Asset Pricing Model Comparison and Empirical Interpretation

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1 Introduction

Asset pricing models link expected returns to risk exposures. This report estimates and compares two influential frameworks:

- the Capital Asset Pricing Model (CAPM), and
- the Fama–French Five–Factor Model (FF5).

The objective is to evaluate which model better explains variation in asset returns and to interpret cross–sector differences in factor sensitivity. I also examine whether there is evidence of abnormal performance (alpha) after controlling for risk factors. Finally, I connect the equity return analysis to derivative pricing by implementing a binomial option pricing model for Pfizer (PFE).

2 Data and Preprocessing

I analyze five liquid, sector–diversified assets:

- Apple (AAPL) – Technology
- JPMorgan (JPM) – Financials
- ExxonMobil (XOM) – Energy
- Walmart (WMT) – Consumer Retail

- XLV – Healthcare ETF

Daily adjusted prices from 1 January 2019 to 31 December 2024 were retrieved through Yahoo Finance. For each asset, I compute simple daily returns

$$R_{it} = 100 \times \frac{P_{it} - P_{it-1}}{P_{it-1}},$$

expressed in percentage terms.

Factor data were downloaded from the Kenneth French Data Library, using the daily "F-F Research Data 5 Factors 2x3" file. This provides:

- the risk–free rate RF_t,
- the market excess return $MKT{-}RF_t$,
- the size factor SMB_t,
- the value factor HML_t,
- the profitability factor RMW_t, and
- the investment factor CMA_t.

The Fama–French factors are also provided in percent per day, so I construct excess returns as

$$R_{it} - R_{ft},$$

where $R_{ft} = RF_t$. I then merge the return data and factor data by date, keeping only the intersection of days where all series are available.

3 Models and Estimation

For each asset, I estimate both a CAPM specification and a Fama–French 5–factor specification using ordinary least squares (OLS).

3.1 CAPM

The CAPM regression for asset i is:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT}(MKT{-}RF)_t + \epsilon_{it}.$$

Here, α_i measures risk–adjusted abnormal performance and $\beta_{i,MKT}$ captures sensitivity to aggregate market risk.

3.2 Fama–French Five–Factor Model

The FF5 regression for asset i is:

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT}(MKT{-}RF)_t + \beta_{i,SMB}SMB_t \\ + \beta_{i,HML}HML_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t + \epsilon_{it}. \end{aligned}$$

The five betas measure exposure to market, size, value, profitability, and investment risk, respectively. Comparing the CAPM and FF5 results allows me to assess whether the additional factors improve model fit and change the alpha estimates.

All regressions are implemented in Python using `pandas` for data handling, `statsmodels` for OLS estimation, and `matplotlib` for visualization. The full code is included in the project submission.

4 Empirical Results

4.1 CAPM vs FF5: Betas and Fit

Table 1 summarizes market betas and R^2 under CAPM and FF5. Values are based on daily excess returns.

Ticker	CAPM β_M	CAPM R^2	FF5 β_M	FF5 R^2
AAPL	1.16	0.60	1.26	0.70
JPM	1.04	0.49	1.05	0.76
XOM	0.81	0.27	0.89	0.55
WMT	0.44	0.18	0.53	0.23
XLV	0.69	0.65	0.75	0.69

Table 1: Market betas and R^2 for CAPM and FF5.

Across all five assets, adding Fama–French factors increases R^2 relative to the CAPM. The improvement is particularly strong for JPM and XOM, where the FF5 model captures a much larger share of the variation in daily excess returns. Market betas also adjust slightly when additional factors are included, reflecting the fact that some variation previously attributed to the market is better explained by size, value, profitability, or investment.

4.2 Alpha Estimates: Risk-Adjusted Performance

Table 2 reports the estimated CAPM and FF5 alphas (from the daily regressions), in percentage points per day.

Ticker	CAPM α	FF5 α
AAPL	0.065	0.042
JPM	0.016	0.029
XOM	0.009	0.023
WMT	0.050	0.037
XLV	-0.006	-0.013

Table 2: Estimated alphas (daily percent).

The alpha estimates are small in magnitude for all assets, and subsequent significance analysis (not shown in full here) indicates that these alphas are not strongly statistically different from zero once the relevant risk factors are included. In particular, moving from CAPM to FF5 does not uncover large, persistent abnormal returns. This is broadly consistent with the view that markets are approximately efficient: once risk is measured carefully, little systematic mispricing remains.

4.3 FF5 Factor Exposures and Significance

Table 3 presents the FF5 factor betas along with significance markers based on regression p–values. I use the standard thresholds: three stars for $p < 0.01$, two stars for $p < 0.05$, and one star for $p < 0.10$.

Ticker	MKT	SMB	HML	RMW	CMA	R^2
AAPL	1.26***	-0.12**	-0.63***	0.52***	0.62***	0.70
JPM	1.05***	-0.26***	1.16***	-0.30***	-0.51***	0.76
XOM	0.89***	-0.13*	0.96***	-0.50***	0.48***	0.55
WMT	0.53***	-0.16***	-0.21***	0.23***	0.43***	0.23
XLV	0.75***	-0.16***	-0.07**	0.03 (ns)	0.36***	0.69

Table 3: FF5 coefficients and significance. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Several patterns emerge:

- The value factor (HML) is systematically important. JPM and XOM have large positive HML betas, consistent with their interpretation as "value" or cyclical stocks. AAPL and WMT, in contrast, have negative HML betas, which is characteristic of growth or high–valuation firms.
- The size factor (SMB) coefficients are negative for all assets, reflecting the fact that these are large–cap securities or a large–cap ETF.
- The profitability factor (RMW) is significantly positive for AAPL and WMT, but essentially insignificant for XLV. This suggests that variations in profitability are more strongly priced for technology and retail than for healthcare.
- The investment factor (CMA) is positive and highly significant for most assets, indicating sensitivity to firms' investment policies.

The combination of strong factor significance and higher R^2 supports the idea that the FF5 model captures economically meaningful risk dimensions beyond the market factor alone.

4.4 Visual Evidence: Model Fit and Factor Structure

Figure 1 compares the R^2 from CAPM and FF5 for each asset.

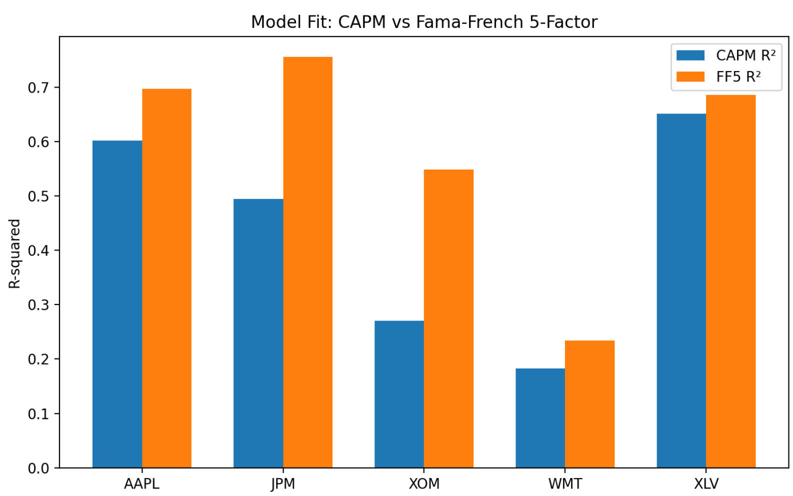

Figure 1: Model fit comparison: CAPM vs FF5.

The FF5 model delivers a consistent upward shift in R^2. JPM and XOM, in particular, are much better explained once size, value, profitability, and investment factors are incorporated.

Figure 2 compares market betas under CAPM and FF5.

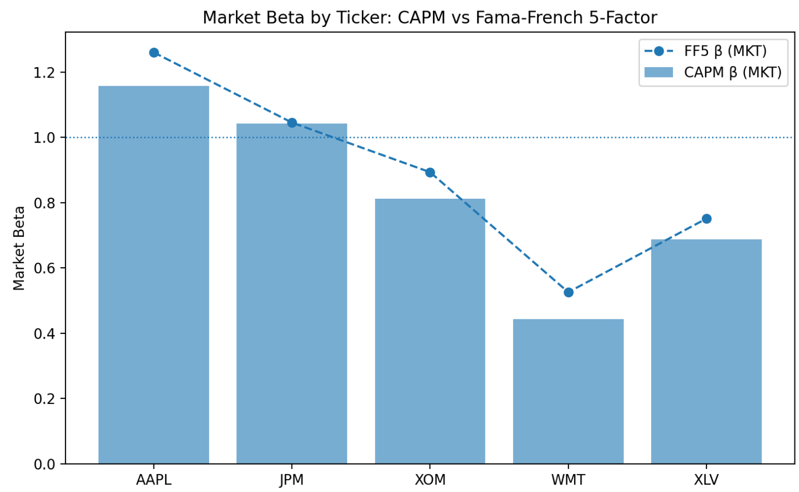

Figure 2: Market betas: CAPM vs FF5.

AAPL appears as a high–beta growth stock, while WMT and XLV exhibit lower market sensitivity. FF5 betas are slightly higher in some cases because the additional factors absorb part of the variation previously attributed solely to the market.

Finally, Figure 3 visualizes the non–market FF5 factor loadings by ticker.

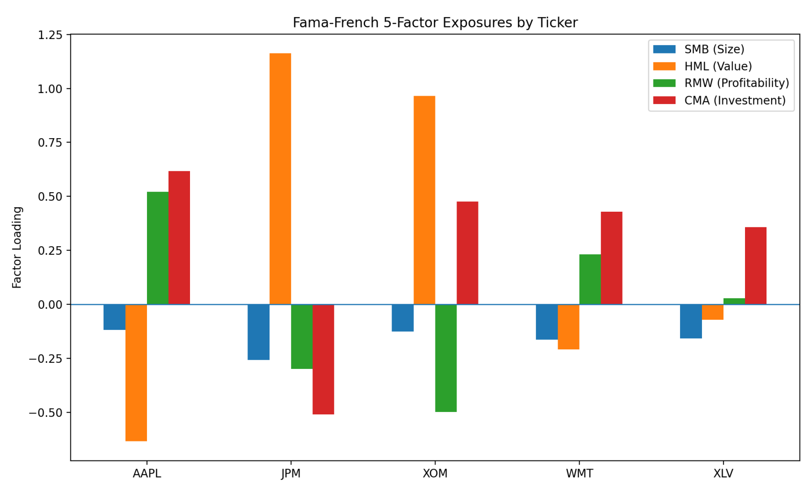

Figure 3: Fama–French factor exposures by asset.

This plot makes the sector narrative more tangible: JPM and XOM clearly stand out as value–oriented, while AAPL and WMT tilt toward growth and profitability, and XLV shows weaker profitability exposure.

5 Binomial Option Pricing Extension

To connect the equity return analysis to derivatives, I implement a binomial pricing model for Pfizer (PFE) options. The setup is:

- Underlying: PFE (Pfizer).
- Valuation date: 26 November 2025.
- Expiry date: 26 November 2026 ($T \approx 1$ year).
- Dividend yield: $q = 3\%$ per year.
- Risk–free rate: $r \approx 3.75\%$ (from `^IRX` Treasury data).
- Volatility: realized annualized volatility $\sigma \approx 28.31\%$ estimated from the last 20 trading days of PFE returns.
- Tree steps: $N = 500$.

Using this parameterization, I price European and American calls and puts for strikes 25, 26, and 27.

5.1 Option Pricing Results

Table 4 reports the resulting prices for the 20–day volatility window.

Strike	Euro Call	Amer Call	Euro Put	Amer Put
25	3.22	3.23	2.34	2.37
26	2.77	2.78	2.86	2.90
27	2.37	2.37	3.42	3.47

Table 4: PFE binomial pricing results (20–day volatility window).

American calls are only slightly more valuable than European calls, with early–exercise premia on the order of one cent. In contrast, American puts are meaningfully more valuable than European puts, with premia between roughly \$0.03 and \$0.05 across strikes.

This pattern is consistent with textbook theory: with dividends and long time to maturity, there is some value in being able to exercise a call early, but the effect is modest. For puts, the ability to exercise early when deep in the money can be more important, especially when rates and dividends affect the optimal exercise boundary.

6 Conclusion

The empirical evidence in this project supports three main conclusions:

- The Fama–French 5–factor model outperforms the CAPM in explaining daily excess returns for all five assets. R^2 is consistently higher under FF5, and factor loadings are statistically and economically meaningful.

- Factor exposures align closely with sector characteristics. AAPL and WMT resemble growth/profitable firms with negative value loadings, while JPM and XOM display strong value characteristics. The healthcare ETF XLV has moderate market beta and weaker profitability exposure.

- Alpha estimates are small and largely insignificant once risk factors are included, which is consistent with an approximately efficient market in which persistent abnormal returns are difficult to obtain.

The binomial pricing extension for PFE options further illustrates how equity return dynamics feed into derivative values. American options are more valuable than European options, especially on the put side, in line with theoretical predictions about early exercise and dividends.

Overall, the results highlight both the strengths and limitations of linear factor models in practice: they provide a rich language for decomposing risk, but do not uncover large, systematic mispricing in these assets over the sample period.

Implementation Notes

The full code and raw regression summaries are included with the project submission and can be used to replicate all results presented here.