

Quantitative Trading and Five Classic Stock Factors

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Abstract. This paper discusses three classical kinds of quantitative trading: the high-frequency trading, arbitrage, and factor investing. It then tests five well-known stock factors on the S&P 500 over 24 months, from August 2024 to August 2026. Only momentum clearly made money, gaining 16.9% a year with a Sharpe ratio of 0.84. Value gained 3.1% and size 0.8%, which is close to nothing given how much both swung. The quality lost 14.2% and low volatility lost 31.4%. The market explains much of this. It was a strong bull market, but a narrow one, and the wildest stocks rose 48% a year while the calmest rose only 6.5%. Sorting stocks inside their own industry lifts value to 12.0% and size to 8.4%, so the plain sorts were partly bets on industries. Two years is a short test. These results mostly show how easily a short window can hide a long-run pattern.

Keywords: quantitative trading, high-frequency trading, arbitrage, factor investing, momentum

1. Introduction

A quantitative investor writes a rule first, then applies it to hundreds of stocks at once. The rule can be simple, such as "buy the cheapest 20% of stocks", or complex, such as a machine learning model fed with live trading data. The big advantage is that a rule can be tested. It can be run over thirty years of old data to see what would have happened, and an opinion cannot be checked that way. A rule also scales, because the same code works for fifty stocks or five thousand. There is a catch. A rule that is easy to test is also easy to fit too closely to the past. Try enough rules and a few will look great by pure luck. Telling luck apart from a real effect is the hardest part of this field.

2. Three families of quantitative trading

2.1. High-frequency trading (HFT)

HFT firms hold a stock for microseconds to minutes, and usually keep nothing overnight. Three common methods are:

- Market making. Post a buy price and a sell price, then earn the small gap between them. The risk is being left holding stock nobody wants. HFT firms have mostly taken this job over from human traders [1].

- Speed arbitrage. The same stock trades on several exchanges. If the price updates faster on one of them, a fast trader can profit from the slower one. Each trade earns a fraction of a cent.

•Very short prediction. Patterns in live buy and sell orders can hint at the next few price moves. These hints last only seconds.

The contest here is about equipment, not clever ideas, and none of it is something an outsider can test.

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2.2. Arbitrage

Riskless arbitrage can occur in the real world. It translates to purchasing a product at one place and selling exactly the same product at another for a higher price. Opportunities such as these disappear as soon as there's awareness of them. The question is why these 'near misses' take so long. The answer – as in the usual case – is that correcting an incorrect price requires funds, funds require borrowing and borrowing takes time, as [2] states. The trader may lose out if the gap will widen before closing up .

In exchange for a lot more opportunities, the statistical arbitrage moves to a risk zone. The classic case is the pair trading. A trader identifies two stocks that tend to follow each other and when they diverge, he or she expects them to converge again. The risk is that the old connection has just snapped and won't be reconnected ever again.

2.3. Factor investing

Factor investing involves scoring the entire market on a single factor (such as cheapness, past performance, company size, profitability or calmness) and allocating money towards the top of the list. There is very little trading and a large amount of money can be run this way, since positions are held for months or years. It is also the only out of the 3 that a student can study at home for free data, so that's why most of this paper is about it, as shown in Table 1.

Table 1. Rules to format sections

	HFT	Arbitrage	Factor investing
Holding time	microseconds to minutes	minutes to weeks	months to years
Where the edge comes from	speed and equipment	prices that do not match	patterns that last
How much money it fits	very little	small	very large
How hard it is to start	almost impossible	hard	easy in theory
Main risk	technology and new rules	the link breaks	the pattern stops working

2.4. Common problems

All three end up fighting the same four problems.

1.A test on past data pretends the market never had this money in it, so it always flatters the result.

2. Costs eat the edge. An edge of 0.3% a month that costs 0.4% a month is not an edge at all.
3. Self-deception is easy. Search long enough and something will turn up that looks good but is only noise.
4. Edges fade. Once a method is known, money floods in and the returns drop.

3. Factor investing in depth

3.1. From one factor to many

The initial approach taken was the Capital Asset Pricing Model [3]. It claimed that the only thing that's a good predictor of a stock's return is beta – how responsive the stock is to the overall market. The rationale for it was that "all the news is in the price" and nothing else can assist.

Then there were exceptions. According to [4], the findings demonstrated that small businesses made higher profits than beta. Fama and French added a third factor - cheap stocks - to their stature of size and value and subsequently added profits and investments [5, 6]. Jegadeesh and Titman originated from the idea of momentum [7], which the authors found that stocks which had a positive performance over the last twelve months were likely to re-rate. That was followed by low volatility and quality [8].

By about 2015 there were far too many factors. Hundreds of them had been published, and many of them are likely false; for if you try out enough ideas, some of them are going to look good by accident. This pile is today known as the "factor zoo".

Table 2. The usual suspects

Factor	How it is measured	What it claims
Market	owning stocks at all	stocks beat cash
Size	company value, flipped	small firms beat big firms
Value	book value over market value	cheap beats expensive
Momentum	return over the past 12 months, skipping the last one	winners keep winning
Quality	profit against book value	profitable beats unprofitable
Low volatility	past ups and downs, flipped	calm beats wild, once risk is allowed for

For size and low volatility, the claim is that being small or calm is the thing that pays, so the sign is flipped on both. As Table 2 shows, a high score always means the "good" end.

3.2. Why factors might work

Here there are three common narratives and each has an entirely different resonance.

The first is risk. Cheap stocks are often cheap for a reason, and during a recession, small companies tend to fail easily; the increased return is just a reward for owning an asset that could be damaged during a downturn. The second is human error. Investors overpay for hot stocks, underreact to bad news and go for a long shot like they would go for a lottery ticket [9]. People with such habits remain as long as such habits. The third is the industry itself. Fund managers are being

compared to an index which incentivizes them to buy riskier stocks, while the list of dates to buy and sell are pre-determined by index rules.

Likely a combination of all three – with differing proportions of all three for various factors.

3.3. Reasons to be careful

Other work should make anyone cautious.

1. Most findings do not repeat. Hou, Xue and Zhang re-tested 452 published effects and 65% of them failed [10]. Low volatility sits on their failure list [8].

2. Published effects get weaker. Returns drop once a method appears in a journal and other people copy it [11].

3. Even a real effect can fail for years. Value did badly through most of the 2010s, yet the long-run evidence for value is strong.

3.4. Building a factor test

The standard steps are:

1. Pick the stocks. Using today's index list is unfair, because the failed companies have already dropped out of it.

2. Use only data that was public. A number for 31 December is not out on that day. Using it early means peeking at the future.

3. Build the signal. Cut off the crazy values and put everything on one scale.

4. Build the portfolios. Sort the stocks into five groups, give each stock the same weight, then redo it every month.

5. Judge the result. Look at the return, the risk, and whether the ranking matched what happened next.

6. Count the costs. How much trading there is, times what a trade costs.

Section 4 follows these steps.

4. Experiment

Table 3. Dataset and back-test specification

Item	Detail
Stocks	Today's S&P 500, 503 tickers
Prices	Daily closing prices, 813 trading days, June 2023 to August 2026
Company numbers	4 years of annual reports and 5 quarters per company
Test window	24 monthly rebuilds, August 2024 to July 2026
Stocks each month	494 to 498 with book value; 436 to 445 with profit data

Three choices about the data mattered a lot. Only data that was already public. Each report is pushed forward by a delay: 120 days for annual numbers and 75 days for quarterly ones. That way only figures published before the sort get used.

Positive book value. 33 companies have negative book value, mostly because they bought back their own shares, which makes their value and quality scores meaningless. They are left out of those two sorts.

As shown in Table 3 and Table 4, a company's market value shares times price, but the two numbers come from different places. Berkshire Hathaway's filing lists about 1.4 million Class A shares while the price series is for Class B, which gave a trillion-dollar company a value of \$0.74 billion. As a check, the market value worked out from shares and price is compared with the reported figure, and any ticker off by more than double is dropped. Four fails: BRK-B, IBKR, MNST and TKO.

Table 4. Factor definitions

Factor	How it is measured	A high score means
Value	book value ÷ market value	cheap
Momentum	return from 12 months ago to 1 month ago	rose recently
Size	−log(market value)	small
Quality	last year's profit ÷ book value	profitable
LowVol	−(how much the price moved over 252 days)	calm

4.1. Method

The same four steps run every month. First the top and bottom 1% of each signal are cut off, so one strange stock cannot take over. Then the signals go onto a common scale. Then the stocks are sorted into five equal groups. Each group is held for one month, with the same amount of money in every stock. The factor return is the top group minus the bottom group.

There is also a check on the ranking itself. Each month the order of the signal is compared with the order of the returns that came after it. A score near zero means the ranking said nothing.

Two points about the maths are worth spelling out. The first is the Sharpe ratio, which compares return against risk. A long-short trade borrows one dollar and lends one dollar, so its return is already an extra return and is measured against zero, while the buy-only portfolios and SPY use a 4% cash rate instead. The second is that two return numbers appear in the tables. "Yearly return" compounds the average month, while "CAGR" compounds the months that really happened, and when a series jumps around a lot the two pull apart.

All the returns leave out trading costs. Section 4.3 deals with those on their own.

4.2. Results

Q5 below is the top fifth of the stocks and Q1 is the bottom fifth, as shown in Table 5 and Table 6.

Table 5. Top fifth minus bottom fifth (Q5 – Q1), 24 months

Factor	Yearly return %	CAGR %	Volatility %	Sharpe e	Worst drop %	Winning months %	Rank score
Value	3.06	2.22	13.11	0.23	−10.6	45.8	0.027
Momentum	16.94	15.01	18.73	0.84	−16.3	62.5	0.020
Size	0.80	0.41	8.99	0.09	−9.7	50.0	0.002
Quality	−14.21	−14.34	5.61	−2.71	−26.5	25.0	−0.024

Table 5. (continued)

LowVol	-31.45	-33.55	24.77	-1.50	-58.1	29.2	-0.076
All five mixed	-3.49	-4.70	16.08	-0.22	-19.0	50.0	-0.005
SPY, just held	18.69	17.83	12.58	1.06	-7.6	66.7	—

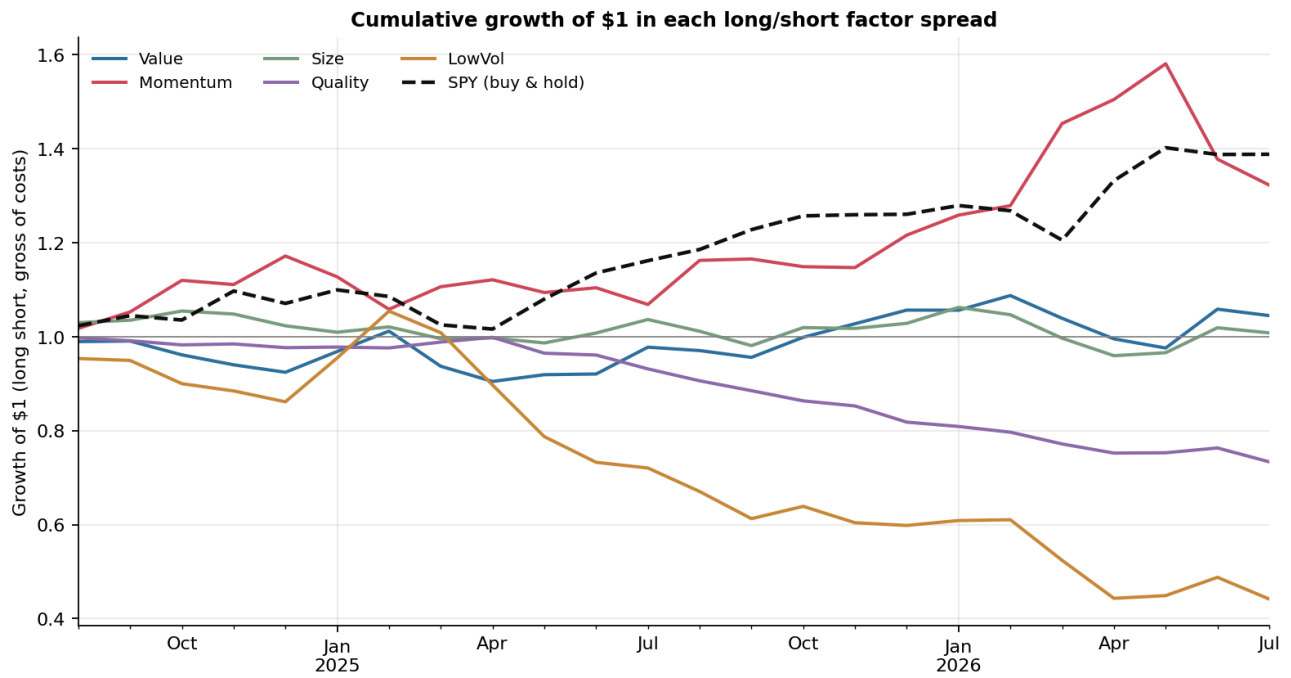


Figure 1. Cumulative growth of \$1

Table 6. Average monthly return of each group (%)

Factor	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Value	1.650	1.412	1.006	1.314	1.902	0.251
Momentum	1.149	1.187	0.933	1.386	2.462	1.312
Size	1.587	1.466	1.224	1.352	1.653	0.066
Quality	2.501	1.015	1.378	1.240	1.232	-1.269
LowVol	3.625	1.305	1.132	0.558	0.527	-3.098
All five mixed	1.852	1.284	1.328	1.295	1.557	-0.296

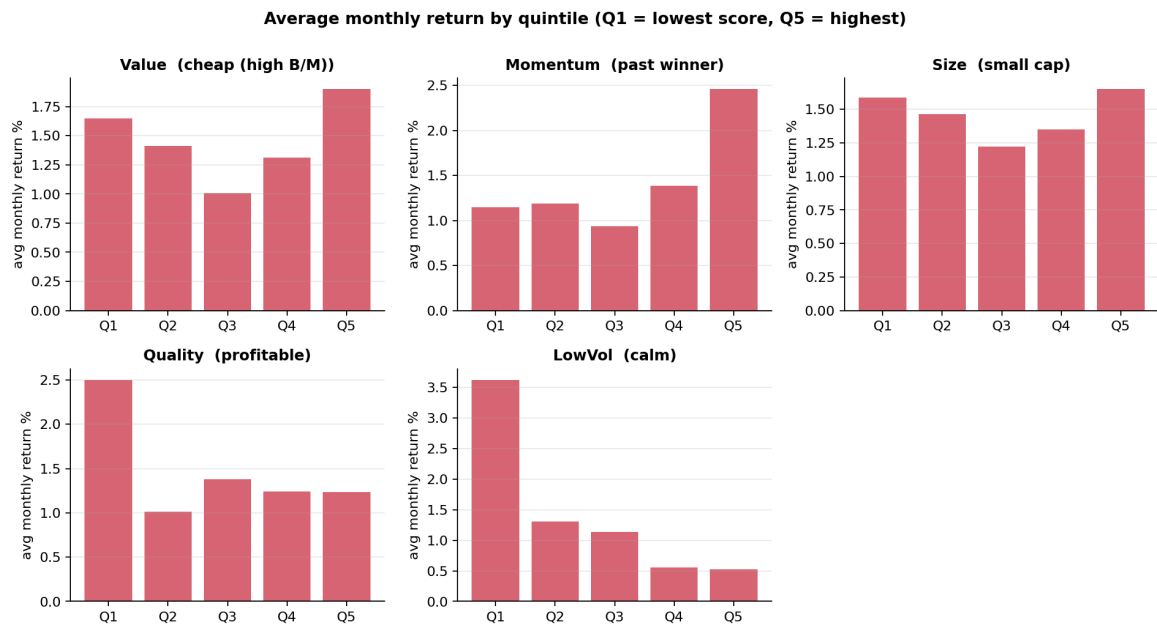


Figure 2. Average monthly return quintile

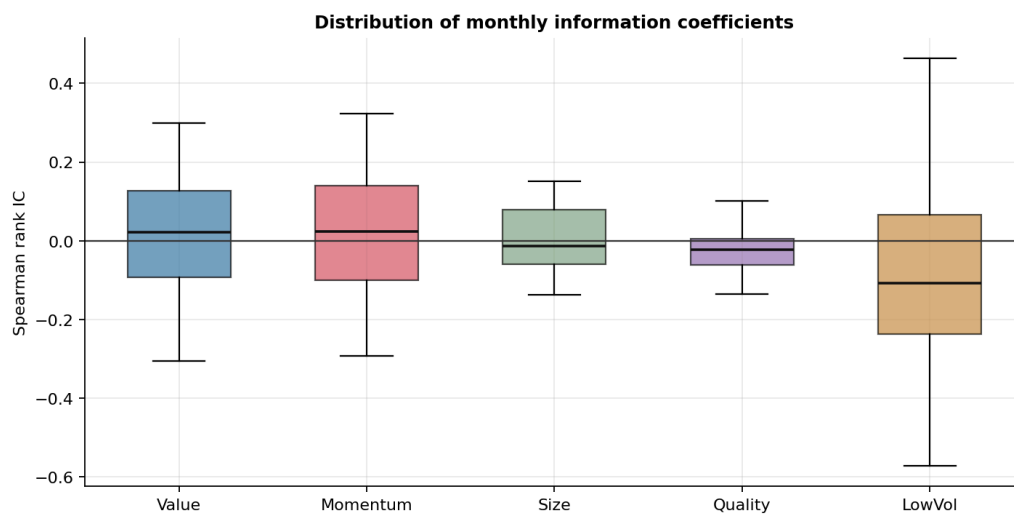


Figure 3. Distribution of monthly information coefficients

As shown in Figure 1, Figure 2, and Figure 3. There are few things stand out, as follows:

1. Momentum did what the books say it should. The return climbs from group to group, and 62.5% of the months were positive.
2. Quality and low volatility went the wrong way, and badly. The bottom group beat the top group by a wide margin, and quality won in only a quarter of the months.
3. Value's ladder bends in the middle. The cheapest fifth did best at 1.90% a month, but the priciest fifth came second at 1.65%. A factor that works should not look like that, as shown in Figure 4.
4. Mixing all five made things worse. One good factor plus two bad ones mostly cancel out.

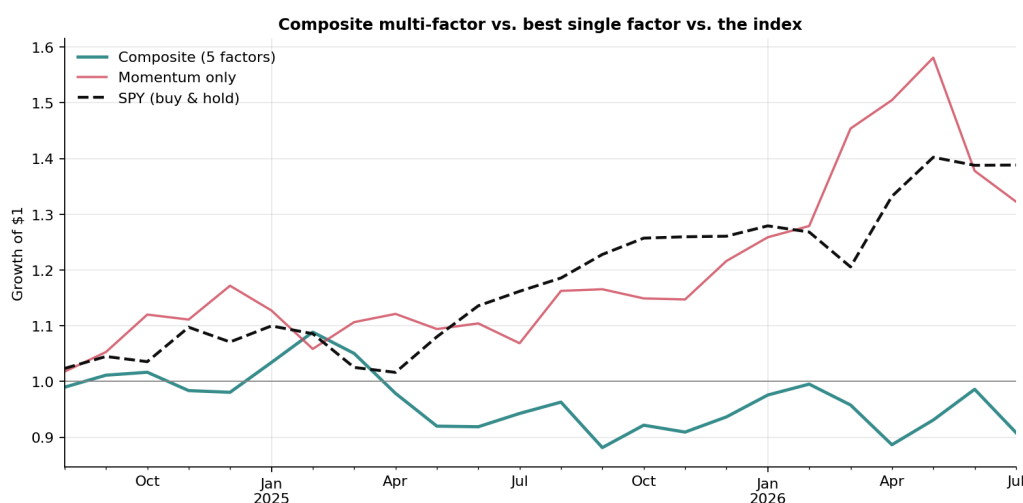


Figure 4. Composite multi-factor vs. best single factor vs. the index

4.3. Extra checks

Sorting inside each industry. Here each stock is scored against the others in its own industry group, not against the whole index, as shown in Table 7 and Table 8.

Table 7. Plain sort against industry sort

Factor	Return, plain	Sharpe, plain	Return, by industry	Sharpe, by industry
Value	3.06	0.23	12.04	1.19
Momentum	16.94	0.84	18.34	0.94
Size	0.80	0.09	8.42	1.14
Quality	-14.21	-2.71	-15.58	-2.07
LowVol	-31.45	-1.50	-26.01	-1.54
All five mixed	-3.49	-0.22	2.11	0.19

Value jumps from 3.1% to 12.0% and size from 0.8% to 8.4%, so the plain sorts were mostly bets on industries. Cheap industries such as banks and energy were cancelling out the stock picking. Quality and low volatility do not improve, so their problem lies somewhere else. Even so, 24 months is too short to trust these nicer numbers either.

Table 8. Trading and the cost each factor could afford

Factor	Monthly trading %	Trades per year	Break-even per trade (bp)	Break-even round trip (bp)
Value	12.0	1.4×	107	213
Momentum	42.8	5.1×	165	330
Size	8.8	1.1×	38	76
All five mixed	25.7	3.1×	—	—

A bp, or basis point, is one hundredth of a percent. These break-even levels are well above what a large fund would normally pay to trade big US stocks, so costs alone would not have killed any of these.

4.4. Buy-only results

Trading long and short needs short selling, which most ordinary people cannot do. So what happens if the top fifth is simply bought and held?

Table 9. Top fifth, buy only, against SPY

Factor	Yearly return %	Volatility %	Sharpe	Beat SPY by (points)
Momentum	33.89	20.42	1.25	+15.20
Value	25.37	12.79	1.48	+6.67
Size	21.74	12.54	1.27	+3.04
All five mixed	20.36	12.19	1.21	+1.67
Quality	15.83	12.29	0.88	-2.86
LowVol	6.52	11.27	0.21	-12.18

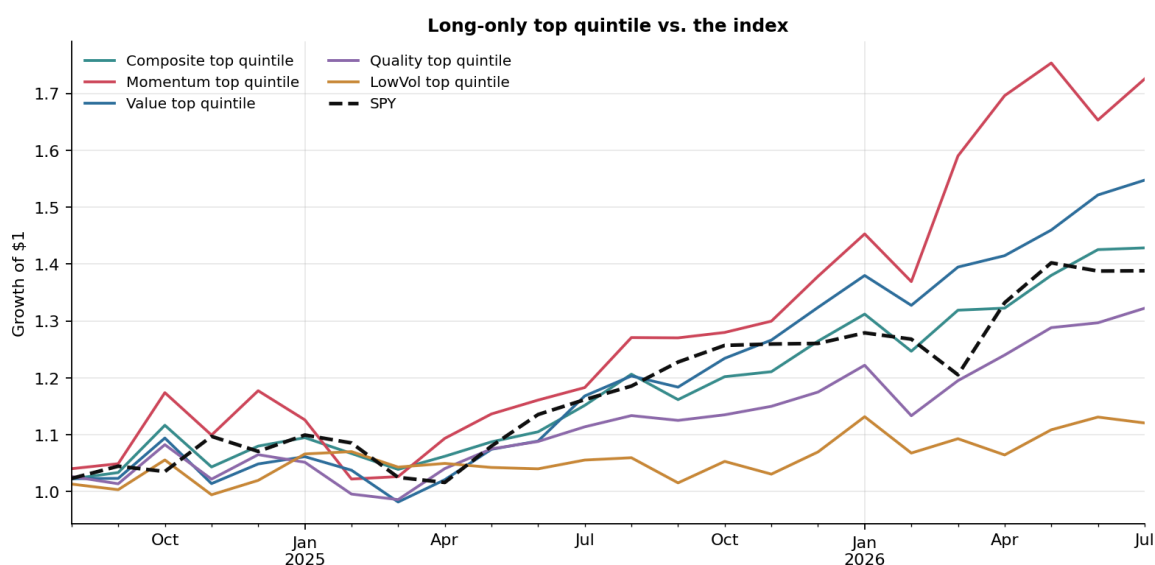


Figure 5. Composite multi-factor vs. best single factor vs. the index

As shown in Table 9, the order here is not the same as in Table 5, because in a rising market the short side is expensive. Value looked flat in Table 5, yet its top fifth still beat SPY by 6.7 points, as shown in Figure 5.

4.5. What the market was doing

Table 10. The market over the test window

Measure	Value
SPY return per year	18.7% (CAGR 17.8%)
SPY volatility	12.6%
Months the index rose	67%
Best and worst month	+10.5% and −5.6%

Table 11. Industry returns (total %)

Industry	Total return %
Information Technology	+134.8
Communication Services	+64.1
Energy	+51.7
Industrials	+39.9
Financials	+39.2
Consumer Discretionary	+28.8
Utilities	+23.3
Materials	+20.9
Health Care	+14.9
Consumer Staples	+6.6
Real Estate	+5.8

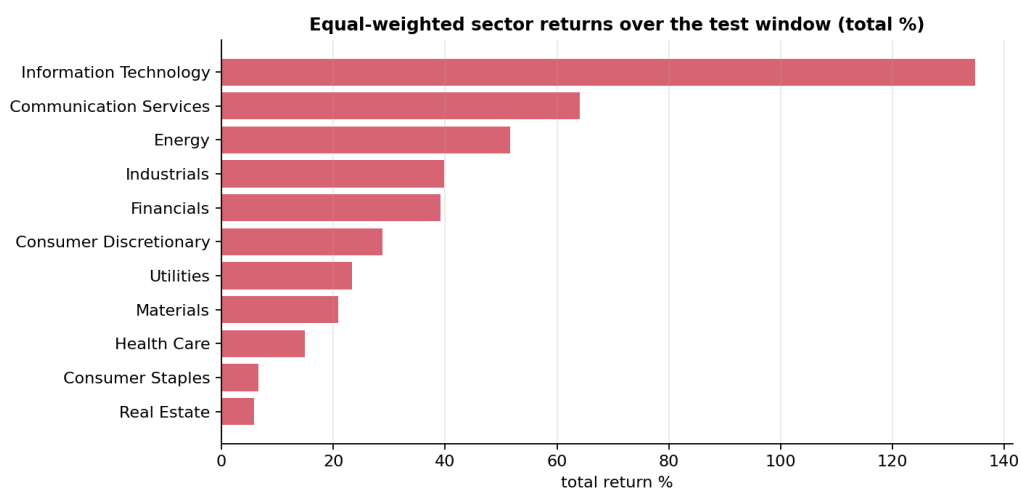


Figure 6. Equal-weighted sector returns over the test window

As shown in Figure 6, this was a strong bull market, but a narrow one. Technology more than doubled while food and household names hardly moved, as shown in Table 10, Table 11, and Table 12. One very simple test makes the point:

Table 12. Bought in August 2024 and held to August 2026

Basket	Return per year
The wildest fifth of stocks	48.0%
The calmest fifth of stocks	6.5%
Gap	41.5 points

5. Discussion

Read Table 5 on its own and the easy conclusion is that the research is wrong. That reading is too quick.

A factor edge is a small tendency measured over decades. For value the long-run edge is a few percent a year, but the value trade here bounced around by 13.1% a year, and there are only 24 months of it. The noise is far bigger than the signal. Two years cannot prove or kill a long-run pattern. It can only show what happened in one particular two-year stretch.

The period was also an odd one, as Section 4.5 shows. Quality and low volatility are defensive ideas, and defensive stocks lose badly in a rally led by risky names. Quality winning in only 25% of months is exactly what that looks like, and it fits the risk story in Section 3.2.

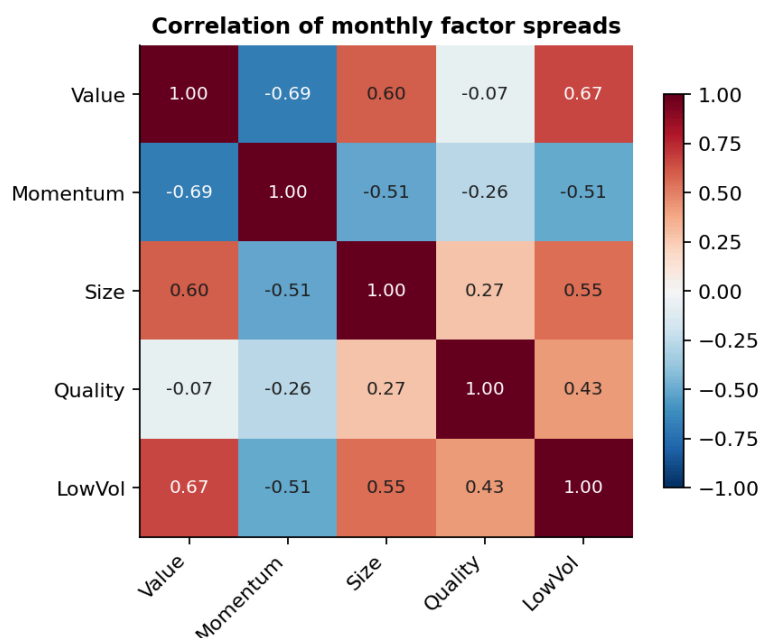


Figure 7. Composite multi-factor vs. best single factor vs. the index

This resulted in a couple of other things. The sorting within the industries was the largest contributor to a shift in the answer, with value rising from 3.1% to 12.0% when looked at against peers in each industry. But the cleaning of the data was as significant as the notion being tested, as Berkshire was in the bottom and smallest basket for all 24 months, which is obviously crazy. Then

the five factor mix was wrong – two of the five factors were negative. It is only when all bets are guaranteed returners that one may profit from spreading bets.

The correlation chart matches the textbooks as shown in Figure 7. Value and momentum move against each other (-0.69), while value and low volatility move together ($+0.67$). In this window, "cheap" and "calm" were nearly the same set of stocks.

6. Limitations

There are following limitations:

1. The stock list is today's list, so companies dropped from the S&P 500 never show up at all. That flatters the results.
2. 2 years is too short to determine anything.
3. The last month runs 27 days but counts as a full one.
4. Trading costs sit outside the returns. Table 8 works them out on the side.
5. Everything comes from one place, Yahoo Finance through yfinance, and free company data has errors in it.
6. Prices are adjusted for dividends, so market value comes out a little too low early in the window for firms that pay them.
7. Sometimes profit is derived from an annual report that is as much as eleven months out-of-date.
8. For the companies that have two tickers, such as GOOG/GOOGL, FOX/FOXA and NWS/NWSA, they are counted twice.

7. Conclusion

This paper looked at three kinds of quantitative trading. HFT competes on speed, arbitrage hunts for prices that do not line up, and factor investing gets by on patience and size. They are very different jobs, but they hit the same four problems set out in Section 2.4.

In the test here, one factor worked: momentum returned 16.9% a year. Value and size came out near zero, and quality and low volatility lost money. None of that proves the research wrong. It is better read as one extreme bull market in which the safe bets did badly.

The real lesson is how much the answer hangs on small choices made along the way: the reporting delay, whether the sort happens inside industries, even the way a Sharpe ratio is worked out. Change one of them and the table changes. Above all it hangs on which two years get tested, and the two here were simply the ones with data available.

References

- [1] Menkveld, A. J. (2013). High frequency trading and the new market makers. *Journal of Financial Markets*, 16(4), 712–740.
- [2] Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, 52(1), 35–55.
- [3] Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, 19(3), 425–442.
- [4] Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3–18.
- [5] Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3–56.
- [6] Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1–22.

- [7] Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48(1), 65–91.
- [8] Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance*, 61(1), 259–299.
- [9] Barberis, N., & Thaler, R. (2004). A survey of behavioral finance. In Constantinides, G. M., Harris, M., & Stulz, R. M. (Eds.), *Handbook of the Economics of Finance, Vol. 1B*, Chapter 18, Elsevier, 1053–1128.
- [10] Hou, K., Xue, C., & Zhang, L. (2018). Replicating anomalies. *Review of Financial Studies*, 33(5), 2019–2133.
- [11] McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, 71(1), 5–32.