **Parameter Stability and Rolling Windows**:
  - Adapting to changes in financial market relationships.
  - Using rolling in-sample windows to dynamically re-estimate parameters over time, ensuring model stability.

Backtesting: Time Period and Structure in Backtesting

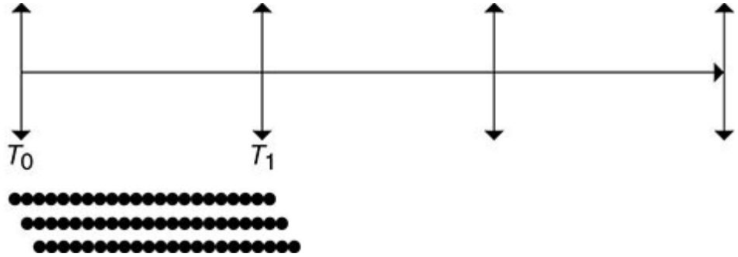
- **Practical Application of Backtesting**:
  - Historical Data Period: 2006 (T0) to 2020 (T2).
  - In-Sample Period: 2006 to 2010.
  - Out-of-Sample Period: 2011 to 2020.
- **Dynamic Rolling In-Sample Window**:
  - Continuously updated model parameters for each rolling period.
  - Ensures reflection of actual changes in stock return-factor relationships, not just statistical noise.
- **Data Interval and Management**:
  - Monthly intervals for factor and stock return data.
  - Handling quarterly and annual data by filling in monthly gaps, avoiding biases in relationships between factors and stock returns.
- **Rebalancing and Model Testing**:
  - Emphasis on balancing historical data integrity and dynamic market conditions in model testing.

Backtesting: Time Period and Structure in Backtesting

The backtesting data.



Backtesting with rolling in-sample windows. (*Note*: Each horizontal series of dots represents a rolling sample.)



Backtesting: Major U.S. Equity Benchmarks

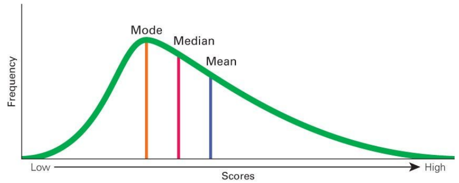
- **Standard & Poor's (S&P) Indices**:
  - S&P 500: Large-cap index, highly recognized.
  - S&P 400: Mid-cap index.
  - S&P 600: Small-cap index.
  - S&P 1500: Combination of S&P 400, 500, and 600, market-cap/float-weighted.
  - Selection by Standard & Poors Index Committee based on specific criteria including U.S. incorporation, positive earnings, and share float percentage.
  - S&P 500 Value and Growth Indices: Differentiated by growth vs. value stock characteristics, market-cap-weighted.
- **Russell Indices**:
  - Russell 3000: Top 3,000 U.S. stocks by market cap.
  - Russell 1000 (Large-Cap): Top 1,000 stocks from Russell 3000.
  - Russell 2000 (Small-Cap): Bottom 2,000 stocks from Russell 3000.
  - Russell 1000 and 2000 Value and Growth Indices: Classified by book-to-price ratio, analyst growth forecasts, and historical sales growth.
  - Float-weighted, less subjective inclusion criteria than S&P.

Backtesting: Major U.S. Equity Benchmarks

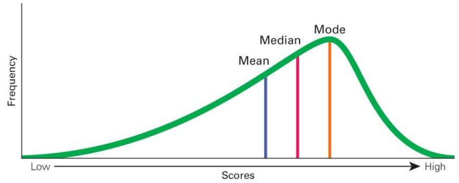
- **NASDAQ 100**:
  - Comprises 100 largest non-financial companies on NASDAQ.
  - Annual re-constitution in December, modified-capitalization weighting.
- **Dow Jones Industrial Average (DJIA)**:
  - Contains 30 stocks representing the U.S. economy.
  - Price-weighted, less popular among professional managers due to its susceptibility to stock splits and corporate actions.
- **Wilshire 5000**:
  - Represents the performance of all publicly traded U.S. companies.
  - Market-capitalization-weighted, often called the total market index.
- **Benchmark Characteristics**:
  - Benchmarks vary in composition, weighting methods, and popularity.
  - Each serves as a standard for different market segments (large-cap, mid-cap, small-cap, total market, etc.).
  - Portfolio managers choose benchmarks based on investment strategies and universe representation.

Backtesting: U.S. Benchmarks - Performance Comparison

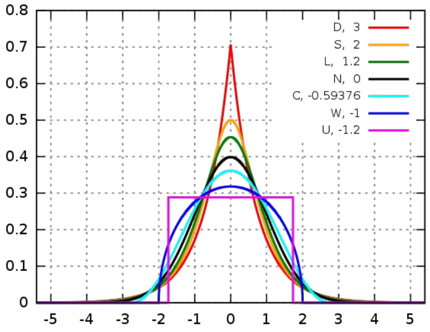
- **Period: 1995-2020**
- **Return Statistics**:
  - Highest Geometric Return: NASDAQ 100 (14.93% annually).
  - Following closely: S&P 400 (12.14%) and S&P 600 (11.21%).
  - Lowest Annual Return: Russell 2000 Growth (9.04%).
- **Risk Metrics**:
  - Highest Annualized Standard Deviation: NASDAQ 100 (24.58%).
  - Second Highest: Russell 2000 Growth (22.74%).
  - Lowest Risk: Dow Jones Industrial Average (14.93%).
- **Distribution Characteristics**:
  - All indices exhibit negative skewness (left-skewed distributions).
  - Positive excess kurtosis (thicker tails than a normal distribution).
  - Jarque-Bara test rejects the assumption of normality for all benchmarks.



(a) Right-skewed distribution



(b) Left-skewed distribution



Backtesting: U.S. Benchmarks - Performance Comparison

Ticker	Benchmark Name	Arithmetic Mean	SD	Geometric Mean	Median	Max	Min	Skewness	Excess Kurtosis	J-B
SPTR	S&P 500	11.19	15.09	10.52	16.67	12.82	−16.79	−0.64	1.18	39.69
SPTRSVX	S&P 500 Value[a]	10.04	15.75	9.15	16.23	12.88	−17.11	−0.74	1.69	65.73
SPTRSGX	S&P 500 Growth[b]	12.15	15.63	11.48	16.45	14.45	−16.51	−0.54	0.80	23.37
SPTRMDCP	S&P 400	13.11	17.71	12.14	18.38	14.87	−21.74	−0.72	2.34	97.90
SPTRSMCP	S&P 600	12.55	19.22	11.21	19.28	18.17	−22.40	−0.62	1.97	70.00
SPRTR	S&P 1500	11.33	15.21	10.64	17.43	12.89	−17.32	−0.68	1.34	47.19
RU10INTR	Russell 1000	11.41	15.32	10.72	16.57	13.21	−17.46	−0.67	1.36	47.32
RU10VATR	Russell 1000 Value	10.53	15.17	9.78	16.27	13.45	−17.31	−0.77	2.25	96.90
RU10GRTR	Russell 1000 Growth	12.06	17.09	11.11	16.75	14.80	−17.61	−0.63	1.15	37.79
RU20INTR	Russell 2000	11.35	19.95	9.74	20.62	18.43	−21.73	−0.54	1.46	43.11
RU20VATR	Russell 2000 Value	11.25	18.48	9.93	18.01	19.31	−24.67	−0.74	2.78	129.43
RU20GRTR	Russell 2000 Growth	11.31	22.74	9.04	19.13	23.27	−23.08	−0.41	1.08	23.72
RU30INTR	Russell 3000	11.33	15.46	10.61	17.77	13.24	−17.74	−0.70	1.42	51.34
RU30VATR	Russell 3000 Value	10.52	15.24	9.75	16.64	13.80	−17.58	−0.80	2.37	105.97
RU30GRTR	Russell 3000 Growth	11.92	17.26	10.92	17.99	14.80	−17.93	−0.64	1.14	38.16
DWCT	Wilshire 5000	11.37	15.54	10.64	18.92	13.50	−17.61	−0.69	1.38	49.79
DJITR	Dow Jones Industrial Average	11.46	14.93	10.84	14.37	12.14	−14.91	−0.58	1.22	37.13
NDXTR	NASDAQ 100[c]	17.04	24.58	14.93	24.12	24.99	−26.40	−0.33	1.45	32.87

Note: The statistics are for the total returns of the indices during the period from January 1995 through December 2020. The data and tickers were obtained from Bloomberg.

Backtesting: U.S. Benchmarks - Performance Comparison

- **Correlation among Indices**:
  - High Correlation with S&P 500: Russell 1000 (0.998), Russell 3000 (0.994), S&P 1500 (0.998), Wilshire 5000 (0.989).
  - Lower Correlation with S&P 500: NASDAQ 100 (0.822), S&P 400 (0.906), S&P 600 (0.826), Dow Jones (0.951).
- **Fundamental Ratios and Market Capitalization** (End of 2020):
  - Highest P/S Ratios: Growth indices like S&P 500 Growth and NASDAQ 100.
  - Highest P/E Ratios: Russell 2000 Growth and Value.
  - Lowest P/E Ratio: Dow Jones Industrial Average (27.12).
  - Largest Market Capitalization: Russell 3000 ($40,930,135 million).
  - Smallest Market Cap: S&P 600 ($938,212 million).

Backtesting: U.S. Benchmarks - Performance Comparison

- **Correlation among Indices**:
  - High Correlation with S&P 500: Russell 1000 (0.998), Russell 3000 (0.994), S&P 1500 (0.998), Wilshire 5000 (0.989).
  - Lower Correlation with S&P 500: NASDAQ 100 (0.822), S&P 400 (0.906), S&P 600 (0.826), Dow Jones (0.951).
- **Fundamental Ratios and Market Capitalization** (End of 2020):
  - Highest P/S Ratios: Growth indices like S&P 500 Growth and NASDAQ 100.
  - Highest P/E Ratios: Russell 2000 Growth and Value.
  - Lowest P/E Ratio: Dow Jones Industrial Average (27.12).
  - Largest Market Capitalization: Russell 3000 ($40,930,135 million).
  - Smallest Market Cap: S&P 600 ($938,212 million).

Backtesting: U.S. Benchmarks - Performance Comparison

Vital Statistics of Common Benchmarks for December 2020

Bloomberg Ticker	Index Name	S_t	SIZE	DY	P/E	P/B	P/S	P/CF	P/EBITDA	EV/ EBITDA	EPS
SPX Index	S&P 500	3756.07	33,166,864	1.57	30.68	4.11	2.81	16.17	16.66	18.96	122.42
MID Index	S&P 400	2306.62	2,162,168	1.47	31.21	2.50	1.63	11.11	13.97	18.87	73.92
SML Index	S&P 600	1118.93	938,212	1.47	57.21	2.05	1.11	9.58	14.70	21.34	19.56
SPR Index	S&P 1500	857.79	36,267,244	1.56	31.08	3.86	2.60	15.49	16.44	19.03	27.60
SVX Index	S&P 500 Value	1267.18	21,543,703	2.46	26.16	2.48	1.83	12.12	12.87	16.20	48.44
SGX Index	S&P 500 Growth	2577.22	22,660,767	0.78	36.24	9.88	5.37	22.98	21.80	22.64	71.12
RAY Index	Russell 3000	2248.44	40,930,135	1.48	34.47	3.90	2.64	16.47	17.40	20.47	65.23
RTY Index	Russell 2000	1974.86	2,938,075	1.19	51.67	2.47	1.43	15.52	23.00	35.30	−3.54
RIY Index	Russell 1000	2120.87	37,992,060	1.50	32.11	4.06	2.81	16.53	17.13	19.75	66.04
RAV Index	Russell 3000 Value	1774.76	26,355,925	2.23	27.86	2.29	1.81	11.86	12.66	16.68	63.71
RAG Index	Russell 3000 Growth	1952.61	26,332,335	0.79	44.25	11.23	4.63	25.79	25.20	26.61	44.12
RLV Index	Russell 1000 Value	1349.62	24,551,133	2.25	26.45	2.38	1.93	12.09	12.59	16.13	51.02
RLG Index	Russell 1000 Growth	2427.77	24,316,644	0.81	40.10	11.93	4.85	25.12	24.46	25.51	60.54
RUJ Index	Russell 2000 Value	1972.38	1,804,792	1.99	118.06	1.50	0.94	9.20	13.79	26.46	16.71
RUO Index	Russell 2000 Growth	1455.25	2,015,691	0.45	143.91	6.06	2.77	42.33	45.71	56.69	−16.49
NDX Index	NASDAQ 100	12888.28	15,083,854	0.76	37.89	8.29	5.21	22.11	21.39	22.24	340.16
W5000 Index	Wilshire 5000	39456.66	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
INDU Index	Dow Jones*	30606.48	9,607,422	2.02	27.12	4.71	2.46	15.47	14.27	17.89	1128.64

Backtesting: S&P 500 as a Benchmark for Backtesting

- **Popularity of S&P 500**:
  - Most popular benchmark among global equity managers.
  - First choice for investors due to its liquidity, manageability, and brand recognition.
- **Advantages of S&P 500**:
  - Liquidity of securities and futures.
  - Easier to manage compared to indices with thousands of stocks.
  - High correlation with other major equity benchmarks.
  - Most liquid futures for trading, beneficial for leveraging.
- **Drawbacks of S&P 500**:
  - Potential distortions in returns due to its popularity as a benchmark.
  - Prices of traded securities may fluctuate due to changes in index composition.
- **Our Choice for Backtesting**:
  - Chosen for data availability and familiarity to readers.
  - Ease of construction using Compustat database.
  - Investment universe extended beyond S&P 500 to include top 1,500 U.S. stocks by market capitalization.

Backtesting: Selecting and Testing Factors for Backtesting

- Factor Selection Process:
  - Initial selection based on theoretical reasoning.
  - Factors chosen to explain stock returns and generate α.
- Data Preparation and Cleaning:
  - Ensuring data accuracy and consistency.
  - Adjusting for correct dates to avoid look-ahead bias.
  - Addressing survivorship bias by including extinct stocks.
- Factor Testing Approach:
  - Computed historical factor exposures monthly, avoiding look-ahead bias.
  - Used simple single-factor regressions and unidimensional zero-investment portfolio testing.
  - Initial tests focused on 2006-2010.
- Criteria for Factor Inclusion:
  - Return-exposure regression coefficient sign and statistical significance.
  - Correspondence with theoretical expectations.
  - Elimination of highly correlated factors.

Backtesting: Selecting and Testing Factors for Backtesting

Factor	Reason	Ex-Ante Sign
Fundamental—Valuation		
1. Dividend Yield (DY)	The rationale is that stocks trading at high dividend yields may have had recent drops in price, which led to overreaction from investors. Also, these stocks are trading at cheaper prices versus valuation criteria.	+
2. EBITDA-to-EV (EBITDAEV)	Same	+
3. Book-to-Price (B/P)	Same	+
4. Cash Flow-to-Price (CF/P)	Same	+
5. Earnings-to-Price (E/P)	Same	+
6. EBITDA-to-Price (EBITDAP)	Same	+
7. E/P times Historical Earnings Growth (IPEGH)	Same	+
8. E/P times Forecasted Earnings Growth (IPEGF)	Same	+
9. E/P times Growth plus Yield (IPEGY)	Same	+
10. Sales-to-Price (S/P)	Same	+

Backtesting: Selecting and Testing Factors for Backtesting

Results of Factor Analysis from 2006–2010

Factor	Obs.	Beg. Period	End Period	$\hat{\beta}$	*t*-stat	r_{ZI}	*t*-stat
	Fundamental—Valuation						
1. Dividend Yield (DY)	60	Jan 2006	Dec 2010	−0.720	−0.202	−0.250	−0.700
2. EBITDA-to-EV (EBITDAEV)	60	Jan 2006	Dec 2010	3.790	2.590	0.877	2.367
3. Book-to-Price (B/P)	60	Jan 2006	Dec 2010	−0.265	−1.251	0.283	0.557
4. Cash Flow-to-Price (CF/P)	60	Jan 2006	Dec 2010	0.344	1.427	0.565	1.345
5. Earnings-to-Price (E/P)	60	Jan 2006	Dec 2010	0.597	1.475	−0.163	−0.451
6. EBITDA-to-Price (EBITDAP)	60	Jan 2006	Dec 2010	−0.211	−0.380	0.558	1.169
7. E/P times Historical Earnings Growth (IPEGH)	60	Jan 2006	Dec 2010	−0.000	−0.606	0.290	0.812
8. E/P times Forecasted Earnings Growth (IPEGF)	60	Jan 2006	Dec 2010	0.037	0.255	0.195	0.529
9. E/P times Growth plus Yield (IPEGY)	60	Jan 2006	Dec 2010	0.004	0.034	0.133	0.346
10. Sales-to-Price (S/P)	60	Jan 2006	Dec 2010	0.070	0.782	0.763	1.291

- Fundamental factors:
  a. regression coefficient sign in accordance with theory
  b. regression coefficient statistically significant (t-stat>1.64).
- Economic factors:
  a. zero-investment portfolio return r_{ZI} in accordance with theory
  b. t-statistic greater than 1.64.

Backtesting: Final Selection of Factors for Stock Return Models

Fundamental Factor Model Selection:

- Initially, 19 factors met the selection criteria, including EBITDA-to-EV, asset growth, turnover ratios, liquidity measures, and confidence growth indicators.
- Reduced to 18 factors by excluding one from pairs with correlation above 0.75, based on smaller t-statistic.
- Final selection through multivariate analysis identified the **five** most significant factors.

Economic Factor Model Selection:

- 13 factors initially met criteria, including equity turnover, inflation, term premiums, and standardized unanticipated earnings.
- Narrowed down to 12 factors by excluding lesser factors in highly correlated pairs (correlation > 0.75).
- **Five** most significant factors selected based on their impact in a multivariate dummy variable regression (values 1 for high, 0 for low).

Factor Group	Factors Selected for Fundamental Factor Model	Factors Selected for Economic Factor Model
Fundamental	LLOGTAG	EBITDAEV
	TACC	
	DED	
Technical	BB	PSL
		BB
Macroeconomic		TP3M
Analyst	SUE	SUE

Backtesting: Final Selection of Factors for Stock Return Models

Fundamental Factor Model Selection:

- Initially, 19 factors met the selection criteria, including EBITDA-to-EV, asset growth, turnover ratios, liquidity measures, and confidence growth indicators.
- Reduced to 18 factors by excluding one from pairs with correlation above 0.75, based on smaller t-statistic.
- Final selection through multivariate analysis identified the **five** most significant factors.

Economic Factor Model Selection:

- 13 factors initially met criteria, including equity turnover, inflation, term premiums, and standardized unanticipated earnings.
- Narrowed down to 12 factors by excluding lesser factors in highly correlated pairs (correlation > 0.75).
- **Five** most significant factors selected based on their impact in a multivariate dummy variable regression (values 1 for high, 0 for low).

Outcomes and Considerations:

- Selection process emphasized theoretical alignment, statistical significance, and uniqueness of factors.
- Multivariate analysis added robustness to factor selection.
- Aimed to comprehensively capture market dynamics influencing stock returns.

*EBITDA-to-EV= income from core business operations over total value

Backtesting: Final Selection of Factors for Stock Return Models

- **Parameter Stability Testing**:
  - Key to ensuring model reflects stable, persistent patterns.
  - Pooled monthly regression analysis used to test factor premium stability over time.
  - Specific tests for parameter stability across different time frames (quarterly, semi-annually, annually – all factor premium are identical/not-identical, and examining the p-value for the test).
- **Rejection Rates Indicating Stability**:
  - Quarterly testing showed 55% rejection rate for the premium of long-term asset growth (indicating quarter-level stability).
  - Higher rejection rates suggest frequent parameter changes.

Rejection Rate in Parameter Stability Tests for Selected Factors

Hypothesis	Long-Term Asset Growth	Total Accruals	Annual Change in D/E	Bollinger Band	Standardized Unanticipated Earnings
Stability for a Quarter	0.55	0.65	0.20	0.80	0.73
Stability for Two Quarters	0.70	0.80	0.35	1.00	0.95
Stability for Three Quarters	0.92	0.92	0.38	1.00	1.00
Stability for a Year	0.80	1.00	0.40	1.00	1.00

Backtesting: Final Selection of Factors for Stock Return Models

- **Parameter Stability Testing**:
  - Key to ensuring model reflects stable, persistent patterns.
  - Pooled monthly regression analysis used to test factor premium stability over time.
  - Specific tests for parameter stability across different time frames (quarterly, semi-annually, annually – all factor premium are identical/not-identical, and examining the p-value for the test).
- **Rejection Rates Indicating Stability**:
  - Quarterly testing showed 55% rejection rate for the premium of long-term asset growth (indicating quarter-level stability).
  - Higher rejection rates suggest frequent parameter changes.
- **Model Re-estimation Frequency**:
  - High quarterly rejection rates led to decision for monthly re-estimation of models.
  - Ensures models stay aligned with current market conditions.

Historical Performance: Fundamental Factor Model

	Tracking Portfolio			Sector-Matched	Factor-Matched	Benchmark
	$TE = 2$	$TE = 5$	$TE = 10$	$TE = 5$	$TE = 5$	
Average return	17.397	20.881	25.159	19.954	14.382	14.043
SD return	15.309	18.830	23.357	17.598	18.448	13.601
Min return	−12.691	−14.495	−19.827	−16.035	−16.657	−12.093
Max return	13.123	15.355	20.502	13.967	15.771	12.900
Average excess return	3.354	6.839	11.117	5.912	0.340	—
Ex-post TE	5.020	10.275	15.850	8.753	8.711	—
Min excess return	−4.955	−9.723	−14.868	−8.909	−9.153	—
Max excess return	3.377	6.253	11.396	5.470	4.822	—
$\hat{\alpha}^B$	0.206	0.376	0.596	0.346	−0.214	—
$t(\hat{\alpha}^B)$	1.515	1.365	1.411	1.467	−0.945	—
$\hat{\beta}^B$	1.065	1.173	1.294	1.130	1.215	—
IR	0.144	0.130	0.134	0.139	−0.090	—
$\hat{\alpha}^{MF}$	0.497	0.361	0.719	0.338	0.233	0.932
SR	0.317	0.311	0.304	0.318	0.216	0.286

Historical Performance: Economic Factor Model

	Tracking Portfolio			Sector-Matched	Factor-Matched	Benchmark
	$TE = 2$	$TE = 5$	$TE = 10$	$TE = 5$	$TE = 5$	
Average return	15.049	16.538	17.463	15.975	16.772	14.043
SD return	15.224	18.606	22.605	17.302	18.818	13.601
Min return	−13.980	−15.869	−19.608	−15.784	−15.692	−12.093
Max return	13.578	17.226	23.946	15.755	18.284	12.900
Average excess return	1.006	2.496	3.421	1.932	2.729	—
Ex-post TE	4.869	9.483	13.862	8.204	9.941	—
Min excess return	−4.148	−7.603	−10.506	−6.824	−8.732	—
Max excess return	4.213	7.099	12.895	7.024	7.234	—
$\hat{\alpha}^B$	0.013	−0.009	−0.123	0.017	0.013	—
$t(\hat{\alpha}^B)$	0.099	−0.037	−0.344	0.078	0.048	—
$\hat{\beta}^B$	1.063	1.193	1.363	1.128	1.191	—
IR	0.009	−0.004	−0.033	0.007	0.005	—
$\hat{\alpha}^{MF}$	0.300	0.357	0.767	0.418	0.345	0.932
SR	0.274	0.248	0.216	0.257	0.248	0.286

Historical Performance: Distribution of Results

	Tracking Portfolio ($TE = 0.05$)			
Return (%)	**Fundamental**	**Z-Score**	**Economic**	**Benchmark**
1 year	56.569	56.821	62.574	19.423
3 year	29.204	30.447	23.872	14.404
5 year	25.574	25.788	19.571	15.470
10 year	20.871	20.693	15.866	13.945
2020	56.569	56.821	62.574	19.423
2019	41.337	43.038	24.919	31.350
2018	−2.531	−1.044	−6.407	−4.543
2017	36.863	36.200	23.402	22.409
2016	5.776	4.163	4.203	11.996
2015	7.479	7.776	1.647	1.005
2014	13.587	11.969	5.877	13.268
2013	44.984	45.292	47.065	33.044
2012	25.011	21.897	16.464	16.032
2011	−3.662	−2.550	−3.209	1.765
Risk (%)	**Fundamental**	**Z-score**	**Economic**	**Benchmark**
SD Return	18.830	18.376	18.606	13.601
$\hat{\beta}^B$	1.173	1.159	1.193	—
Ex-post TE	10.275	9.671	9.483	—

Historical Performance: Attribution

GICS Sector	Portfolio w_j^P	Portfolio r_j^P	Benchmark w_j^B	Benchmark r_j^B
Energy (10)	0.009	19.23	0.023	4.38
Materials (15)	0.022	4.17	0.027	2.50
Industrial (20)	0.072	8.09	0.087	1.16
Consumer discretionary (25)	0.124	4.52	0.121	2.45
Consumer staples (30)	0.067	4.34	0.077	1.17
Health care (35)	0.193	6.99	0.136	3.98
Financials (40)	0.040	12.56	0.109	6.18
Information technology (45)	0.302	6.45	0.277	5.87
Telecommunication services (50)	0.060	2.88	0.114	2.91
Utilities (55)	0.038	4.70	0.028	0.70
Real estate (60)	0.002	18.02	0.001	9.54
Unclassified	0.071	9.71	0.000	—

$r_P = 6.584$

$r_B = 3.858$

$r_P - r_B = 2.726$

$AE = -0.284$

$SSE = 3.010$

Return Decomposition

Source	Value
EBITDAP	0.426
BB	−0.060
SUE	0.196
PSL	−0.085
TP3M	−0.016
$\hat{\alpha}$	2.266

Risk Decomposition

Source	Value
EBITDAEV	0.490
BB	0.903
SUE	0.343
PSL	0.094
TP3M	0.000
$\hat{\omega}^2$	27.134
Adjustment for factor correlation	−0.537

Historical Performance: Market Neutral

	Sector-Neutral	Factor-Neutral	S&P 500	Cash
Average return	6.572	0.946	13.982	0.547
SD return	8.786	8.730	13.542	0.229
Min return	−8.688	−9.186	−12.351	0.000
Max return	5.425	4.859	12.819	0.210
ρ^B	0.205	0.339	—	—
$\hat{\alpha}^B$	0.351	−0.213	—	—
$t(\hat{\alpha}^B)$	1.482	−0.943	—	—
$\hat{\beta}^B$	0.135	0.220	—	—
IR	0.141	−0.090	—	—
$\hat{\alpha}^{MF}$	−0.559	−0.670	—	—
SR	0.198	0.013	0.286	—

Historical Performance: Market Neutral

	Sector-Neutral			Factor-Neutral			S&P 500	Cash
	Long-Short	Long	Short	Long-Short	Long	Short		
Average return	13.057	19.198	6.688	11.202	19.982	9.328	13.982	0.547
SD return	13.086	19.600	17.038	16.028	23.518	16.618	13.542	0.229
Min return	−10.888	−13.908	−13.670	−27.726	−39.198	−12.169	−12.351	0.000
Max return	13.315	21.758	16.762	17.115	24.118	16.270	12.819	0.210
ρ^B	0.081	0.765	0.816	0.179	0.770	0.916	—	—
$\hat{\alpha}^B$	0.955	0.317	−0.638	0.649	0.124	−0.525	—	—
$t(\hat{\alpha}^B)$	2.664	0.912	−2.354	1.495	0.301	−2.850	—	—
$\hat{\beta}^B$	0.078	1.105	1.027	0.213	1.335	1.122	—	—
IR	0.253	0.087	−0.224	0.142	0.029	−0.271	—	—
$\hat{\alpha}^{MF}$	0.055	1.559	1.504	−0.955	0.962	1.917	—	—
SR	0.277	0.275	0.104	0.192	0.238	0.152	0.286	—

Disclaimer

This course is for educational purposes only and does not offer investment advice or pre-packaged trading algorithms. The views expressed herein are not representative of any affiliated organizations or agencies. The main objective is to explore the specific challenges that arise when applying Data Science and Machine Learning techniques to financial data. Such challenges include, but are not limited to, issues like short historical data, non-stationarity, regime changes, and low signal-to-noise ratios, all of which contribute to the difficulty in achieving consistently robust results. The topics covered aim to provide a framework for making more informed investment decisions through a systematic and scientifically-grounded approach.