Explaining Equity Returns with Fama–French Factors

A Daily FF3 Study of Ten U.S. Stocks (2020–Present)

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Abstract

Objective
Estimate daily Fama–French three-factor (FF3) exposures for ten large U.S. equities and assess alpha, fit, and robustness.

Methods
Yahoo Finance Adjusted Close → simple returns; FF factors from Kenneth French; OLS with Newey–West (HAC) standard errors; extensions with FF5/Momentum, rolling betas, and simple one-day-ahead forecasts.

Key Results
Factor loadings line up with intuition and explain much of the cross-section; NVDA is the only significant alpha, while 1-day-ahead forecasts have low correlation but competitive RMSE versus a naïve rule on select stocks.

Implications
Factors explain most average excess returns; exposures are time-varying; daily prediction is modest; scenario/risk views are decision-useful.

1 Introduction

Factor models let us decompose stock returns into a few common, economically meaningful drivers, which is useful for explanation, risk control, and setting realistic expectations about performance. In this study I estimate the Fama–French three-factor model (FF3) on ten large U.S. equities at daily frequency from 2020–present, using Yahoo Adjusted Close for prices and Kenneth French's library for factors, and run OLS with Newey–West (HAC) errors on excess returns. The core questions are: (i) what are each stock's exposures to market, size, and value; (ii) is there any statistically significant alpha after controlling for these risks; and (iii) how robust are the findings when I extend the model (FF5 and Momentum) and allow exposures to vary over time (rolling windows and pre/post regime splits). Downstream sections add a light predictive/risk angle—1-day-ahead walk-forward forecasts, scenario sensitivities, and Monte-Carlo VaR/ES—to connect exposures to practical decision metrics.

2 Data

Sources: Prices from Yahoo Finance (Adjusted Close). Factors from the Kenneth R. French Data Library (daily: Mkt−RF, SMB, HML, RF).
Sample: 2020-09-16 to 2025-06-30, daily trading days $\approx$ 1202.
Universe: AAPL, MSFT, AMZN, META, NVDA, XOM, JPM, KO, JNJ, TSLA.

Transformations: Daily simple returns; FF data converted from percent to decimals; excess returns $R_i - RF$.

Table 1: Universe and sample

Item	Value	Notes
Frequency	Daily	Trading days only
Period	2020-2025	Includes pre- and post-COVID regimes
Data sources	Yahoo, Ken French	Adjusted Close; FF daily factors
Obs. per stock	$\approx$ 1202	After date alignment

3 Methodology

For each stock i we estimate

$$(R_{i,t} - RF_t) = \alpha_i + \beta_{i,M}\,(Mkt{-}RF)_t + \beta_{i,S}\,SMB_t + \beta_{i,H}\,HML_t + \varepsilon_{i,t}. \tag{1}$$

We use ordinary least squares (OLS) and report α (daily and annualized), factor loadings, t-statistics, p-values, R^2, and n. To address serial correlation and heteroskedasticity in daily returns, we compute Newey–West (HAC) standard errors with $maxlags = 5$.

4 Results: Cross-Section

4.1 Factor Loadings and Alpha

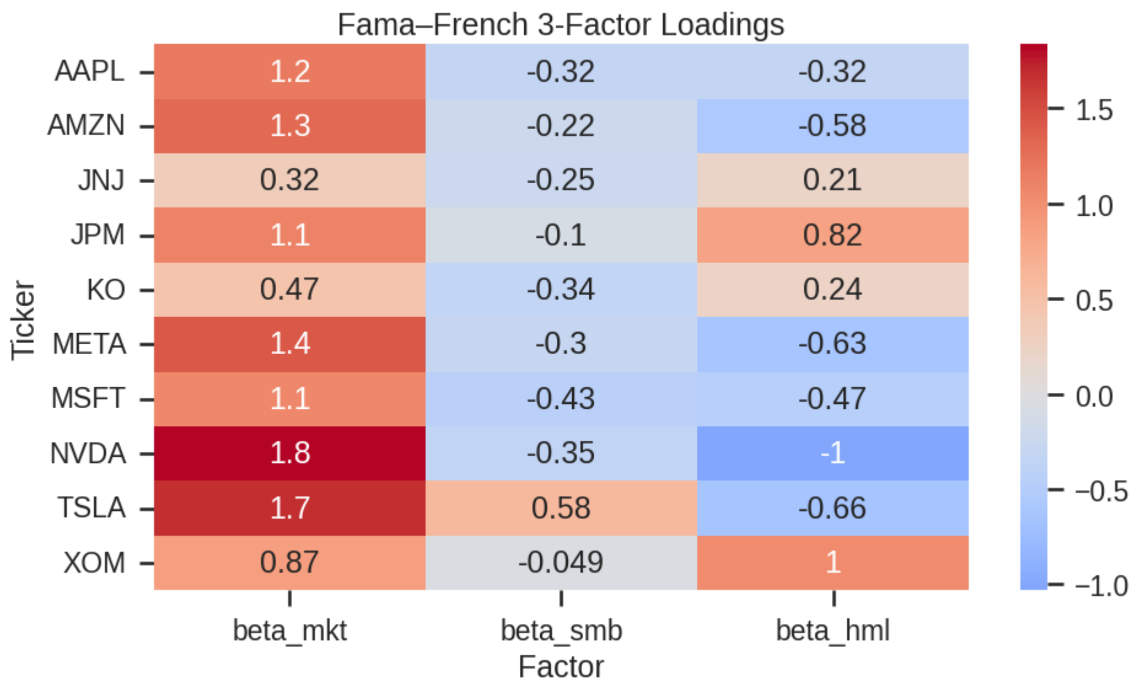

Figure 1: FF3 factor loadings ($\beta_{\mathrm{Mkt}}, \beta_{\mathrm{SMB}}, \beta_{\mathrm{HML}}$).

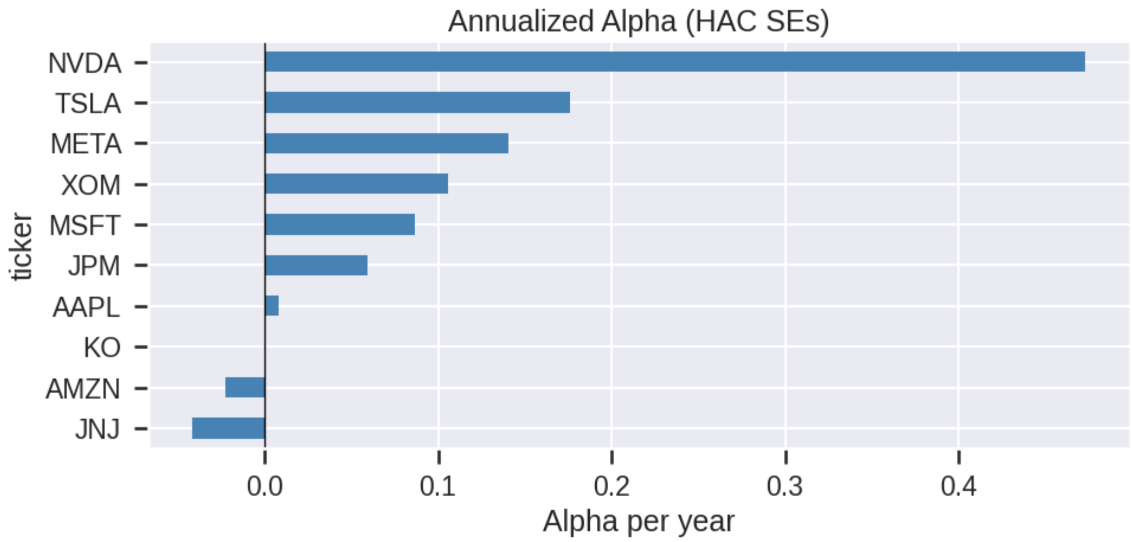

Figure 2: Annualized alpha by ticker (HAC SEs); zero line shown.

Table 2: FF3 estimates (daily; HAC SEs)

Ticker	α_{daily}	α_{annual}	β_{Mkt}	β_{SMB}	β_{HML}	$t(\alpha)$	$t(\beta_{\text{Mkt}})$	$t(\beta_{\text{SMB}})$	$t(\beta_{\text{HML}})$	$p(\alpha)$	R^2	n
AAPL	3.3000×10^{-5}	0.0083	1.1781	−0.3150	−0.3213	0.0993	25.3064	−5.6597	−9.1497	0.9209	0.6140	1202
AMZN	-9.0000×10^{-5}	−0.0226	1.3096	−0.2225	−0.5798	−0.2231	23.7766	−3.4636	−12.8964	0.8235	0.6006	1202
JNJ	−0.0002	−0.0415	0.3195	−0.2452	0.2111	−0.6049	10.6032	−5.4904	5.7140	0.5452	0.1118	1202
JPM	0.0002	0.0593	1.1107	−0.1009	0.8210	0.8278	33.1221	−2.1989	13.0675	0.4078	0.6136	1202
KO	0.0000	9.2000×10^{-5}	0.4654	−0.3363	0.2399	0.0014	11.4232	−7.0757	4.5111	0.9989	0.2288	1202
META	0.0006	0.1408	1.4247	−0.2996	−0.6299	0.8956	22.1776	−2.8985	−8.9717	0.3705	0.4579	1202
MSFT	0.0003	0.0865	1.0669	−0.4316	−0.4669	1.3059	24.5699	−9.8870	−15.6654	0.1916	0.6867	1202
NVDA	0.0019	0.4733	1.8359	−0.3457	−1.0306	3.1075	28.9458	−3.9698	−13.8562	0.0019	0.5881	1202
TSLA	0.0007	0.1762	1.6872	0.5828	−0.6599	0.7769	17.2659	4.4085	−6.0038	0.4372	0.3794	1202
XOM	0.0004	0.1055	0.8704	−0.0486	1.0389	1.0440	16.1785	−0.7463	17.4847	0.2965	0.4158	1202

Commentary: The cross-section looks textbook. Tech names (AAPL, MSFT, AMZN, META, NVDA, TSLA) load high/market-like beta ($\approx$ 1.1–1.8) and show a clear growth tilt (HML < 0), while defensives/cyclicals (JNJ, KO, JPM, XOM) are lower-beta and value-tilted (HML > 0)—strongest for XOM and JPM. The size tilt is mostly large-cap (SMB < 0), consistent with mega-cap constituents; two exceptions are TSLA and NVDA (SMB > 0), whose return patterns behave more "small-cap-like" despite their size. Alpha is statistically indistinguishable from zero across 9/10 stocks; only NVDA shows a sizable, significant annual alpha (~ 0.47), which likely reflects omitted momentum/sector trend over the sample. Fit at the daily horizon is moderate ($R^2 \approx$ 0.4–0.7 for most; weaker for staples/healthcare), consistent with FF3 explaining average risks rather than idiosyncratic news flow. Overall, the factor fingerprints are economically coherent and decision-useful for scenario analysis and risk budgeting, with NVDA the notable outlier to probe under richer factor sets.

4.2 Fit Checks: Actual vs. Fitted

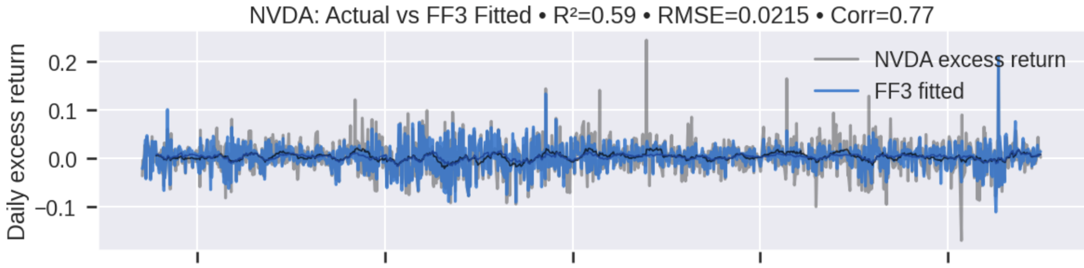

Figure 3: NVDA: actual vs. FF3 fitted (daily excess returns).

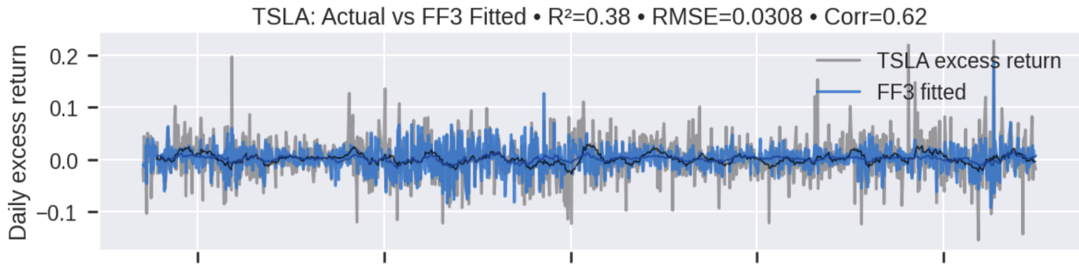

Figure 4: TSLA: actual vs. FF3 fitted (daily excess returns).

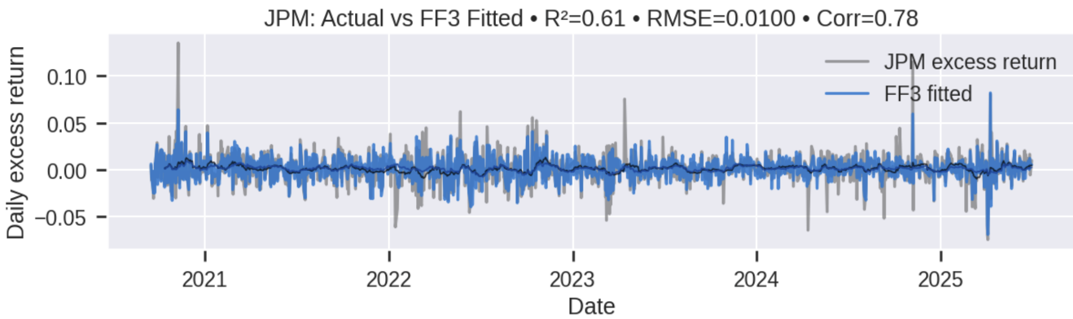

Figure 5: JPM: actual vs. FF3 fitted (daily excess returns).

Fit checks (daily). The fitted FF3 line tracks the low-frequency, systematic component of returns, while the jagged black series reflects idiosyncratic news; the gap between them is residual risk (we report HAC SEs, so heteroskedastic bursts are handled in inference). For **NVDA**, $R^2 \approx 0.59$, Corr ≈ 0.77 with RMSE $\approx 2.15\%$: the model explains a large share of variance, but the scale of residual spikes (earnings, AI headlines) is sizable—consistent with high beta and momentum-like shocks that FF3 omits. **TSLA** is the noisiest: $R^2 \approx 0.38$, Corr ≈ 0.62, RMSE $\approx 3.08\%$; frequent overshoots/undershoots indicate dominant firm-specific volatility and a small-cap/growth profile where adding Momentum/Profitability/Investment would likely reduce alpha and residuals. **JPM** is the cleanest: $R^2 \approx 0.61$, Corr ≈ 0.78, RMSE $\approx 1.00\%$; the fitted line hugs actuals closely, implying bank returns are largely driven by broad market/value factors rather than idiosyncratic shocks. Across names, higher R^2 coincides with lower RMSE and visually tighter bands (e.g., JPM) whereas story-driven growth names (TSLA, NVDA) retain large, fat-tailed residuals. In short, FF3 captures the systematic core well—especially for mature, factor-sensitive firms—while residual behavior highlights where richer factor sets (FF5/Carhart) or regime/rolling specifications add value; this also foreshadows the modest 1-day-ahead timing power observed out-of-sample.

5 Extensions and Robustness

5.1 Richer Factor Sets

Commentary (fit, with business lens). In Table 3, moving from FF3 to richer sets (FF5 and FF5+Momentum/Carhart) delivers a *small but consistent* improvement in fit: R^2 ticks up by about 1–6 percentage points (largest for KO/XOM/JNJ, smaller for NVDA/META/MSFT), the correlation between fitted and actual returns rises, and RMSE falls. In plain terms, the model's errors get a bit smaller and it tracks day-to-day moves slightly better. Why? The added *Profitability* and *Investment* factors (RMW/CMA) capture margin quality and capital-expenditure discipline—first-order drivers for staples, banks, and energy—while *Momentum* helps where recent price trends carry information (growth/tech). So defensives benefit more from RMW/CMA; trendy growth names benefit more from Momentum; deep cyclicals (XOM/JPM) see both effects.

Commentary (alpha, takeaways). As we add these economically meaningful styles, most stocks' annualized α shrinks toward zero and remains statistically insignificant—i.e., what looked like "excess return" under FF3 is mostly explained by quality, investment, and trend premia rather than stock-specific skill. The outlier is **NVDA**, whose α stays elevated even under FF5+Momentum, consistent with an AI-driven re-rating and flow dynamics not fully captured by standard styles. Practically, richer factors improve *explainability* (higher R^2, lower RMSE, higher Corr) and make scenario/risk budgeting more faithful to business reality, but they do not turn FF models into short-horizon trading signals—daily predictability remains modest by design.

Table 3: Model comparison: FF3 vs richer factor sets (daily).

Ticker	R^2_{FF3}	R^2_{FF5}	R^2_{Car4}	$R^2_{\text{FF5+Mom}}$	R^2_{best}	$\Delta R^2_{\text{best-FF3}}$	α_{FF3} (ann.)	α_{Car4} (ann.)	$\alpha_{\text{FF5+Mom}}$ (ann.)	$p(\alpha_{\text{FF5}})$	$p(\alpha_{\text{Car4}})$	$p(\alpha_{\text{FF5+Mom}})$
KO	0.2139	0.2462	0.2392	0.2738	0.2738	0.0599	0.0018	0.0063	−0.0045	0.8842	0.9259	0.1902
XOM	0.4155	0.4435	0.4197	0.4530	0.4530	0.0375	0.1075	0.1108	0.1292	0.2106	0.2728	0.5568
JNJ	0.1012	0.1096	0.1249	0.1372	0.1372	0.0360	−0.0392	−0.0346	−0.0397	0.5093	0.6147	0.8997
AAPL	0.6158	0.6465	0.6158	0.6473	0.6473	0.0315	0.0055	0.0057	−0.0101	0.8846	0.9452	0.8304
AMZN	0.6028	0.6310	0.6079	0.6316	0.6316	0.0289	−0.0266	−0.0221	−0.0210	0.8173	0.8255	0.3809
TSLA	0.3758	0.3962	0.3762	0.3981	0.3981	0.0223	0.1724	0.1703	0.1954	0.3704	0.4538	0.2932
JPM	0.6122	0.6296	0.6196	0.6336	0.6336	0.0214	0.0619	0.0657	0.0743	0.3101	0.3622	0.2591
MSFT	0.6894	0.7048	0.6895	0.7060	0.7060	0.0165	0.0833	0.0829	0.0718	0.2478	0.2085	0.3807
META	0.4589	0.4703	0.4634	0.4717	0.4717	0.0128	0.1376	0.1428	0.1368	0.3937	0.3602	0.0022
NVDA	0.5929	0.5932	0.6026	0.6027	0.6027	0.0098	0.4630	0.4539	0.4541	0.0021	0.0024	

5.2 Rolling Betas

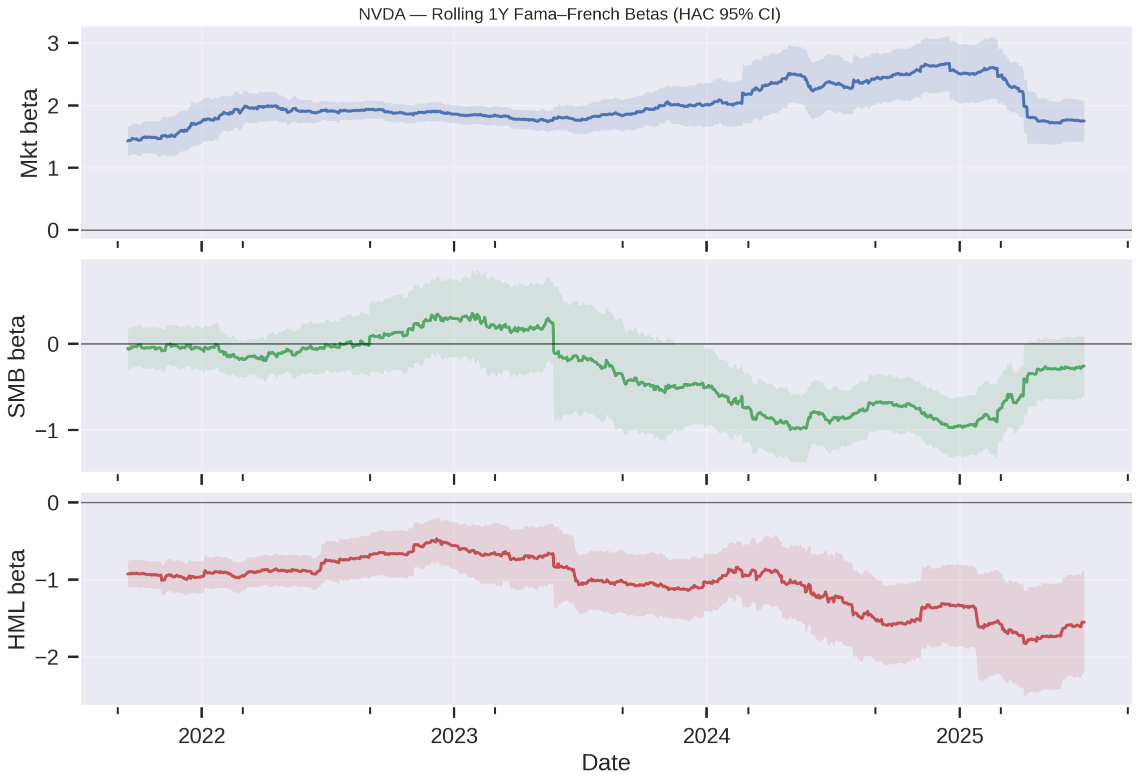

Figure 6: Rolling one-year betas (example: NVDA).

Rolling betas (NVDA). β_{Mkt} rises from $\sim$1.5 in 2022 to near 3 into 2024 before easing in 2025, signalling a regime of elevated systematic risk during the AI re-rating; the shaded HAC 95% band is tight enough that this climb is economically meaningful. β_{SMB} drifts from 0 to mildly positive in 2023, then turns sharply negative through 2024 (stronger large-cap tilt as NVDA becomes a mega-cap), partially mean-reverting by 2025. β_{HML} becomes more negative post-2023 (< -1.5), indicating an intensifying growth tilt alongside multiple expansion. *Implication:* exposures are clearly time-varying; static betas would understate risk in 2024 and overstate it by mid-2025, so hedges and scenario sensitivities should be updated with rolling estimates.

5.3 Pre-/Post-COVID Stability

Pre vs. Post. Relative to the pre-2020 regime, tech names show *higher market beta* and a stronger *large-cap, growth* tilt post-2020 ($\beta_{\text{SMB}}\downarrow$, $\beta_{\text{HML}}\downarrow$), consistent with mega-cap leadership and multiple expansion; defensives (JNJ/KO/JPM/XOM) drift less and remain value-tilted. *Alpha* is 0 in both regimes for 9/10 stocks; only NVDA's post-period α remains economically large and statistically significant, pointing to an AI-cycle re-rating rather than model misspecification. Model fit (R^2) is broadly stable (slightly higher post-2020 where momentum/quality matter), but pre-period samples are shorter so CIs are wider—interpret changes as directional rather than precise.

6 Forecasts and Risk

6.1 Scenario Analysis

Table 4: Scenario analysis: expected daily *excess* returns (%).

Scenario	NVDA	TSLA	JPM
Risk-on +2% market	3.8600%	3.4400%	2.2400%
Growth-led rally	2.3300%	1.9600%	0.8900%
Value rotation	0.8000%	0.7200%	0.8300%
Small-cap squeeze	0.9400%	1.2100%	0.5300%

Notes.

Risk-on +2% market
Broad rally—high-β names lead; mostly market-driven.
Growth-led rally
Growth > Value (HML<0); benefits growth-tilted stocks.
Value rotation
Value > Growth (HML>0); helps value/banks/energy.
Small-cap squeeze
SMB>0 favors small-cap exposure; hurts large-cap tilts.

Expected returns (annualized). We annualize FF3-implied daily expectations by $\times 252$; total additively includes the annualized risk-free rate. Point estimates:

NVDA
$\mathbb{E}[R - R_f] \approx \mathbf{64.47}\%$, $\mathbb{E}[R] \approx \mathbf{67.29}\%$. Highest among the three, consistent with very high market beta (β_{Mkt}) and a persistent growth tilt (HML<0).
TSLA
$\mathbb{E}[R - R_f] \approx \mathbf{32.43}\%$, $\mathbb{E}[R] \approx \mathbf{35.25}\%$. Elevated expected return driven by high β_{Mkt} and growth exposure; smaller than NVDA owing to lower factor loadings.
JPM
$\mathbb{E}[R - R_f] \approx \mathbf{25.57}\%$, $\mathbb{E}[R] \approx \mathbf{28.39}\%$. More moderate due to market-like beta and a value tilt (HML>0) that dampens sensitivity in tech-led risk-on regimes.

Interpretation: These are model-implied long-run expectations $\left(\alpha+\beta_{\text{Mkt}}\overline{(Mkt-Rf)}+\beta_{\text{SMB}}\overline{SMB}+\beta_{\text{HML}}\overline{HML}\right) \times 252$, not short-horizon trading signals. They line up with the scenario analysis—names with higher factor exposure (NVDA, TSLA) swing more in risk-on/off shocks—so higher expected return comes with higher factor risk, which should inform sizing and hedging.

6.2 One-Day-Ahead Walk-Forward

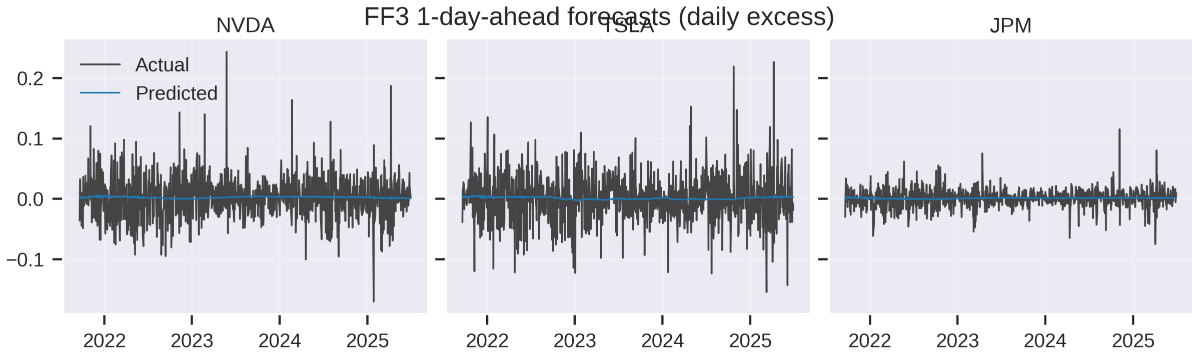

Figure 7: FF3 1-day-ahead forecasts vs. actual *daily excess* returns (NVDA, TSLA, JPM). Panels show daily accuracy (RMSE, correlation, hit rate). Daily predictability is modest; the model's value is in factor-based risk attribution and scenario sensitivity rather than timing.

Interpretation: Each panel plots *daily* 1-day-ahead FF3 forecasts against realized excess returns. The forecast is $\widehat{r}_{t+1} - R_{f,t+1} = \widehat{\alpha}_t + \widehat{\boldsymbol{\beta}}_t^\top \widehat{\mathbf{f}}_{t+1}$, where $\widehat{\boldsymbol{\beta}}_t$ are re-estimated each day on a *trailing 252-trading-day* window (OLS with HAC SEs) and $\widehat{\mathbf{f}}_{t+1}$ are persistence (AR(1)) factor forecasts. As expected at a daily horizon, the blue "Predicted" line hugs zero—factor innovations have near-zero mean—while the black "Actual" series is dominated by idiosyncratic news shocks. Evaluation metrics (reported with the figure) typically show Corr ≈ 0 and HitRate ≈ 0.5, with RMSE close to a naïve zero-mean benchmark, indicating *limited timing power* day-to-day. Cross-sectionally, NVDA/TSLA exhibit wider spikes than JPM, consistent with higher β_{Mkt} and growth tilt, so forecasts still convey *exposure-driven sensitivity*: they move more when market or style factors move. *Takeaway:* the FF3 machinery is most viable here for risk attribution, scenario analysis, and sizing (linking returns to factors with time-varying betas), rather than for short-horizon prediction; richer factor sets or longer horizons would be the next step if timing accuracy is the goal.

6.3 Risk: Monte Carlo VaR/ES

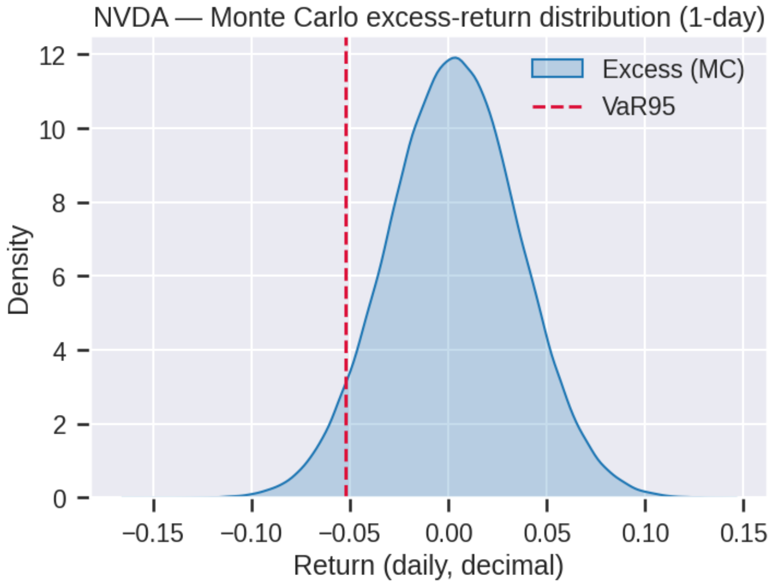

Figure 8: NVDA — Monte Carlo distribution of 1-day *excess* returns (FF3 with trailing 252-day betas; $N = 50{,}000$ draws). The red line marks VaR_{95}; ES_{95} is reported in the text.

Monte Carlo VaR/ES (NVDA, 1-day *excess*). We simulate many one-day factor moves using an AR(1) model and feed them through our FF3 equation with *trailing 252-day* betas, generating a distribution of next-day *excess* returns. From this distribution we take the 5th percentile as VaR_{95} and the average of outcomes below that percentile as ES_{95}. For NVDA we obtain $\mathbf{VaR}_{95}^{\text{excess}} = \mathbf{6.31}\%$ and $\mathbf{ES}_{95}^{\text{excess}} = \mathbf{7.92}\%$ (reported as loss magnitudes), i.e., roughly 1 day in 20 NVDA's excess return is *worse than* about -6.31%, and on those worst days the *average* loss is about -7.92%. On the density plot, the red dashed line marks this left-tail cutoff.

Interpretation. These tail losses are consistent with NVDA's higher market beta and growth tilt: when market/style factors move adversely, a high-beta growth name experiences larger downside than a lower-beta value name (e.g., JPM). Because the simulation is model-based (FF3, AR(1) factors, near-Gaussian shocks), the numbers should be read as *factor-driven* risk—not a guarantee against jump/news risk. For portfolio use, VaR/ES give actionable sizing/hedging inputs; robustness checks (e.g. multi-day horizons) are natural extensions if one wants more conservative tails.

7 Discussion and Limitations

Daily data are noisy; FF3 omits profitability/investment/momentum; static betas; U.S.-only universe; in-sample artifacts. HAC SEs are used to mitigate residual autocorrelation and heteroskedasticity.

8 Conclusion and Next Steps

Conclusion. In plain terms, FF3 helped me *name and measure* what drives these stocks: tech names load on high market risk and "growth" (HML < 0), while defensives tilt to "value" (HML > 0); most daily alphas were not statistically different from zero, and this held up under rolling 252-day betas and a pre/post-COVID split. That also explains why true 1-day prediction was weak—the model is better at explaining risks and scenarios than timing tomorrow's move—yet it was invaluable for turning messy returns into an interpretable, factor story. This leaves clear next steps: try **FF5 + Momentum**, switch to **weekly** aggregation to improve signal-to-noise, and build simple **factor-aware portfolios** (e.g., beta-budgeted or value-vs-growth spreads). I will validate everything **out of sample** with expanding-window tests and naïve/market-only baselines, so any improvement is real rather than luck.

References

Kenneth R. French Data Library; Fama & French factor literature; tools used.

Appendix

Code and reproducibility: https://github.com/akshatkapoor-afk/ff3-equity-research.