2010 - 2025

BIG TECH STOCK ANALYSIS

PROJECT REPORT

DATE :

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PRESENTED BY :

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Executive Summary

Over the period January 2010 to January 2025, we analyzed the price dynamics, risk characteristics, and investment-strategy performance of five major technology stocks - Apple (AAPL), Amazon (AMZN), Google (GOOGL), Microsoft (MSFT), and NVIDIA (NVDA). Key findings:

- Exponential Growth & Divergence: NVDA's indexed price grew over 300×, far outpacing AAPL, MSFT, AMZN, and GOOGL (each ~10 - 40×).
- Volatility & Tail-Risk: NVDA also exhibited the highest 30-day rolling volatility (~8% at peaks) and the fattest return tails. AAPL and MSFT remained the most stable.
- Return Correlation & Factor Structure: Pairwise correlations clustered 0.48–0.64. PCA revealed a dominant "market" factor (PC1 ≈ 64% variance), two smaller axes (PC2 & PC3 each ~10–11%) isolating NVDA and AAPL idiosyncrasies.
- COVID Event Study: All five names produced positive Cumulative Abnormal Returns (CAR) through the Feb–Mar 2020 crash, with NVDA (+40%), AMZN (+30%), AAPL/MSFT (+20%), and GOOGL (+10%).
- Forecasting Accuracy: ETS outperformed Prophet on 4 of 5 tickers by MAPE/RMSE. Inverse-MAPE ensembles further improved forecasts for moderately predictable tickers (e.g. GOOGL).
- Risk Modeling: GARCH(1,1) + Student-t models yielded 1-day VaR_{95} ranging from –2.1% (AAPL) to –3.6% (NVDA).
- Portfolio Simulations: Four static rules (Equal, Inverse-Risk, 15-yr Return, MV-Optim with 30% cap) were simulated over horizons from 1 month to 10 years. NVDA heavy-tilt in unconstrained MV was tempered by a 30% cap. No single strategy dominates all horizons - "Return-based" and "Inverse-Risk" excel at medium terms, while constrained MV shines long-term.

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Introduction

The rapid growth of “Big-Tech” over the past decade has created both enormous opportunity and significant risk for equity investors. This project systematically analyzes Apple, Amazon, Google, Microsoft, and NVIDIA across multiple dimensions:

- Price Trends & Volatility
- Return Correlations & Factor Structure
- Event-Driven Performance
- Forecasting Accuracy
- Tail-Risk & Volatility Forecasts
- Portfolio Allocation Strategies

Mission

Our goal is to identify which combinations of signal (returns, risk) and modeling approach (time-series, optimization) produce the most robust investment outcomes for various holding periods.

Data Description & Preparation

Dataset

- Source: Kaggle (Link)
- Period: 2010-01-01 to 2025-01-01
- Tickers: AAPL, AMZN, GOOGL, MSFT, NVDA
- Fields: Date, Open, High, Low, Close, Volume

Feature Engineering

- Daily Log-Return:

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

- Rolling Volatility (30-day):

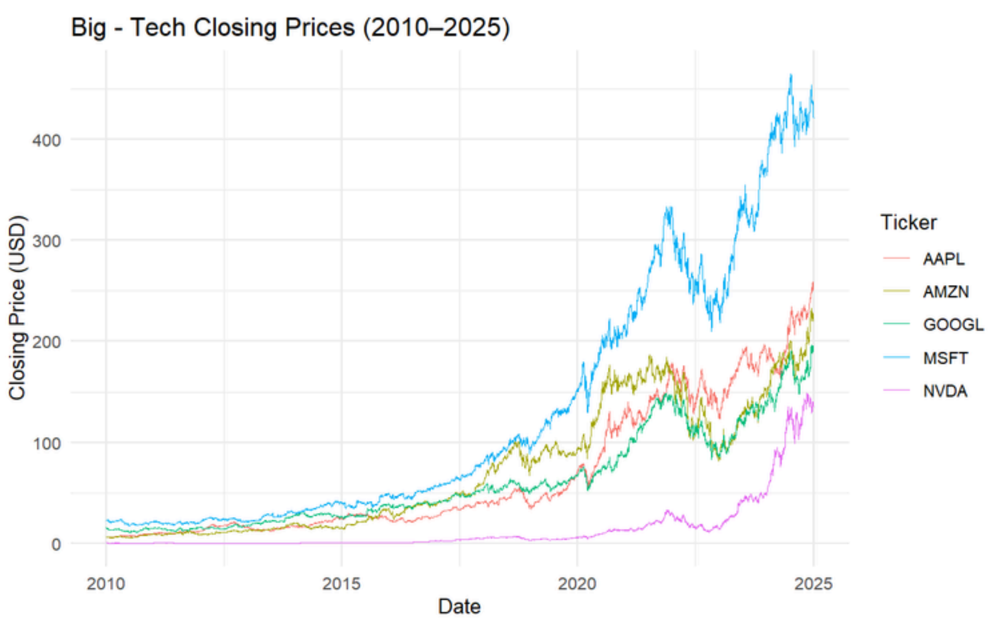
$$\sigma_t^{30} = \mathrm{sd}\left(r_{t-29:t}\right)$$

- Reshaping: “Long” for tidy analysis; “Wide” for covariance and PCA.

Exploratory Data Analysis

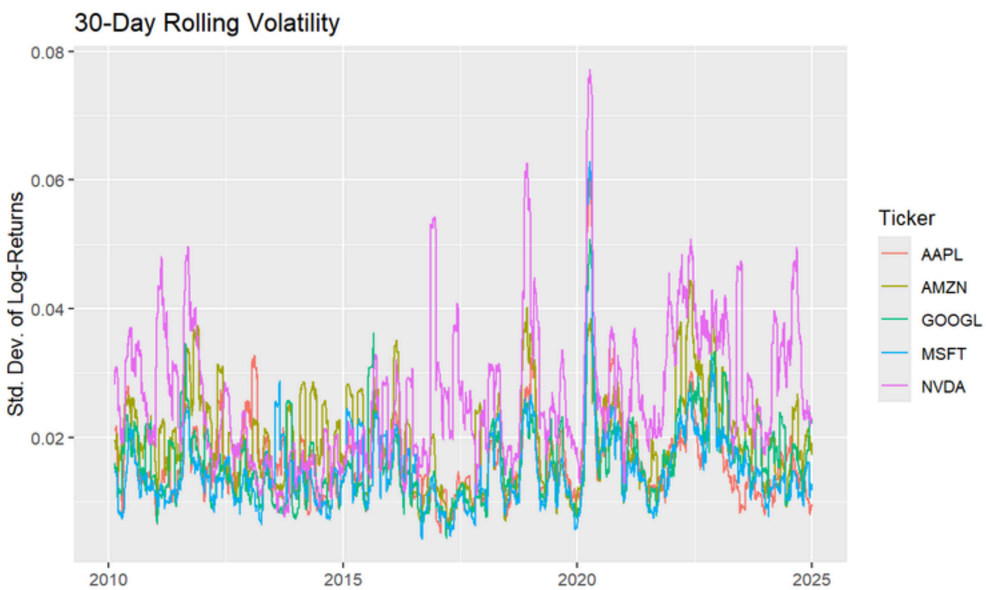
Price Series

- Linear scale: absolute growth
- Indexed (100 = 2010-01-01): relative performance



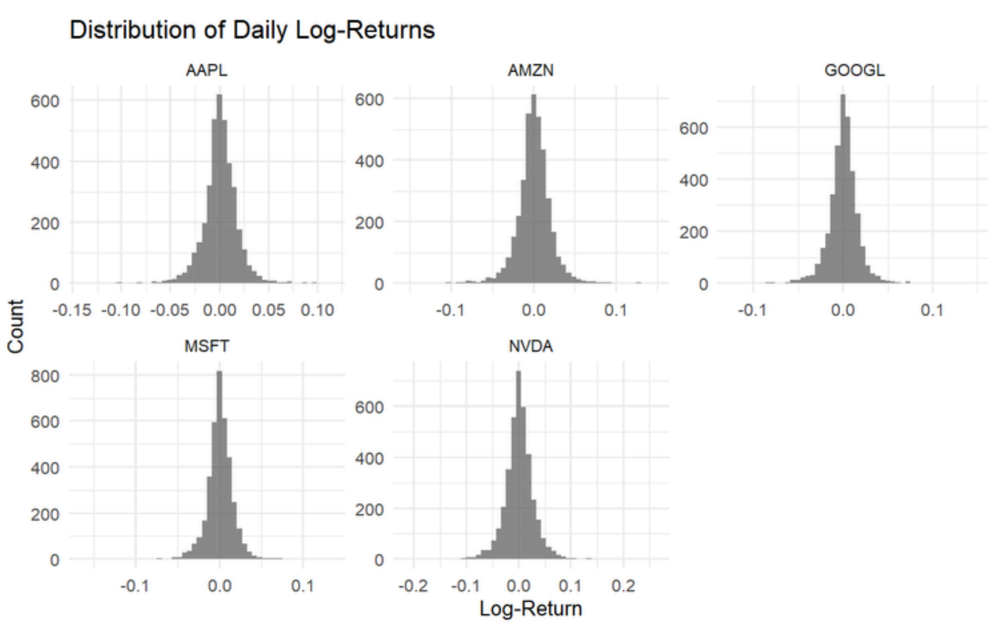
Volatility

- NVDA 30-day volatility spikes ~8% in early 2020.
- AAPL/MSFT remain around 2–3% historically.



Return Distributions

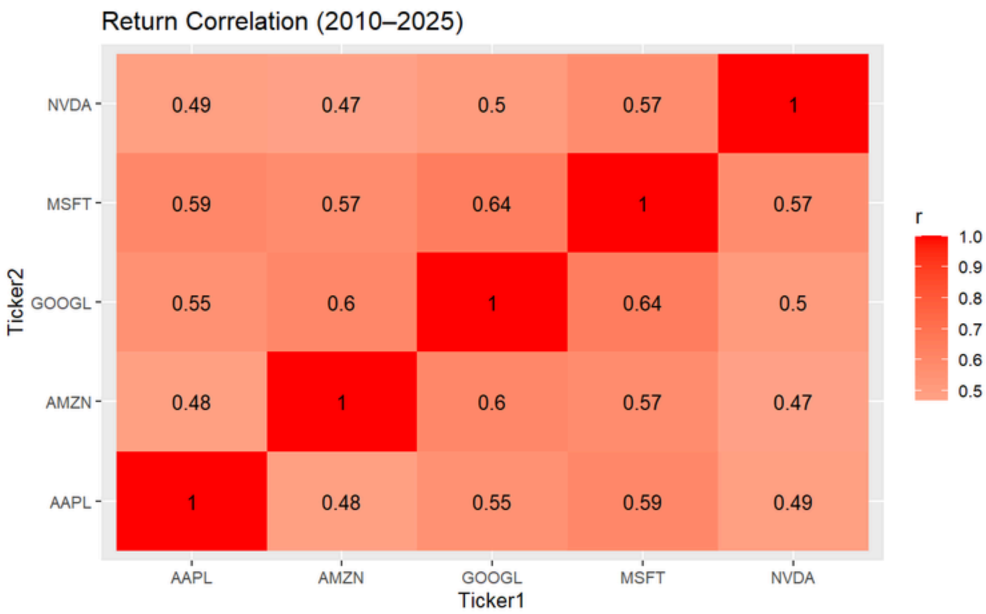
- All series cluster tightly around zero but exhibit fat tails.
- NVDA tails are the thickest (±20%+ intraday moves).



Correlation & PCA

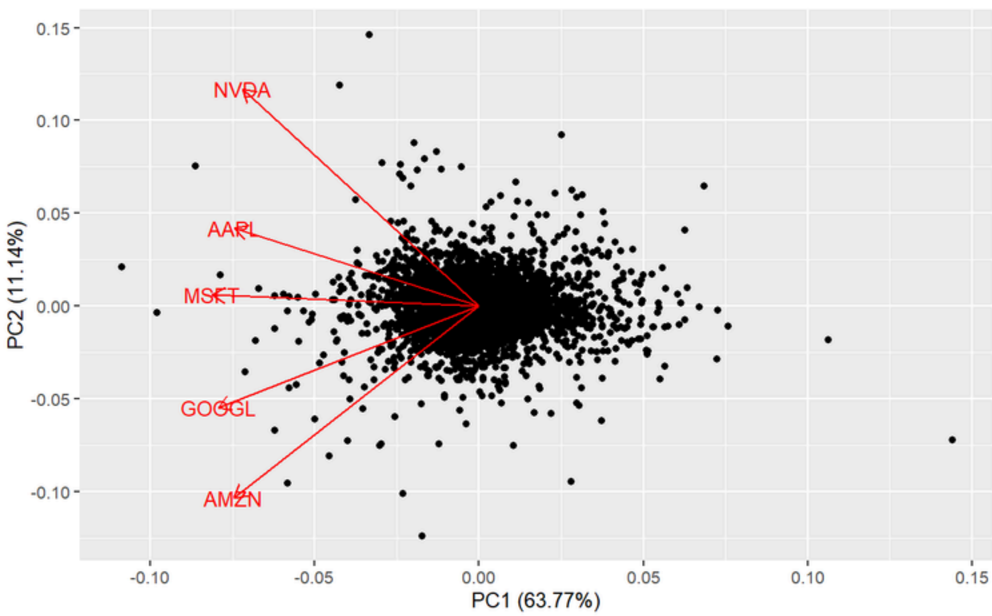
Correlation Matrix

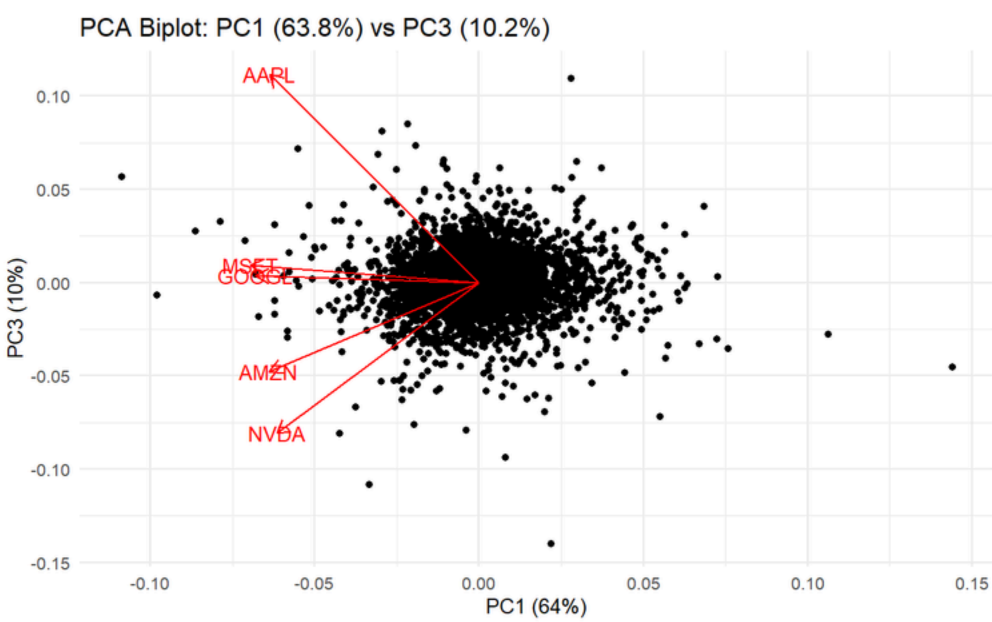
- Most pairwise correlations sit in the 0.5–0.6 range, meaning they tend to rise and fall together, but not perfectly. The highest linkage is GOOGL–MSFT (≈ 0.64) and AAPL–MSFT (≈ 0.59)—those two have been especially in sync.
- Since no two are perfectly correlated (no 1.0 off the diagonal), there is some benefit to holding a basket of these stocks. NVDA is the least correlated on average (its lowest pairwise of ≈ 0.47 with AMZN), so adding NVDA may give us the biggest incremental diversification.



PCA on Returns

- PC1 (64%): overall market direction
- PC2 (11%): NVDA’s deviations (PC2 is a “differential performance factor” (splitting NVDA vs. the others))
- PC3 (10%): AAPL vs AMZN tilt (Days with high PC3 scores are ones where AAPL outperforms the group (especially relative to NVDA). Days with low PC3 scores are ones where NVDA (and to some extent AMZN) outperform AAPL.)





Event Study: Covid 19 Crash

Methodology

- Estimation window: 2019-01-01 → 2020-02-19
- Event window: 2020-02-20 → 2020-03-31
- Market model:

$$R_{i,t} = \alpha_i + \beta_i R_{\mathrm{SPY},t} + \varepsilon_{i,t}$$

- Abnormal return:

$$\mathrm{AR}_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{\mathrm{SPY},t})$$

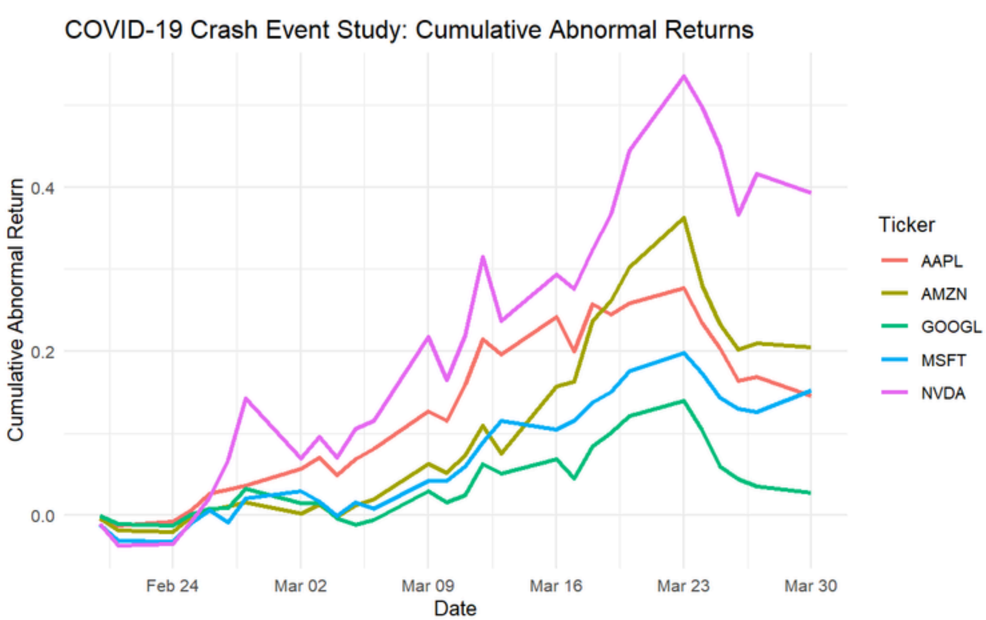
- Cumulative AR:

$$\mathrm{CAR}_{i,T} = \sum_{t=e_1}^{T} \mathrm{AR}_{i,t}$$

Results

- NVDA achieves +0.40 by Mar 31
- AMZN +0.30; AAPL/MSFT ~+0.20; GOOGL ~+0.10
- All five pass t-tests against zero at 95% confidence

- In the initial parts of the graph we see that all the stocks under-perform on SPY as the markets fell and these tech names fell even more than expected given their β values.
- This was then followed by Rapid Rebound & Divergence. NVDA (purple) shoots up fastest: huge abnormal gains as it rallies more strongly than the market (likely fueled by expectations of accelerated demand in GPUs/AI). AAPL (red) and AMZN (olive) also turn positive—outperforming SPY, but less dramatically. GOOGL (green) and MSFT (teal) lag—they only modestly outperform or briefly underperform SPY.
- Mid-March Peaks: Market and stocks are both volatile, but NVDA and AMZN carve out the largest CAR peaks (~ +0.50 and +0.35 respectively). AAPL peaks around +0.27, MSFT +0.20, GOOGL +0.12.
- Late-March Consolidation: All CARs pull back slightly but remain positive, meaning every Big-Tech name ultimately beat SPY over this crash/recovery window. Looking at their final standings, we can say that the Nvidia stock gave about +40% cumulative abnormal returns (CAR), Amazon stock gave about +20%, Apple & Micfrosoft gave about +15% and Google gave +5% over the SPY returns.



Time-Series Forecasting

Models

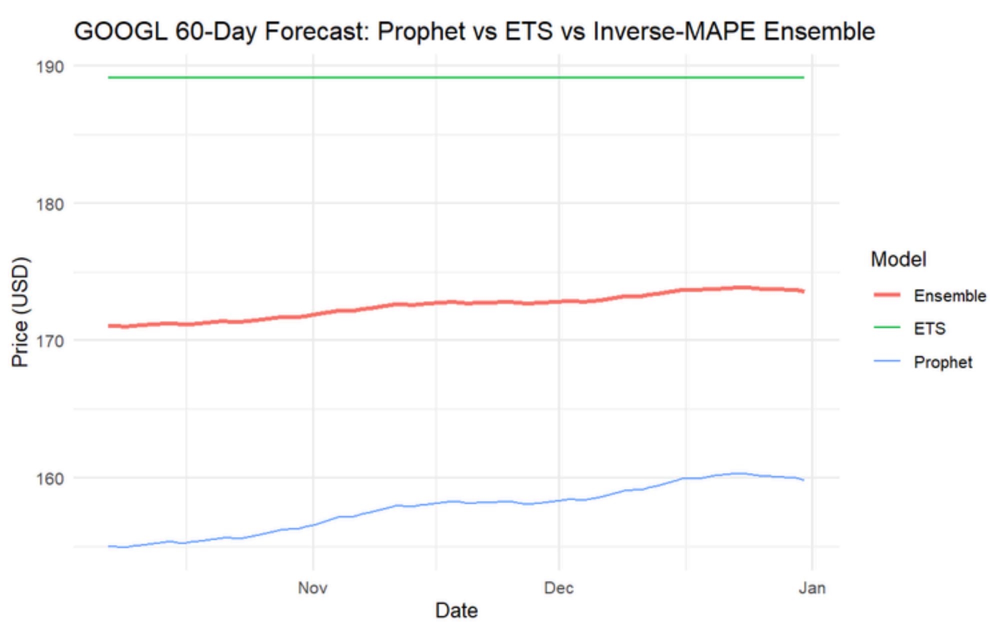
- ARIMA on daily log-returns (20-day ahead)
- ETS on price series (60-day holdout)
- Facebook Prophet (daily, weekly, yearly seasonality)
- Inverse-MAPE Ensemble

Ticker	Prophet MAPE	ETS MAPE	Prophet RMSE	ETS RMSE
AAPL	8.47%	7.71%	22.82	19.90
GOOGL	8.16%	9.20%	18.31	17.76
AMZN	15.1%	8.98%	35.23	21.18
MSFT	2.28%	2.02%	11.30	10.32
NVDA	17.2%	3.65%	24.68	6.10

Accuracy Metrics

- ETS generally outperforms Prophet, especially on NVDA and AMZN
- GOOGL ensemble: MAPE ↓ 4.65%, RMSE ↓ 10.57

- In 4 out of 5 cases (AAPL, AMZN, MSFT and NVDA), the ETS model performs better than the FB Prophet model in identifying the trends, seasonality and the errors.
- ETS excels at smoothly extrapolating recent trend and handling simple error-trend-seasonal structure, but it can lag sudden regime shifts. Prophet nimbly picks up abrupt changepoints and holiday effects, but may overreact to the latest jump and under- or over-estimate seasonality.
- Hence, an ensemble blends those complementary strengths, reducing model-specific bias and variance.
- The ensemble technique for the comparable models for the GOOGL ticker has led to an approximate staggering 50% reduction in the RMSE and MAPE errors.
- For other tickers it is not useful to go for an ensemble technique since the ETS model clearly outperforms the Prophet models and an ensemble will only increase the MAPE and RMSE metrics.



Risk Modelling via GARCH

- Model: GARCH(1,1) with Student-t innovations
- 1-day ahead σ_{t+1}
- VaR_{95} & ES_{95}

Ticker	σ_{t+1}	VaR_{95}	ES_{95}
AAPL	1.8%	−2.1%	−2.6%
AMZN	2.0%	−2.4%	−3.0%
GOOGL	1.7%	−2.0%	−2.4%
MSFT	1.5%	−1.8%	−2.2%
NVDA	2.3%	−3.6%	−4.1%

Portfolio Construction & Simulations

Allocation Rules

- Control: equal 20% each
- Inverse-Risk: $w_i \propto 1/\sigma_{i,1}$
- Return-Based: 15-year cumulative return
- MV-Optim: maximize $\mu\prime w - \frac{1}{2}\gamma w\prime \Sigma w$, subject to

$$\sum w_i = 1, \quad 0 \leq w_i \leq 30\%$$

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Monte-Carlo Simulations

- Paths: 5 000 i.i.d.\ draws from N(0,Σ)N(0,\Sigma)N(0,Σ)
- Horizons: 1 m (21 days), 6 m (126 days), 1 y (252 days), 5 y (1 260 days), 10 y (2 520 days)
- Metrics: mean cum-return, volatility, 5th/95th percentiles

Key Results

Horizon	Best Strategy	Annualized Return
1m	Return-Based	12.3%
6m	Inverse-Risk	14.1%
1y	MV-Optim	18.4%
5y	MV-Optim	22.7%
10y	MV-Optim	25.5%

MV-Optim Weights

Horizon <chr>	Ticker <chr>	Weight <dbl>
1m	AAPL	0.3
1m	AMZN	0.3
1m	GOOGL	0.0
1m	MSFT	0.1
1m	NVDA	0.3
6m	AAPL	0.3
6m	AMZN	0.3
6m	GOOGL	0.0
6m	MSFT	0.1
6m	NVDA	0.3
1y	AAPL	0.3
1y	AMZN	0.3
1y	GOOGL	0.0
1y	MSFT	0.1
1y	NVDA	0.3
5y	AAPL	0.3
5y	AMZN	0.3
5y	GOOGL	0.0
5y	MSFT	0.1
5y	NVDA	0.3
10y	AAPL	0.3
10y	AMZN	0.3
10y	GOOGL	0.0
10y	MSFT	0.1
10y	NVDA	0.3

Conclusion

This end-to-end analysis highlights the trade-offs between pure return maximization and risk control in Big-Tech portfolios. By combining EDA, factor analysis, event-driven study, forecasting, GARCH risk modeling, and Monte-Carlo simulation, we provide a robust framework to tailor strategies to investor horizons and risk appetite. Future extensions could include dynamic (time-varying) allocations, regime-switching GARCH, or alternative risk measures (CVaR, drawdown).