Replicating an Asset Allocation Mode

Testing Two Award-Winning Allocation Papers

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Hi there. A paid subscriber recently asked if I could replicate two award-winning allocation papers that claim to deliver extraordinary Sharpe ratios and returns with ve mild drawdowns. The papers build on an elegant rotation framework, ranking assets such as sector ETFs by multiple signals and combining them with a hedging portfolio meant to protect against turbulent periods and black-swan events.

I took up the challenge, ran the data, and quickly found myself unable to replicate the main results, just as the subscriber had struggled as well. However, despite my very different replication results, I find the rotation signals interesting and useful in a broa allocation framework.

More below on the two papers, how I tested the models, what the results look like, an how the sector rotation signals still can be useful…

Background

The two papers, written by Gioele Giordano, are titled *Ranked Asset Allocation* (201 and *Antifragile Asset Allocation Model* (2019). Both papers have received awards: Or received the Charles H. Dow Award in 2018, the other received the NAAIM Wagner Award in 2019. At their core, they propose a systematic allocation model designed t be “antifragile”, able to outperform in normal markets but also withstand shocks. Th framework consists of two parts: A growth sleeve that rotates among ETFs (most oft sector ETFs) using a composite of predictive signals, and, in the 2019 version, a hedging sleeve that aims to counteract equity drawdowns during turbulent periods Together, the model is presented as a way to capture upside while limiting downsid

The 2018 version reports a Sharpe of 1.94 for the period July 2004 to November 20 experiencing only one down year. The 2019 version achieves a Sharpe ratio of 2.53, again with only one down year, in 2015. Hence, both papers report unusually smoot return streams, piquing one’s interest in replicating the results.

Signals and Portfolio Construction in the Papers

The allocation model in the two papers relies on four signals, each designed to capt a different aspect of market behavior.

- **Momentum:** Absolute momentum measured over the past four months, using simple rate of change. Assets with stronger momentum receive higher ranks.
- **Volatility:** Estimated with a GARCH model. Lower-volatility assets are ranked m favorably.
- **Correlation:** For each ETF, the average correlation with all other ETFs in the universe is calculated. Assets with lower average correlation are preferred, since they add diversification.
- **Trend:** A "trend strength" metric based on an upper and lower band, where the "*upper band = 42 periods ATR + Highest Close of 63 periods and the lower band 42 periods ATR + Highest Low of 105 periods*". This formulation is unusual, and i not entirely clear how it was implemented in practice, but it is meant to capture whether the asset is trading strongly relative to recent extremes.

The 2018 paper applies this framework to a universe of 12 broad ETFs spanning multiple asset classes, U.S. sectors, bonds, commodities, and currencies. Each ETF is ranked on the four signals, and the average of the ranks forms its overall score. At each month-end rebalance, the top five ETFs are selected for the portfolio, providec they show positive absolute momentum; if not, their allocation is redirected to cash

The 2019 follow-up develops the approach further by splitting it into two portfolios The first is a sector rotation portfolio, based on 11 U.S. sector ETFs and managed wi the same four-signal ranking process as above. The second is a "Black Swan Hedgin Portfolio" designed to perform during periods of market stress. It consists of gold, Treasuries, the Swiss franc, the Japanese yen, and a short S&P 500 ETF.

At each rebalance, if one of the top-ranked sectors fails the absolute momentum fil its weight is redirected into the hedging sleeve instead of cash. This way, the strateç

maintains full capital deployment into growth sectors when conditions are favorabl
or into defensive hedges when momentum turns negative.

My Replication Results

When I applied these rules to adjusted-close ETF data from EODHD, my results diverged substantially from those in the papers. Instead of Sharpe ratios above 2 wi shallow drawdowns, I found Sharpe ratios closer to 0.6–0.7, with drawdowns about three times larger and a drawdown-to-volatility ratio of roughly 2.

It's not entirely clear what drives this large discrepancy. The subscriber who original suggested these papers also found results far from those in the papers, which sugg the issue isn't just in my replication. Part of the gap may stem from the ambiguity ir how the trend signal is defined, though this alone is unlikely to explain such a wide performance difference. Another factor may be the data source. The papers rely on Yahoo Finance and note: *"Where necessary, interpolations have been made with consistent historical series in order to achieve temporal homogeneity."* In practice, suc interpolation can artificially smooth returns, reduce measured volatility, and boost Sharpe ratios, though the exact impact here is uncertain.

Either way, the stellar performance reported in the papers did not carry over when tested with proper ETF data.

Still, I find the rotation signals themselves potentially useful, which is why I decided test them further in a different context.

My Modifications and Testing Framewor

Building on the four signals described above, I adjust the definitions to make them more robust and easier to replicate in practice. I then test the framework on the 11 SPDR sector ETFs.

- **Momentum:** Absolute momentum measured over the past 21, 63, 126, and 252 trading days, using a simple rate of change. The values are averaged across horizons, with stronger momentum receiving higher ranks.
- **Volatility:** Historical volatility calculated over the same four lookback windows and averaged. In practice, this produces results very similar to a GARCH estimat but with greater transparency. Lower-volatility assets are ranked more favorably
- **Correlation:** For each ETF, the average correlation with all other ETFs in the universe is computed over 21, 63, 126, and 252 days and then averaged. Assets with lower average correlation are preferred for their diversification potential.
- **Trend:** Redefined as the ratio of the most recent closing price to its rolling high over the past 21, 63, 126, and 252 days, averaged across horizons. Assets tradin closer to their highs are ranked better.

These modifications preserve the spirit of the original signals but make the implementation clearer, more transparent, and less prone to data-snooping effects.

Data and Methodology

I test the signals on adjusted-close ETF data from EODHD covering the period from December 1999 to August 2025. The universe consists of the SPDR sector ETFs: XLC XLY, XLP, XLE, XLF, XLV, XLI, XLB, XLRE, XLK, and XLU.

Rebalancing is performed at the end of each month, using information available up and including the day before month-end. Each ETF is ranked on the four signals, an the average of these ranks determines its overall score. The top five ETFs are then selected and allocated equal weights. To qualify for inclusion, an ETF must also disp positive absolute momentum; otherwise, its allocation is shifted into cash, which ea the 3-month T-bill rate. A one-way transaction cost of 5 basis points is applied.

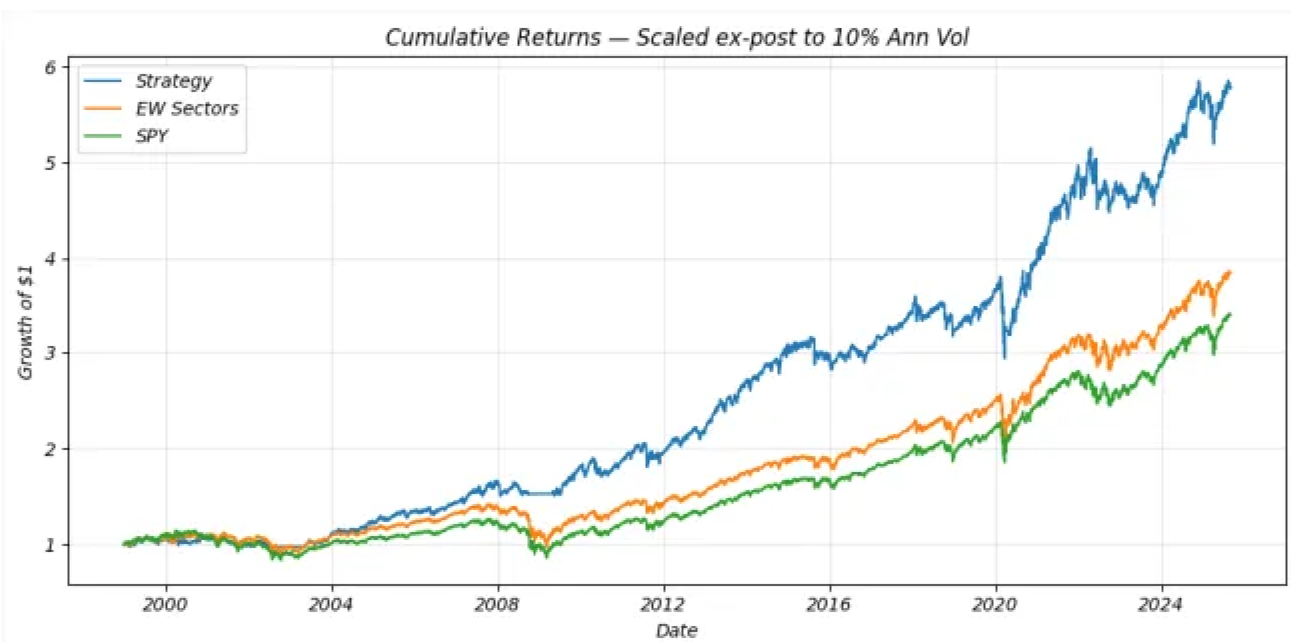
Results

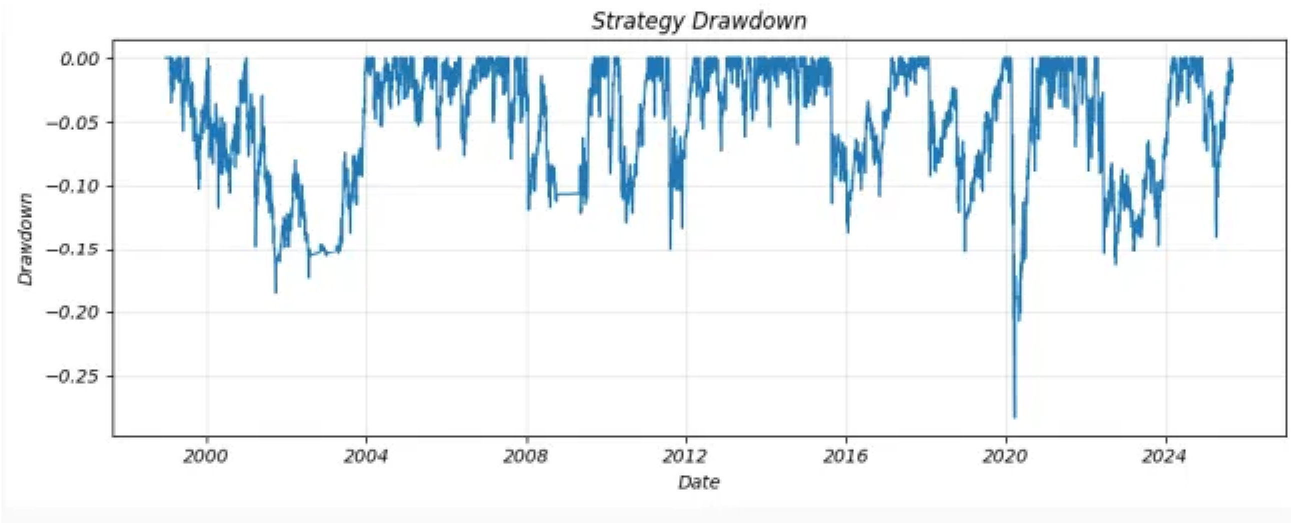
I evaluate each signal individually and then combine them into a single composite r
for each ETF.

=== Summary Stats: Single Signals vs Composite vs Benchmarks ===

	CAGR_%	AnnVol_%	Sharpe	MaxDD_%	DD/Vol
Momentum only	8.67	14.72	0.55	-31.67	-2.15
Vol only	6.37	10.91	0.50	-24.08	-2.21
Corr only	7.37	11.07	0.58	-26.20	-2.37
Trend only	7.90	12.90	0.55	-25.47	-1.97
All 4 (Composite)	8.51	12.66	0.60	-28.30	-2.24
EW Sectors	7.86	15.90	0.47	-46.19	-2.90
SPY	8.38	19.42	0.44	-55.19	-2.84

Individually, the four signals deliver Sharpe ratios between 0.50 and 0.58, with drawdown-to-volatility ratios slightly above 2. When combined, by averaging the ra across all signals, the strategy achieves a Sharpe ratio of 0.60. This composite appro clearly outperforms both an equal-weighted sector portfolio and SPY, while also delivering meaningfully smaller drawdowns.





If any of the top five-ranked ETFs fail the positive absolute momentum filter, their allocations are redirected to cash. As a result, the strategy's cash exposure fluctuate considerably over time.

Overall, applying these four relatively simple signals to sector ETFs and combining them produces returns that outperform both SPY and an equal-weighted sector portfolio.

That said, while the strategy's drawdowns are smaller than those of the benchmarks maximum drawdown above 20% may still be uncomfortable for many investors. On way to address this is to use the sector rotation strategy as a *fallback asset* within th defensive-first model I have discussed in earlier posts, here and here.

Adding Sector Rotation to the Defensive-First Model

I won't go into full details on the defensive-first framework here (see earlier posts), in short, it combines a fallback asset, often SPY or a leveraged version, with five defensive assets that have low correlation to equities: TLT, GLD, DBC, UUP, and BTAI

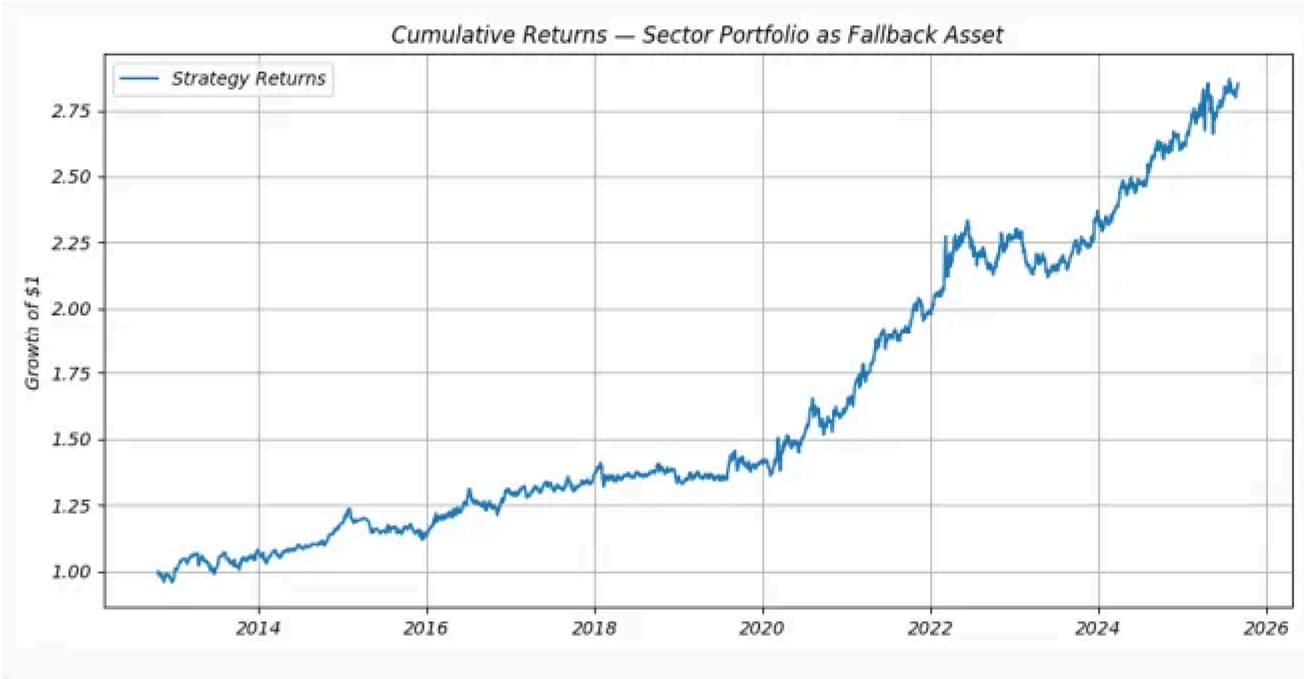
In this test, I replace SPY as the fallback with the sector rotation strategy described above. Whenever any of the defensive assets show momentum weaker than the risk free rate, that portion of the allocation is redirected into the sector rotation sleeve.

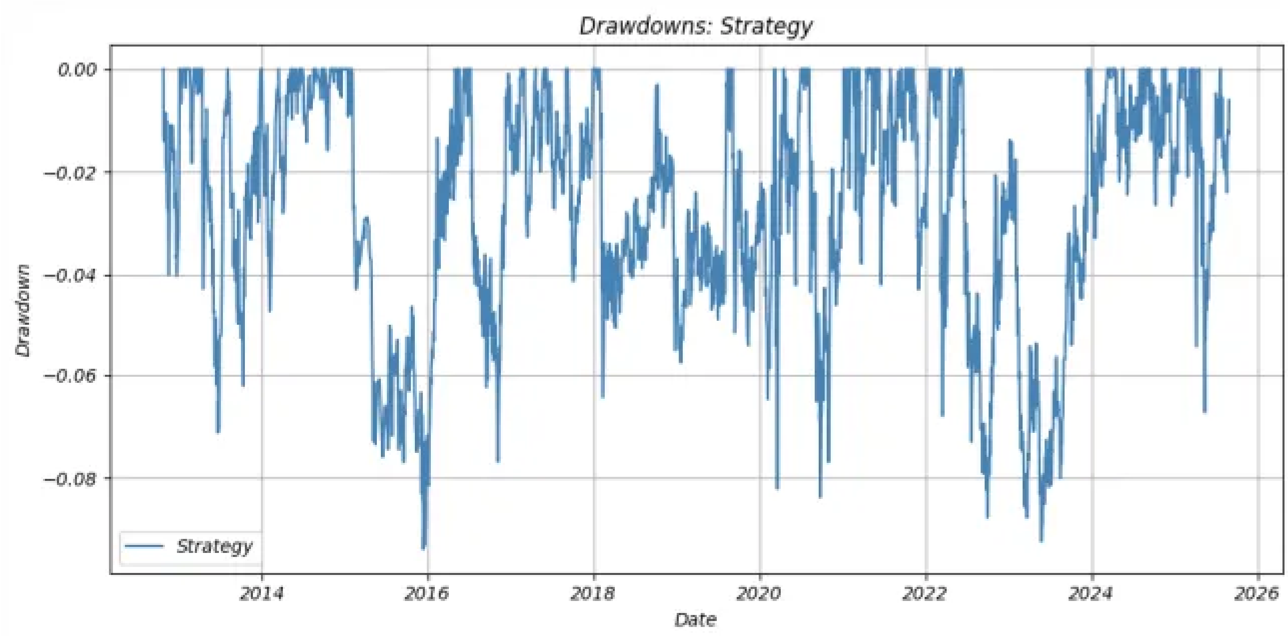
The results are encouraging. The combined model delivers a Sharpe ratio of 0.93 an CAGR of 9.5%, with a maximum drawdown of only about 9%. That's higher risk-adjusted performance and materially smaller drawdowns than SPY. During the 2022 bear market, the model gained 14%, demonstrating its ability to pivot into defensiv assets when they are most needed. Year-to-date in 2025, it is up roughly 9%. In addition, the strategy has a very low correlation of 0.2 to SPY.

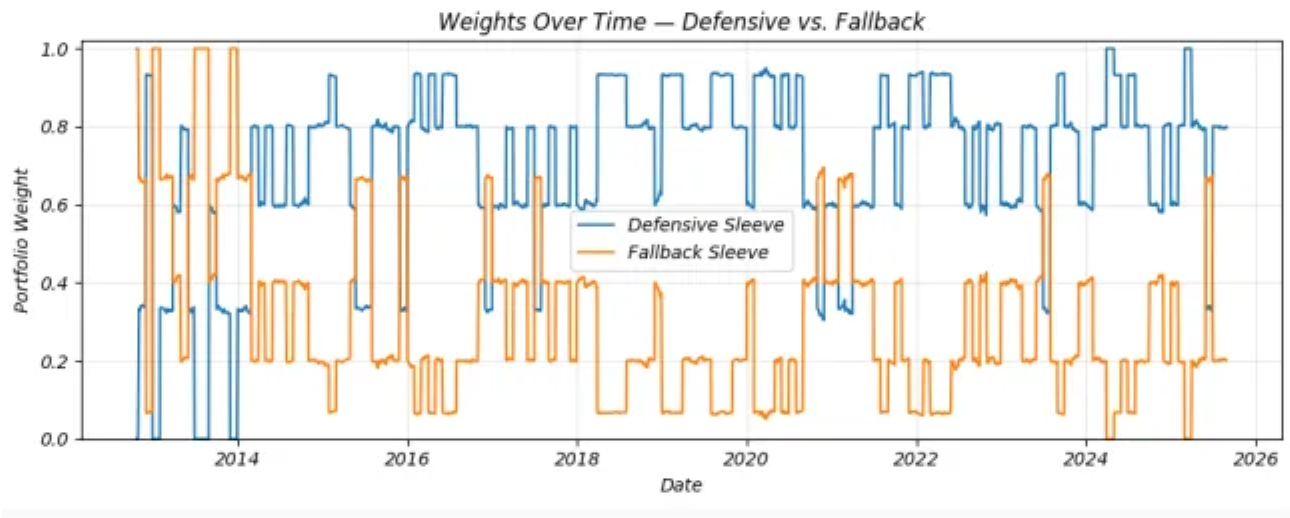
	Strategy	SPY
CAGR	9.51	16.19
Ann. Volatility	8.91	17.93
Max Drawdown	-9.38	-33.72
Sharpe Ratio	0.93	0.86
Correlation with SPY	0.20	1.00
Drawdown-to-Vol Ratio	-1.05	-1.88

Annual Returns:

Date	Strategy	SPY
2012	-3.19	-1.66
2013	11.68	33.92
2014	9.35	15.61
2015	-3.87	-0.17
2016	13.73	12.00
2017	5.61	21.71
2018	-0.75	-4.57
2019	3.91	31.22
2020	15.38	18.33
2021	22.49	28.73
2022	14.10	-18.18
2023	3.77	26.18
2024	10.95	24.89
2025	9.18	10.72


Cumulative Returns — Sector Portfolio as Fallback Asset
Strategy Returns
Growth of $1
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
2014
2016
2018
2020
2022
2024
2026


Drawdowns: Strategy
0.00
−0.02
−0.04
−0.06
−0.08
Drawdown
Strategy
2014
2016
2018
2020
2022
2024
2026
Date



The weight plot shows that the model is currently allocated 20% to the sector rotati strategy (the 'fallback sleeve') and 80% to the defensive assets.

Conclusions

Bottom line: I couldn't reproduce the papers' "near-frictionless" Sharpe >2 results. T said, the underlying framework, multi-horizon momentum, volatility, correlation, an transparent trend proxy, does add real value for sector rotation. As a standalone, though, the strategy's drawdowns (approaching ~25-30%) would likely be unacceptable for many investors. Used as a sleeve within a defensive portfolio, it lo more compelling: In my tests, pairing sector rotation with defensive assets lifts risk-adjusted returns, delivering ~9.5% CAGR with ~9% max drawdown and a higher Sharpe than the market.

I plan to keep refining this sector rotation approach, with the goal of potentially making it a model portfolio in the future. The broader takeaway is simple: Treat exceptional backtests with caution. Many are difficult, or impossible, to replicate outside the author's exact setup. Instead, focus on implementations that are simple auditable, and resilient to small specification changes.

If you do manage to reproduce the original paper's results, I'd love to hear how you did it. :)

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References

Giordano, Gioele, 2018, Ranked Asset Allocation Model, Charles H. Dow Award, Working Paper.

Giordano, Gioele, 2019, Antifragile asset allocation model, NAAIM Wagner Award, Working Paper.

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Discussion about this post

AA AA Sep 6

Good stuff. Not the same thing, but this reminded me of this [https://allocatesmartly.com/financi
mentors-optimum3-strategy/]

LIKE REPLY

1 reply by QuantSeeker

Flo Sep 6

Great content! What are your thoughts about the hedging sleeve from the second paper?

LIKE REPLY

1 reply by QuantSeeker

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