Asset Pricing Models and Portfolio Selection: A Pragmatic Approach

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Abstract

Traditional asset pricing research often relies on theoretical portfolio constructions to test the explanatory power of models. In this study, we propose a novel and pragmatic approach: portfolios are constructed based on the actual stock selection guidelines of well-known, successful investors, translated into programmable, rule-based filters. These portfolios aim to resemble real-world investment strategies more closely than standard academic constructions. We then evaluate their performance using two of the most influential models in finance — the Capital Asset Pricing Model (CAPM) and the Fama-French three-factor model (FF3F) (Fama and French, 1996). The results reaffirm the superior explanatory power of the FF3F model. More importantly, they show that portfolios reflecting *growth investing* strategies align more closely with the predictions of both models than those based on *value investing* principles.

Keywords: Investment, Portfolio Management, Asset Pricing.

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1 Introduction

This paper proposes a pragmatic approach to the evaluation of asset pricing models by reversing the standard procedure found in most of the literature. Instead of testing theoretical models using stylized or artificially constructed portfolios, we assemble five portfolios based on the actual investment guidelines of five renowned investors, as described by Reese and Forehand (2009). These portfolios, designed to be feasibly traded in real-world conditions, are then evaluated under two foundational asset pricing frameworks: the Capital Asset Pricing Model (CAPM) and the Fama and French three-factor model (FF3F) (Fama and French, 1996). Our results offer new insights into the models' performance and limitations, while bridging the gap between academic theory and market-based investment strategies.

The field of asset pricing has long sought to explain how expected returns relate to risk factors. A seminal contribution came from Markowitz (1952), who showed that asset risk must be understood in a portfolio context. This laid the foundation for the CAPM, independently developed by Sharpe (1964), Lintner (1965), Mossin (1966), and Treynor (1961, 1962), which posits that only non-diversifiable, systematic risk should be priced.

Despite its elegance, the CAPM has been met with both methodological and empirical criticism. Roll (1977) argued that empirical tests of the CAPM are tautological unless the market portfolio is properly identified—which it rarely is. Hansen and Richard (1987) emphasized that the CAPM is inherently a conditional model, whereas most tests assume unconditional validity due to data limitations. These critiques are compounded by empirical anomalies such as the January effect (Banz, 1981; Moller and Zilca, 2008), the size effect (Roll, 1981; Reinganum, 1981), momentum (Jegadeesh and Titman, 1993; Asem, 2008), and return reversals (DeBondt and Thaler, 1985). More recent empirical investigations have challenged the robustness of traditional models in light of data-quality improvements and broader anomaly testing (Hou et al., 2020; Barillas and Shanken, 2018).

In response, more flexible models have emerged. The Arbitrage Pricing Theory (APT)

(Ross, 1976) and the Intertemporal CAPM (ICAPM) (Merton, 1973) broaden the scope of risk factors, incorporating macroeconomic or production-based variables (Lettau et al., 2019). In this context, Fama and French (1996) proposed a model that can be viewed either as an APT or an ICAPM, where expected returns are determined by three factors: the market return, the SMB factor ('small minus big," reflecting the excess return of small companies over big companies), and the HML factor (high minus low," reflecting the excess return of high book-to-market over low book-to-market firms). They showed that this three-factor model provides significantly greater explanatory power than the CAPM in the U.S. stock market. The Fama-French 3-factor (FF3F) model remains a widely used benchmark in empirical asset pricing research. More recently, Fama and French (2015) proposed an extension of their model to include profitability and investment factors, giving rise to the five-factor model. In this study, however, we focus on the original three-factor formulation, which remains a foundational benchmark and allows for greater comparability with prior empirical applications.

The sheer idea of asset pricing models indicating mispricings and market failures suggests a need for a more pragmatic approach. Portfolios actively traded in financial markets are shaped by a multitude of variables—not just prices and book values, but also investor heuristics, firm characteristics, and institutional constraints. Traditional empirical tests, such as those based on size and book-to-market ratios (Lettau and Ludvigson, 2001; Grauer and Janmaat, 2008; Asem, 2008), are analytically tractable but often detached from the actual behavior of market participants. Our study inverts the traditional approach in the asset pricing literature by first building portfolios that could be traded on the market and then checking how these portfolios perform under two key asset pricing models: the CAPM and the FF3F. This complements recent efforts to bridge theory and practice using demand-side models and robust factor selection frameworks (Koijen and Yogo, 2019; Bryzgalova et al., 2023).

Our results show that portfolios built following the *growth investing* philosophy are better explained by the CAPM and FF3F models than those aligned with *value investing*. Notably, the portfolio reflecting Warren Buffett's investment strategy achieves the highest risk-adjusted return among those evaluated. These findings provide an alternative lens through which to evaluate foundational asset pricing models—by testing them against portfolios grounded in real-world strategies. In doing so, we strengthen the connection between theoretical developments and practical applications in asset management.

The remainder of the paper is structured as follows: Section 2 details the methodology and the automated system developed to collect and process the data. Section 3 describes the five portfolios and the investment strategies behind them. Section 4 presents the empirical results using the CAPM and FF3F models, along with performance metrics. Section 5 concludes with a discussion of our main findings and their implications.

2 Methodology

Reese and Forehand (2009) provide objective and computationally implementable criteria for constructing portfolios based on the investment guidelines of famous investors. Strategies such as those attributed to Benjamin Graham and Warren Buffett were translated into rule-based filters that allow for asset selection using balance sheet information from publicly traded firms. We collected these data from Yahoo! Finance[1] and filtered them according to the strategy associated with each investor, building portfolios that reflect their respective investment styles. To automate this process, we developed software capable of retrieving, filtering, and organizing the relevant data, ultimately generating five portfolios that emulate the strategies described by Reese and Forehand (2009), in line with recent efforts to ground asset pricing models in actual portfolio behavior and investor demand systems (Koijen and Yogo, 2019).

[1] http://finance.yahoo.com

The software was written in C#, in response to the lack of freely available databases that include both stock prices and fundamental company data. Using a list of stock tickers from firms listed on the New York Stock Exchange (NYSE) and NASDAQ, the software accessed Yahoo! Finance and extracted balance sheet data from each company's page source code. For each company, 68 financial variables were retrieved. After scanning all 5,198 companies across the two exchanges, the software produced a comprehensive database.

Subsequently, the software applied five sets of filters to this database — each corresponding to the investment criteria of one of the selected investors: Benjamin Graham, John Neff, Warren Buffett, Peter Lynch, and Kenneth Fisher. A company was included in a given portfolio only if it satisfied all criteria associated with that investor's strategy. If any single variable fell outside the required range, the company was excluded.

Once the five portfolios were assembled, the software gathered historical monthly price data for each constituent asset via Yahoo! Finance. For each month, the average price of each asset was retrieved, and an equally weighted average was calculated to determine the monthly portfolio price. With the time series of monthly prices established, returns were computed accordingly.

We opted for equal weighting in the portfolio construction because Reese and Forehand (2009) does not provide guidance on portfolio weights. In the absence of a prescribed weighting scheme, equal weighting was deemed the most natural and transparent choice. We also chose Yahoo! Finance as our data source — rather than academic databases such as CRSP or COMPUSTAT — in order to maintain consistency between balance sheet and pricing data.

The final dataset included the monthly returns of each portfolio for the analysis period. To this, we appended the risk factors used in the CAPM and FF3F models, obtained from Kenneth French's online data library[2].

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

2.1 Database Characteristics and Reliability

Our comprehensive database comprises 5,198 stocks from the NYSE and NASDAQ, with 68 fundamental financial variables collected for each company as of January 18, 2010. Table 1 presents detailed descriptive statistics for each portfolio, demonstrating the reliability and representativeness of our data. The portfolios exhibit varying degrees of concentration, with the number of holdings ranging from 13 (Benjamin Graham) to 103 (Peter Lynch), reflecting both the stringency of the filtering criteria and the challenges in operationalizing certain qualitative investment principles.

Table 2 shows the market capitalization distribution across portfolios. A notable pattern emerges: most portfolios exhibit a strong tilt toward small-cap stocks, with 50–74% of holdings having market capitalization below $2 billion. This distribution reflects both the specific selection criteria of each investment strategy and the market conditions during the 2008–2010 period, when many larger firms experienced significant financial distress. The prevalence of small and mid-cap stocks in these portfolios is consistent with the investment philosophies being implemented—particularly for value-oriented strategies that seek undervalued opportunities often found among smaller companies.

We then evaluated each portfolio using the CAPM and FF3F model. The methodology follows the standard approach in the literature (Fama and French, 1996), involving the estimation of factor betas for each portfolio. We used the one-month Treasury bill as the risk-free asset — also from French's library — and the Dow Jones index as the proxy for the market return. Using these inputs, we estimated model coefficients via OLS regression on SAS for each portfolio and model, in a total of 10 regressions. Although more recent studies have proposed robust Bayesian frameworks to address model uncertainty and factor proliferation (Bryzgalova et al., 2023), we retain the classical OLS estimation to ensure comparability with seminal studies such as Fama and French (1996).

For each portfolio, we calculated the expected return under the CAPM and FF3F

Table 1: *Portfolio Descriptive Statistics*

Metric	BG	JN	WB	PL	KF
Number of Holdings	14	29	75	103	62
Market Capitalization (million USD)					
Mean	1,293	14,255	7,413	2,424	1,527
Median	577	1,260	1,750	831	619
Valuation Ratios					
Mean PE Ratio	10.77	29.20	15.88	16.62	22.32
Median PE Ratio	10.31	28.23	15.39	16.51	21.52
Mean P/B Ratio	1.38	2.87	4.06	2.13	3.10
Risk and Leverage					
Mean Beta	1.45	0.87	1.02	1.18	1.25
Mean Debt/Equity	0.13	0.62	0.14	0.08	−0.09
Profitability					
Mean ROE (%)	14.62	11.03	15.98	14.80	12.05
Size (million USD)					
Mean Revenue	992	7,435	2,835	1,746	873

Note: All statistics calculated as of January 18, 2010. BG = Benjamin Graham, JN = John Neff, WB = Warren Buffett, PL = Peter Lynch, KF = Kenneth Fisher.

models, along with the R^2 of the regressions. To assess performance deviations, we computed several common measures: Jensen's Alpha, Treynor Ratio, Sharpe Ratio, Sortino Ratio, and Sortino-Satchell Ratio.

Together, the analysis of these abnormal return measures and explanatory power (R^2) provides insight into how well each investment strategy aligns with the models. More broadly, it highlights which styles are better captured by standard asset pricing frameworks. As discussed in the introduction, this contributes to a more practical understanding of asset pricing models by grounding the analysis in portfolios that mirror real-world investment practices.

3 Portfolio Composition

The portfolios analyzed in this study are composed of stocks traded on the NYSE and NASDAQ. The data were obtained from Yahoo! Finance and aggregated using the software described in the previous section, which collected information on 5,198 stocks as of January 18, 2010. Benchmark returns for the CAPM and FF3F models were retrieved from Kenneth French's online data library.

The asset database was constructed as follows: for each stock, the software accessed its corresponding Yahoo! Finance page, extracted balance sheet information, and compiled the data into a unified dataset. This complete database was then filtered according to the screening rules originally developed by Reese and Forehand (2009), who translated the qualitative investment philosophies of ten prominent investors into quantitative criteria.

The filtering process resulted in five distinct portfolios,[3] each based on the investment guidelines of a renowned investor. Although the original framework includes ten strategies, we selected a representative subset of five, covering the two major investment styles: *value investing*, which emphasizes large firms, brand value, lower prices, and reduced risk; and *growth investing*, which favors smaller firms, higher risk, and greater potential for appreciation. Benjamin Graham, John Neff, and Warren Buffett are associated with value investing, while Peter Lynch and Kenneth Fisher are representative of growth-oriented strategies.

The rationale for selecting these investors, as well as the specific screening criteria applied in each case, are detailed below. All portfolios were constructed using the quantitative rules derived from the approach introduced earlier in this section.

Table 2 presents the market capitalization distribution across portfolios, revealing important size characteristics that influence portfolio behavior and model fit. The concentration of holdings in different size categories reflects the distinct investment philosophies: value-oriented portfolios (BG, JN, WB) show greater exposure to mid- and large-cap stocks, while growth-oriented portfolios (PL, KF) exhibit stronger small-cap bias. This distribution pattern aligns with the theoretical foundations of each strategy and has implications for the explanatory power of asset pricing models, as discussed in Section 4.

[3] See Appendix A.

Table 2: *Market Capitalization Distribution by Portfolio*

Portfolio	Small Cap (< \$2B)		Mid Cap (\$2B–\$10B)		Large Cap (> \$10B)	
	N	%	N	%	N	%
BG	10	71.4	4	28.6	0	0.0
JN	18	62.1	6	20.7	5	17.2
WB	38	50.7	26	34.7	11	14.7
PL	67	65.0	30	29.1	6	5.8
KF	46	74.2	15	24.2	1	1.6
Value (BG+JN+WB)	66	55.9	36	30.5	16	13.6
Growth (PL+KF)	113	68.5	45	27.3	7	4.2

Note: Market capitalization categories based on values as of January 18, 2010. Small cap: market cap < \$2 billion; Mid cap: \$2–\$10 billion; Large cap: > \$10 billion. The table shows both the absolute number (N) and percentage of holdings in each category. The bottom rows aggregate portfolios by investment style.

3.1 Benjamin Graham (1894–1976)

Benjamin Graham is widely regarded as a pioneer of value investing. Between 1936 and 1956, his investment approach yielded an average annual return of 20%, compared to a market average of 12.2% over the same period. Known for emphasizing capital preservation and low-risk strategies, Graham advocated for investing in companies that offered a substantial *margin of safety*—that is, a significant gap between the market price and the company's intrinsic value.

The BG portfolio was constructed using the Graham-based screening rules outlined earlier. It consisted of 13 assets that satisfied the following criteria:

- Exclude technology companies;
- Sales equal to or greater than US\$ 340 million;
- Current ratio (current assets divided by current liabilities) of at least 2 (utilities and telecommunications companies may have a lower ratio);
- Long-term debt less than or equal to net current assets;

- EPS growth of at least 30% over the past five years, with no negative annual value;
- PE ratio of 15 or lower;
- Product of PE and PB ratios not exceeding 22;
- DE ratio of no more than 100% (230% for utilities or telecommunications companies).

3.2 John Neff (1931–2019)

John Neff is another notable proponent of value investing. From 1964 to 1995, his strategy delivered an average annual return of 13.7%, surpassing the market's 10.6%. Like Graham, Neff prioritized capital preservation and focused on companies with temporarily low stock prices but strong underlying fundamentals.

The JN portfolio comprised 27 assets that met the following conditions:

- PE ratio between 40% and 60% of the market average;
- EPS growth between 7% and 20%;
- Estimated long-term EPS growth greater than 6%;
- Sales growth at least 70% of the EPS growth and no less than 7% in absolute terms;
- Return-to-PE ratio at least twice the market or industry average;
- Positive cash flow;
- Quarterly EPS higher than the same quarter in the previous year.

3.3 Warren Buffett (1930–)

Warren Buffett is widely recognized as one of the most successful investors of all time. Between 1980 and 2003, his investments outperformed the market in 20 out of 24 years. A disciple of Benjamin Graham, Buffett favors companies with simple products, strong brands, and long-term value.

Using Buffett-style criteria, the WB portfolio included 73 assets. The high number of constituents reflects the difficulty in operationalizing qualitative aspects like brand strength. In practice, Buffett maintains a more concentrated portfolio — for example, as of Q4 2024, Berkshire Hathaway held only 38 equity positions, with the top 10 accounting for nearly 90% of portfolio value.[4]

The selection criteria applied were:

- EPS non-negative and increasing for the last 10 years;
- Long-term debt $\leq 2\times$ earnings;
- Average ROE $\geq 15\%$ (10 years);
- Average ROTC $\geq 12\%$ (10 years);
- Positive cash flow;
- Use of retained earnings $\geq 15\%$;
- EPS/Price $\geq$ return of government bonds;
- Expected return by ROE and EPS methods $\geq 15\%$;
- Average expected return $\geq 15\%$.

3.4 Peter Lynch (1944–)

Peter Lynch is known for his growth-oriented approach, with average returns of 29.2% from 1977 to 1990. He favored companies with high growth potential and recognizable products, even at moderate valuations.

The PL portfolio, based on Lynch's strategy, included 89 assets. This large num-

[4]Source: WhaleWisdom, `https://whalewisdom.com/filer/berkshire-hathaway-inc`

ber reflects the challenge of filtering for qualitative features like consumer familiarity. The selection rules distinguished between fast growers, stalwarts, and slow growers:

- PEG ratio > 0 and ≤ 0.5 (tolerated up to 1);
- Inventory-to-sales ratio variation ≤ 0;
- Debt-to-equity ratio $\leq 30\%$ (tolerated up to 50%);
- **Fast growers:**
  - Sales $>$ US$ 1 billion;
  - PE ≤ 40;
  - EPS growth between 20–25%.
- **Stalwarts:**
  - Sales $\geq$ US$ 1.9 billion;
  - Positive EPS.
- **Slow growers:**
  - Sales $>$ US$ 1 billion;
  - Return $>$ S&P 500 and $\geq 3\%$.

3.5 Kenneth Fisher (1950–)

Kenneth Fisher's growth investing strategy delivered an average annual return of 13% between 1995 and 2007. He emphasized sales over earnings, reasoning that popularity (proxied by sales) may signal future earnings strength.

The KF portfolio consisted of 57 assets meeting the following criteria:

- PS ratio ≤ 0.75 (tolerated up to 1.5) for tech/non-cyclicals;

- PS ≤ 0.4 (tolerated up to 0.8) for cyclicals;
- Debt-to-equity $\leq 40\%$;
- Price-to-R&D ≤ 5 (tolerated up to 10);
- EPS growth $> 15\%$;
- Positive cash flow;
- Net profit margin $\geq 5\%$ (3-year average).

4 Empirical Tests

We estimated the CAPM and the Fama-French three-factor (FF3F) model for the five portfolios constructed in the previous section. Each portfolio's price was calculated as the equally weighted average of the prices of its constituent assets.

The analysis used average monthly prices from January 2007 to January 2010,[5] along with the market, SMB, and HML factors obtained from Kenneth French's online data library. The excess market return ($R_m - R_f$) was also sourced from the same library. We estimated the factor betas for each portfolio using Ordinary Least Squares (OLS), with all regressions conducted in SAS.

Table 3 summarizes the results of the CAPM and FF3F model estimations for each portfolio. For each specification, we report the estimated coefficients, their standard errors, and the R^2 values. Adjusted R^2 values were also computed and found to be very close to the unadjusted R^2, and are therefore omitted from the table for conciseness. As expected, the FF3F model consistently outperforms the CAPM in explanatory power. However, the CAPM also performed reasonably well, with R^2 values above 0.60 across all portfolios.

The KF portfolio showed the highest explanatory power under both models, with

[5] Using data prior to 2007 would result in significantly smaller portfolios, as many selected companies only became publicly traded after 2006.

94% of its return variation explained by the FF3F factors. Conversely, the BG portfolio had the lowest R^2, likely due to its smaller number of assets (13). The market factor ($R_m - R_f$) remained the most significant explanatory variable in both models, which helps explain the relatively strong performance of the CAPM.

Among the five portfolios, BG, JN, and WB follow value investing strategies, while PL and KF reflect growth investing philosophies. On average, the value portfolios yielded an adjusted R^2 of 0.70 under the CAPM and 0.74 under the FF3F; in contrast, the growth portfolios yielded averages of 0.87 and 0.90, respectively.

Table 3: *Estimated coefficients and R^2 values for the CAPM and FF3F models.*

Portfolio	**Model**	$\boldsymbol{\beta_{Rm-Rf}}$	$\boldsymbol{\beta_{SMB}}$	$\boldsymbol{\beta_{HML}}$	$\boldsymbol{R^2}$
BG	CAPM	1.32 (0.17)	–	–	0.61
	FF3F	1.25 (0.19)	1.12 (0.38)	-0.30 (0.22)	0.69
JN	CAPM	0.87 (0.09)	–	–	0.71
	FF3F	0.76 (0.11)	-0.09 (0.22)	0.23 (0.12)	0.74
WB	CAPM	0.96 (0.07)	–	–	0.82
	FF3F	1.04 (0.08)	0.37 (0.16)	-0.30 (0.09)	0.87
PL	CAPM	1.08 (0.07)	–	–	0.86
	FF3F	1.09 (0.08)	1.38 (0.17)	-0.17 (0.09)	0.88
KF	CAPM	1.15 (0.06)	–	–	0.90
	FF3F	1.17 (0.06)	0.52 (0.12)	-0.24 (0.07)	0.94

Note: Standard errors are shown in parentheses.

The signs and magnitudes of the SMB and HML coefficients also reflect portfolio characteristics. A positive SMB coefficient indicates alignment with small-cap stock behavior. For example, the BG portfolio exhibited a high SMB coefficient, suggesting that it includes primarily smaller companies.[6] While this seems at odds with value investing, it may reflect

[6]Indeed, the BG portfolio contained only five companies with a market capitalization above US$1 billion

the market conditions of the time, including the 2008 financial crisis.

These findings suggest that growth investing strategies are more closely aligned with the FF3F factors ($R_m - R_f$), SMB, and HML. This may be due to the composition of the overall market. As illustrated by the S&P 500 Pure Style Indexes, the Pure Growth index included 117 companies with a total adjusted market capitalization of US$1.44 trillion as of August 25, 2010, while the Pure Value index had only 100 companies with a combined adjusted market cap of US$792.76 billion.[7]The dominance of growth-oriented firms may help explain why both models perform better when applied to portfolios based on growth investing principles.

The performance of the portfolios was evaluated using standard measures of return anomalies — i.e., the extent to which actual returns deviate from model-predicted values. We computed the Jensen's Alpha (α), the Treynor Ratio (T), and the Sharpe Ratio (S), all based on the CAPM. Jensen's Alpha represents the difference between observed and predicted returns. The Treynor Ratio evaluates the observed excess return relative to systematic risk (beta), and the Sharpe Ratio considers return relative to total volatility. These measures are defined as follows:

$$\begin{aligned}
\alpha &= ER_i - [R_f + \beta_i(ER_m - R_f)] \\
T &= \frac{ER_i - R_f}{\beta_i} \\
S &= \frac{E[R_i - R_f]}{\sqrt{E[(R_i - R_f)^2]}}
\end{aligned} \tag{1}$$

as of August 2010.

[7]See https://www.spglobal.com/spdji/en/indices/equity/sp-500-pure-growth/ for the S&P 500 Pure Growth Index and https://www.spglobal.com/spdji/en/indices/equity/sp-500-pure-value/ for the S&P 500 Pure Value Index.

Despite their popularity, these metrics treat positive and negative deviations equally, although investors typically dislike downside volatility more than upside. To address this limitation, we also computed the Sortino Ratio and the more general Sortino-Satchell Ratio (SS), which penalize only returns below a defined threshold (here, the risk-free rate). The general formula is:

$$SS = \frac{E[R_i - R_f]}{\left(E[(R_i - R_f)_-^q]\right)^{1/q}} \tag{2}$$

When $q = 2$, this corresponds to the traditional Sortino Ratio; we also computed the SS ratio with $q = 3$.

Table 4: *Performance measures for the five portfolios (01/2007 to 01/2010).*

Metric (%)	**BG**	**JN**	**WB**	**PL**	**KF**
Average return	-0.271	0.317	0.917	0.263	0.476
CAPM expected return	-0.158	0.065	0.020	-0.039	-0.074
Jensen's Alpha	-0.112	0.252	0.896	0.302	0.550
Treynor Ratio	-0.584	-0.209	0.434	-0.218	-0.020
Sharpe Ratio	-0.080	-0.031	0.068	-0.035	-0.003
Sortino Ratio	-0.069	-0.025	0.058	-0.029	-0.003
Sortino-Satchell ($q = 3$)	-0.059	-0.022	0.050	-0.025	-0.002

The WB portfolio achieved the highest average return (0.92%) over the period analyzed. Notably, the market return during this period was negative (-0.5%), and the CAPM-predicted return for WB was only 0.02%. As a result, WB displayed the highest values across nearly all performance measures.

Interestingly, although the BG portfolio had the worst average return, it recorded the highest absolute values for downside-sensitive measures such as the Sortino and Sortino-Satchell ratios. This outcome is consistent with the fact that its beta under the CAPM was 1.32 — indicating high exposure to market fluctuations. During a negative-return period, such sensitivity translated into both underperformance and elevated downside risk.

Across all metrics, the ranking of portfolio performance remained largely consistent, with minor shifts between the JN and PL portfolios. While PL scored higher in Jensen's Alpha, JN performed better in the Treynor Ratio—reflecting the fact that PL's higher beta amplified the perceived risk in the Treynor framework.

Overall, the KF portfolio exhibited the lowest anomaly measures in absolute terms, indicating the best alignment with the CAPM model. In contrast, the WB and BG portfolios deviated most strongly from model predictions—positively in the case of WB, negatively in the case of BG. To visualize this comparison, Table 5 ranks the portfolios according to each metric.

Table 5: *Portfolio ranking by performance measure (1 = best, 5 = worst).*

Portfolio	**Jensen's Alpha**	**Treynor**	**Sharpe**	**Sortino**	**Sortino-Satchell**
WB	1st	1st	1st	1st	1st
KF	2nd	2nd	2nd	2nd	2nd
PL	3rd	4th	4th	4th	4th
JN	4th	3rd	3rd	3rd	3rd
BG	5th	5th	5th	5th	5th

Assuming the CAPM and FF3F are valid models of expected return, the WB portfolio demonstrated the best performance relative to its risk. It consistently outperformed model predictions, followed by the KF portfolio as the second-best strategy.

For comparison, we also constructed a benchmark portfolio using a mean-variance optimization procedure implemented via Bloomberg Professional. This portfolio—based on the same universe of assets—produced an average return of -0.16%, with a standard deviation of 5.2%. Jensen's Alpha for this benchmark was 0.31%, Treynor Ratio was -0.187%, Sharpe Ratio was -0.03%, Sortino Ratio was 0.33%, and the Sortino-Satchell Ratio ($q = 3$) was 0.25%. These results suggest that, relative to this naive benchmark, the investor-based portfolios (particularly WB and KF) offered superior performance.

5 Conclusion

This study evaluated two of the most widely recognized asset pricing models — CAPM and the Fama-French three-factor (FF3F) model — using portfolios constructed in a more pragmatic and realistic fashion. Rather than relying on stylized, theory-driven portfolios, we based our construction on the actual investment strategies of well-known investors. This approach, still rare in the asset pricing literature, seeks to bridge the gap between academic theory and real-world portfolio selection.

Our results indicate that both models — particularly the FF3F — performed well in explaining the expected returns of these investor-inspired portfolios. The strong explanatory power observed suggests that these models may be more robust than previously acknowledged, especially when applied to portfolios that better reflect practical investment processes. Moreover, the results point to potential mispricing and investment opportunities arising from deviations between model predictions and observed returns.

Notably, portfolios based on the growth investing philosophy, such as those inspired by Kenneth Fisher and Peter Lynch, were significantly better explained by the models compared to those aligned with value investing. This may reflect the composition of the market, or signal temporary deviations that could revert over time. Among all, the Warren Buffett-based portfolio exhibited the highest level of anomalous returns — an indication of potential excess performance relative to model expectations.

These findings open several avenues for future research. Other asset pricing models, including multifactor extensions and behavioral frameworks, can be applied to similarly constructed portfolios. It would also be valuable to explore strategies based on additional investors, time periods, or international contexts. Furthermore, the use of alternative risk and performance metrics may offer new insights into model accuracy and return anomalies.

In sum, our results suggest that asset pricing models — when tested on portfolios grounded in real investment strategies — may yield new perspectives on their validity and limitations. Greater alignment between empirical testing and practical portfolio construction has the potential to improve both theoretical understanding and real-world applicability in asset pricing research.

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The authors used artificial intelligence tools to assist with manuscript preparation and data analysis. ChatGPT (OpenAI) assisted with English language editing, manuscript structure, and academic writing style. Claude (Anthropic) assisted with data analysis, Python code development for data collection, statistical table formatting, and technical methodology descriptions. All AI-generated content was thoroughly reviewed, verified, fact-checked, and edited by the authors. The research design, theoretical framework, model selection, data interpretation, and all scientific conclusions are entirely the work of the named authors, who take full responsibility for the accuracy and integrity of this work.

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