Diversify the Decisions, Not Just the Assets

A Practical Architecture for Dynamic Asset Allocation When Strategy Choice Is Uncertain

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Abstract

Diversification usually starts with assets, but a multi-strategy portfolio can remain concentrated if its rules respond to markets in similar ways. Dynamic asset allocation can adapt to changing market evidence without requiring a precise forecast of the next regime, yet many practical rules are variations on the same momentum idea. A portfolio can therefore hold several strategies and still depend on much the same decision logic.

This paper examines diversification at the decision level: what each rule holds, when it changes, and how much risk it takes. We use Autonomous Dynamic Asset Allocation (ADAA) as an empirical case, comparing published allocation rules with their investable adaptations and asking whether the resulting sleeves continue to make meaningfully different portfolio decisions.

In a June 2008-July 2026 historical simulation using a common ETF sample, the five ADAA sleeves differ materially in holdings, transition timing, and defensive exposure, even when return correlations are high. A separate comparison of 16 published allocation rules, based only on portfolio decisions and not performance, places the five-rule portfolio documented in the 2023 analysis above most of the possible five-rule combinations while also revealing redundancy within the original set.

Weight-robustness analysis shows that many materially different sleeve allocations produce similar risk-adjusted outcomes and that estimated optimal weights vary across samples. ADAA does not outperform the strongest standalone sleeve over the full sample and does not protect in every stress episode. The evidence supports a modest practical conclusion: diversification should extend to the decision process, and a multi-rule portfolio should not depend on identifying either the future winning rule or one precise set of sleeve weights.

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1. Start With a Response, Not a Forecast

Dynamic allocation starts from a simple ambition: take less risk when the evidence weakens without pretending to know exactly when the next regime begins.

Momentum is one practical answer. It replaces the question, 'What will happen next?' with a more observable one: 'Is this exposure still being rewarded, or has the evidence changed?'

> ***Takeaway.*** *The aim is not to call the turn. It is to decide in advance how the portfolio will respond when the evidence changes.*

A systematic rule cannot see the future either. Its advantage is more modest but practical: the response is specified before the next market story arrives. That makes the process easier to review, reduces the scope for after-the-fact changes, and makes failures easier to identify.

In ADAA, 'autonomous' means rule-governed rather than discretionary: the response rules are specified in advance. It does not imply a self-learning or self-optimizing system, and it does not remove the need for human oversight.

There are several plausible reasons trends can persist. Information reaches investors at different speeds. Institutions adjust large portfolios gradually. Economic and policy regimes can last for months or years rather than days. Investors may underreact at first and extrapolate later. The argument in this paper does not depend on any one explanation.

Momentum is well documented in equities and across asset classes (Jegadeesh and Titman 1993; Moskowitz, Ooi, and Pedersen 2012; Asness, Moskowitz, and Pedersen 2013). Behavioral and information-diffusion models offer possible explanations for its persistence (Barberis, Shleifer, and Vishny 1998; Hong and Stein 1999).

That intuition has produced a large family of practical allocation rules. Faber uses simple trend rules to alter risky-asset exposure, while Antonacci combines relative and absolute momentum. Keller and collaborators add canary assets, defensive universes, breadth, volatility, and correlation inputs. Adaptive Asset Allocation takes a broader portfolio-construction view and changes portfolio inputs as market conditions change (Faber 2007; Antonacci 2017; Butler et al. 2012; Keller and van Putten 2012; Keller 2022; Keller and Keuning 2023).

Despite the different mechanics, the common discipline is to let observed market behavior change risk exposure rather than hold the same allocation through every environment.

Every adaptive rule also has to choose a speed. Too slow and it can give back protection. Too fast and it can get whipsawed. Defensive at the wrong moment, it can miss the first stage of a sharp rebound.

Momentum's success creates a second uncertainty: strategy choice. Once a useful idea is widely understood, it can be expressed through many reasonable lookbacks, universes, canary rules, defensive assets, breadth filters, and weighting schemes. The menu grows, but certainty does not. Part of the problem shifts from forecasting the market to choosing among rules: which reasonable expression of momentum will work best in the next regime?

Momentum can therefore be useful and still create concentration: several rules built on the same successful idea may end up making much the same decision. More strategy names do not necessarily create more decision diversity. The practical question is whether the rules actually disagree when it matters.

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2. Five Strategies Can Still Be One Decision

Imagine a portfolio with five dynamic-allocation strategies. On paper it looks diversified: five sleeves, five rule sets, five names. Five is incidental in this example; the same question applies to any multi-rule portfolio.

Now imagine that all five depend heavily on momentum, turn defensive in roughly the same month, and return to risk after roughly the same signal. The investor owns five strategies but may still be making one underlying decision.

The analogy is familiar. Owning five technology stocks is not the same as owning five independent sources of risk. Strategy diversification can fail in the same way.

Return correlation is a useful first check, but it describes outcomes more directly than decisions. Two rules can have correlated returns while changing portfolios at very different times, or hold different assets while de-risking on the same date.

Related research reaches the same problem from several directions. Forecast-combination and thick-modeling research studies diversity across forecasts or models (Batchelor and Dua 1995; Granger and Jeon 2004; Aiolfi and Favero 2005; Pesaran, Schleicher, and Zaffaroni 2009). Portfolio research warns against overconfidence in precisely estimated optimal weights (Michaud 1989; DeMiguel, Garlappi, and Uppal 2009), while practitioner work compares strategy correlations and overlapping positions (Ludlow 2022).

This paper contributes a transparent way to examine decision-level diversification in dynamic asset-allocation rules.

We describe each rule in three simple dimensions:

- **What?** Which assets does the rule choose?
- **When?** When does it change its portfolio?
- **How much?** How much risk or defensive exposure does it take?

These three questions turn the abstract idea of strategy diversification into observable behavior. In the Decision-Space measure used below, target-weight distance captures What and How Much together, holdings overlap adds a separate composition check, and transition-date overlap captures When. These questions remain relevant even when the specific strategies change.

A slow rule can add decision diversity to a faster rule even when their returns are moderately correlated. Two rules can hold different assets yet de-risk on the same dates. A portfolio can therefore be diversified in assets and concentrated in its decision clock.

ADAA is diversified at the decision level only if its sleeves make meaningfully different decisions and that diversity remains when individual sleeves are adapted or replaced.

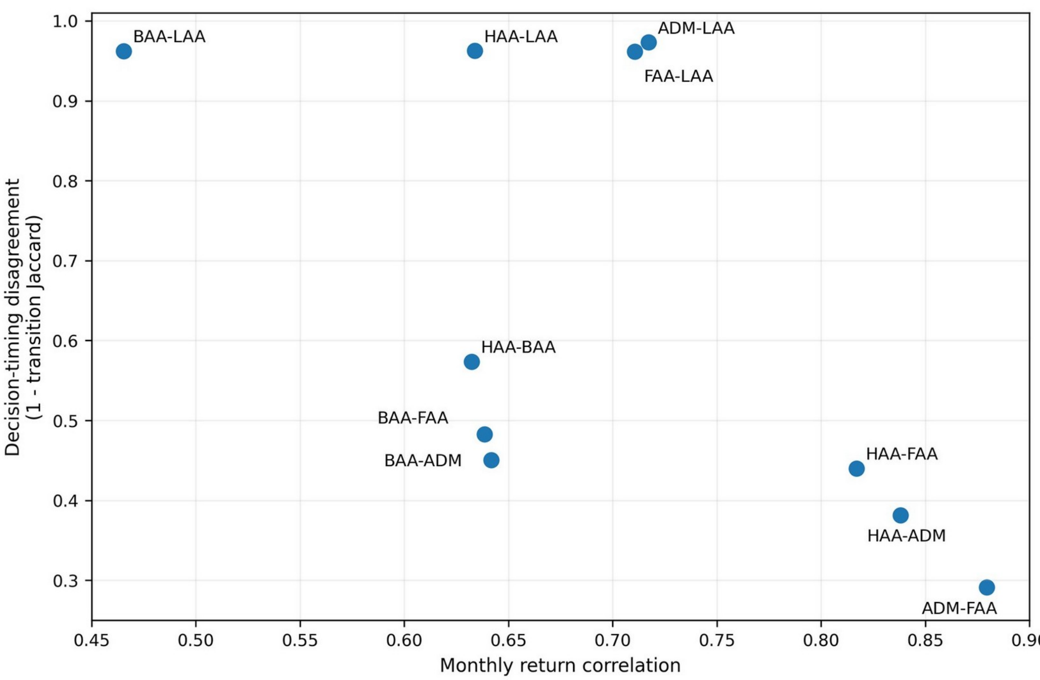

Figure 1. Similar returns do not imply similar decisions. The horizontal axis shows monthly return correlation. The vertical axis shows disagreement in portfolio-transition timing, measured as one minus the Jaccard overlap of their transition months. A value near one means the pair rarely changes its target weights in the same month. Return correlation remains useful, but it does not fully describe how rules behave.

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3. A Strategy Is More Than Its Tickers

A published rule is a blueprint, not an investable portfolio. New ETFs appear; some original instruments are unavailable, expensive, or narrower than the intended exposure. The practical difficulty is that changing the assets used to implement the rule can also change the strategy itself.

The ADAA sleeves studied here are therefore not presented as exact replicas of the published strategies. They are practitioner adaptations of those strategies.

The comparison therefore asks three questions: What did the published rule actually do? What changed when it was adapted for ADAA? Did the adaptation preserve the decision role that motivated the original strategy?

The trap is familiar: modify a rule or universe, observe a better history, and then use that same history as the justification for the modification.

To avoid this circularity, we classify an adaptation as role-preserving only when it retains the published strategy's core decision role; otherwise we treat it as a redesign.

Table 1. From published rules to investable sleeves

Sleeve	Published strategy	Main ADAA adaptation	Classification	What the comparison shows
HAA	Keller & Keuning HAA	Wider offensive universe, Top-6, modified replacement logic	Substantial practitioner adaptation	The TIP-canary regime clock is preserved, but breadth and composition change materially.
BAA Aggressive	Keller BAA Aggressive	Mainly VEA/VWO/BND replaced by EFA/EEM/AGG ETF substitutions	Close rule adaptation	With the rule held fixed, changing only the ETF set changes the portfolio state in 12 of 216 months.
ADM	Hanly Accelerating Dual Momentum	Narrow one-position selector broadened to a multi-asset Top-6 sleeve	Substantial redesign	The broader role is better viewed as a redesign than as a close adaptation of published ADM.
FAA	Keller & van Putten FAA	Larger universe, 3/6/12 momentum structure, peer-only correlation, exact Top-6	Substantial rule and universe adaptation	Both rule and universe changes materially alter decisions.
LAA	Keller LAA	Core timing logic retained; IWD allocation replaced by a SPY/EEM/EWY mix	Role-preserving adaptation	Holdings change while the slow transition clock is largely preserved.

Source note: The public replication materials provide the full rule histories, reasons for each modification, and measured effects of the adaptations.

A strategy is more than its ticker list, but the assets used to implement it still matter. We therefore distinguish the published strategy from the changes needed to make it an investable ADAA sleeve. Where possible, we first keep the published rule unchanged and vary only the investable universe; we then keep the universe fixed and vary the rule. Where that comparison is not meaningful, as with the original ADM and the broader Top-6 multi-asset ADAA version, we do not force a mechanical two-by-two comparison.

Table 1B. Changes to the universe and rule can change the decision

Sleeve	Most direct comparison	Observed decision difference	Interpretation
HAA	Rule fixed: original vs ADAA universe	L1 = 0.563; timing agreement = 0.692	The wider universe changes portfolio decisions before the Top-N and replacement modifications are applied.
BAA Aggressive	Rule fixed: original vs ADAA ETF set	L1 = 0.275; timing agreement = 0.814	Mostly role-preserving; ETF substitution changes some decisions.
ADM	Original ADM vs ADAA redesign	L1 = 2.000; timing agreement = 0.314	The redesign is too broad for a one-factor-at-a-time comparison.
FAA	Rule fixed: original vs ADAA universe	L1 = 1.336; timing agreement = 0.686	Universe expansion changes decisions; additional rule changes add further differences.
LAA	Rule fixed: original equity allocation vs ADAA allocation	L1 = 0.500; timing agreement = 1.000	Holdings change; the original switching schedule is unchanged.

Measurement note: L1 is the average sum of absolute target-weight differences after mapping equivalent ETF exposures to common economic exposures (range 0-2). Appendix A divides this quantity by two for its 0-1 Decision-Space scale. Timing agreement is the Jaccard overlap of transition dates. No return statistic enters the table.

The LAA comparison is especially clean. Replacing the original equity allocation changes what the sleeve holds, but under the original timing rule the QQQ/SHY switching state is unchanged across the common sample. The holdings change; the decision clock does not.

The ADAA-ADM sleeve differs too much from the original ADM strategy to be considered a minor adaptation. It is better described as a practitioner redesign inspired by the published ADM strategy.

The comparison is intended to show which elements changed and how those changes affected portfolio decisions, not to assume that every investable adaptation closely reproduces the published strategy.

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4. Different Rules Need Different Jobs

In this paper, ADAA combines five sleeves: HAA, BAA Aggressive, ADM, FAA, and LAA. Five has no special status and is not part of the framework definition. It is simply the portfolio studied here. In plain English, the five strategies have different jobs:

- **HAA —** Uses a canary signal to turn defensive when the regime signal weakens and selects more broadly across offensive assets when risk is on.
- **BAA Aggressive —** An explicit offensive/defensive regime switch between risk-on candidates and a defensive universe.
- **ADM —** A fast relative-momentum Top-6 selector across a broad multi-asset universe.
- **FAA —** A broad cross-sectional sleeve combining momentum with volatility and correlation information.
- **LAA —** A deliberately persistent sleeve with a much slower switching clock.

The current five-sleeve configuration reflects practitioner judgment rather than an optimization over candidate strategies. A predecessor ADAA configuration and its design rationale were documented in a 2023 research report prepared at the time. The report records three elements of that rationale: reliance on systematic rules rather than subjective market views, concern about common momentum dependence, and the inclusion of a slow-moving sleeve with explicit attention to drawdown. We use the report only to establish the historical design and distinguish it from subsequent practitioner modifications.

> ***Historical source note.*** *The report was prepared as part of a university project and was not publicly released. It is used as historical documentation, not as validation evidence. Contemporaneous records are incomplete for some later ticker substitutions and sleeve changes; those historical details are therefore treated as contextual rather than evidentiary.*

The rationale was to spread reliance across several reasonable rules rather than concentrate on whichever backtest appeared strongest. That rationale explains the portfolio construction; it does not establish that the portfolio is well diversified.

> ***Takeaway.*** *The sleeves can change, and their number can change as well. The architecture is the part meant to survive.*

A natural concern is that combining familiar allocation rules may not produce meaningful decision diversity. We examine that concern in three stages:

1. Reconstruct the published strategy rules represented in the 2023 portfolio and compare them without using performance data.
2. Compare each published rule with its investable ADAA adaptation.
3. Evaluate the five investable ADAA sleeves together as a portfolio.

This ordering avoids a circular argument in which differences created by later modifications are then used as evidence that the original strategy set was diverse.

The comparison reveals an important trade-off. Using the same return-free Decision-Space measure, the five published strategy rules represented in the 2023 portfolio have an average pairwise distance of about 0.82. Their investable ADAA versions average about 0.64, roughly 22% lower.

For the five strategy families corresponding to the current portfolio, rather than the documented 2023 set, the same comparison gives an average pairwise distance of about 0.85 for the published rules and 0.66 for their ADAA adaptations. Much of the compression comes from ADM and FAA, whose broad multi-asset redesigns make the two sleeves more similar to other parts of the portfolio.

That compression is not automatically a design failure. A sleeve can become more diversified internally, less concentrated, or easier to implement while becoming more similar to the other sleeves. The portfolio problem therefore has two levels: diversify within each strategy, while preserving useful disagreement between strategies.

The measure is intended to reveal hidden concentration as sleeves are adapted or replaced; it is not an automated strategy-selection rule.

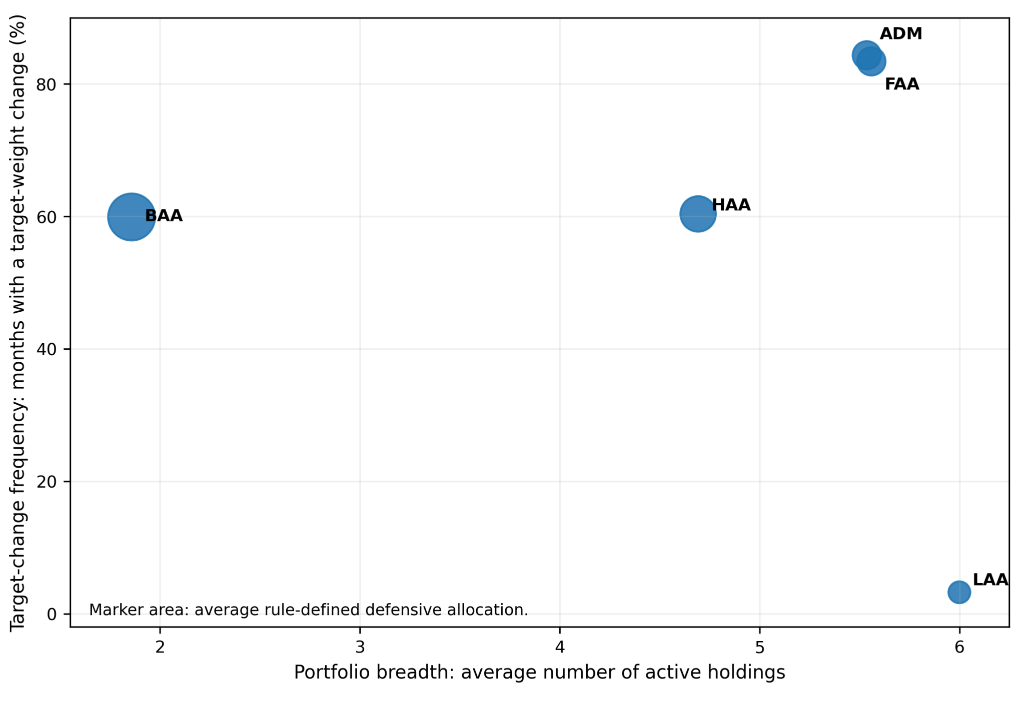

Figure 2. Decision fingerprints: What, When, and How Much. Portfolio breadth, target-change frequency, and average defensive allocation are descriptive proxies rather than a single optimized score. Their purpose is to reveal which kinds of disagreement each sleeve adds.

Figure 2 makes LAA's distinct clock easy to see. It does not make LAA a crash hedge: in the historical sample it did not always reduce drawdowns and was a material drag in 2022. Its contribution is better described as persistence - a different decision clock - than as guaranteed protection.

5. How the ADAA Portfolio Works

The ADAA portfolio examined here follows five steps:

1. Each sleeve observes its own signals at month-end.
2. Each sleeve produces a target portfolio.
3. The sleeve targets are combined at the underlying-asset level.
4. Month-end targets take effect in the next holding period.
5. Offsetting trades across sleeves are netted before transaction costs are applied at the final-account level.

We use equal 20% sleeve weights for the main cross-sleeve comparison so that the chosen allocation does not drive the result. We also report a practitioner allocation used later in implementation: HAA 25%, BAA Aggressive 15%, ADM 17.5%, FAA 17.5%, and LAA 25%. Because contemporaneous records do not document a formal rule for selecting these weights, we treat the allocation as a practical sensitivity case rather than as prespecified or optimal.

If success depends on identifying both the future winning rule and its exact weight, the portfolio places too much reliance on foresight. The analysis therefore separates uncertainty about which reasonable rule will work best from uncertainty about the exact sleeve weights.

6. Do the Rules Actually Disagree?

They do, but unevenly. That is why disagreement has to be measured rather than assumed.

ADM and FAA have a gross monthly return correlation of about 0.88, the highest among the five sleeves, and their average target-weight distance is also relatively small. They are therefore the clearest pair to examine for redundancy. Because this finding is identified ex post in the reported sample, it is not used to redefine the portfolio. Any replacement rule would require separate evaluation under prespecified criteria.

Other pairs show why return correlation is not enough. HAA and LAA have a monthly return correlation of about 0.63, but their transition-timing disagreement is about 0.96. ADM and LAA have a return correlation above 0.71, yet their timing disagreement is about 0.97. The rules can have correlated returns while changing at very different times.

Returns describe realized outcomes, while transition overlap reveals part of the decision process behind them. The two measures answer different questions, and Figure 3 makes the timing dimension concrete.

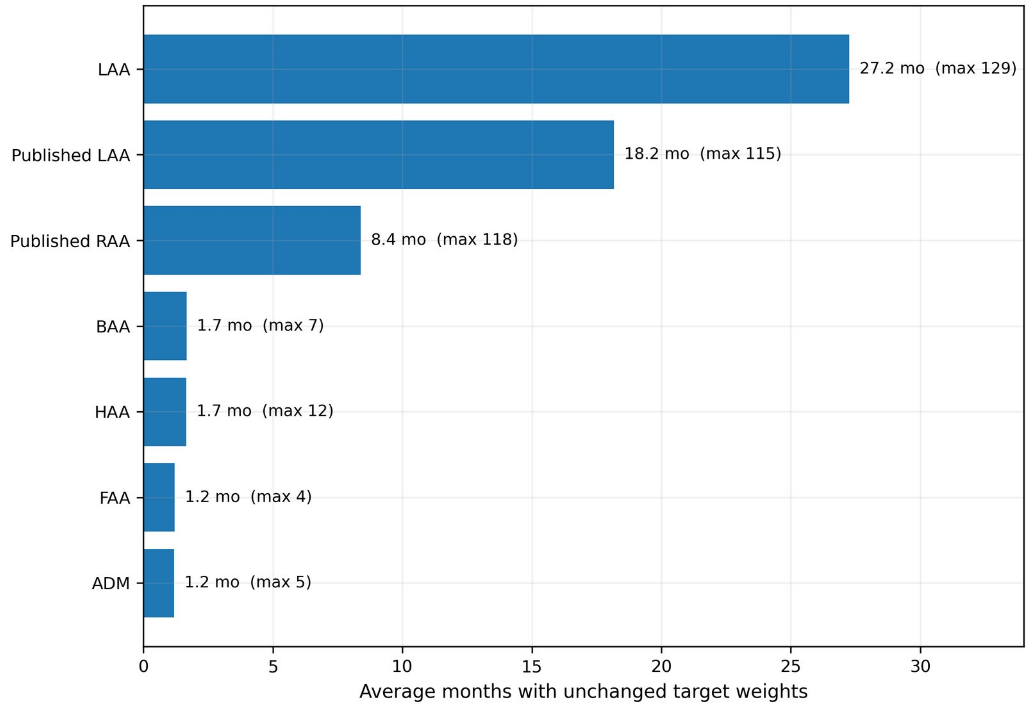

Figure 3. Different rules operate on different decision clocks. The HAA and BAA targets remain unchanged for roughly 1.7 months on average; ADM and FAA for about 1.2 months; and the ADAA LAA sleeve for about 27 months. The published LAA strategy and the published RAA comparator, which is not included in the ADAA portfolio, are also materially more persistent than the faster dynamic sleeves.

RAA is shown only as a comparator and is not included in the ADAA portfolio. To avoid treating closely related slow-moving Keller rules as independent strategy families, we do not count RAA as an additional source of strategy-family diversification. The persistence of both published rules is consistent with the broader idea that a slow-moving sleeve can add a distinct decision-speed dimension.

That does not mean every multi-rule portfolio needs LAA, or that persistence is always beneficial. Persistence is a portfolio property, not a permanent job assignment. A future portfolio can seek the same property through a different sleeve if the evidence warrants it.

Even after the decision roles are visible, another uncertainty remains: which reasonable rule will perform best next? Figure 4 shows why hindsight is a difficult standard. The identity of the best standalone sleeve changes as the trailing window moves. HAA is the most frequent 60-month Sharpe winner, BAA also leads for long stretches, and LAA briefly leads in earlier windows. ADM and FAA never lead on this particular 60-month metric.

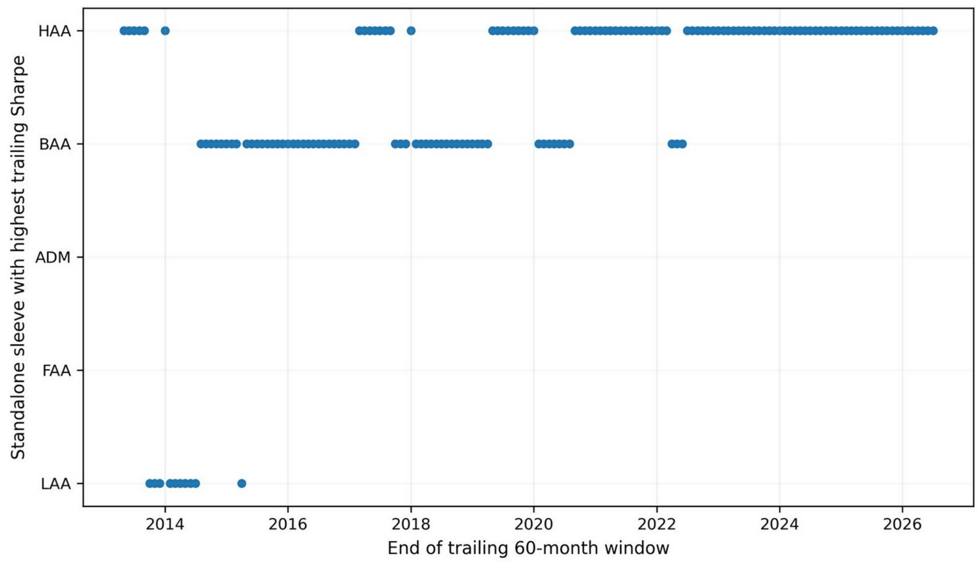

Figure 4. The hindsight winner changes as the window moves. Each point identifies the standalone sleeve with the highest trailing 60-month BIL-excess Sharpe. The chart is not a timing strategy and does not allow ex-post switching. It illustrates strategy uncertainty: the rule that looks best depends on where the evaluation window ends. Relative to the five standalone sleeves, the practitioner-weighted ADAA portfolio ranks above the median sleeve in 98.7% of 60-month Sharpe windows, ranks within the top two positions in 69.2% of windows, and never falls within the bottom two (0%).

> ***Takeaway.*** *A multi-rule portfolio need not beat the best rule after the fact. Its practical role is to reduce dependence on knowing beforehand which reasonable rule will be best while remaining transparent as relative performance changes.*

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7. Weight Robustness: Test the Near-Optimal Region

The June 2023 analysis explicitly explored optimized sleeve weights. It examined 100,000 Monte Carlo weight vectors and reported maximum-Sharpe and minimum-variance allocations subject to a 10% minimum sleeve weight. The practitioner weights analyzed here were adopted subsequently and differ from those optimized allocations; they should therefore not be interpreted as outputs of the 2023 optimization.

Contemporaneous records do not document a formal rule for selecting the subsequent practitioner weights. We therefore treat them as a practical portfolio specification rather than as a prespecified or optimized allocation.

Over the full sample, an ex-post maximum-Sharpe search subject to a 10% minimum sleeve weight assigns roughly half the portfolio to HAA and the 10% floor to several other sleeves. The practitioner allocation differs materially from this solution, yet achieves about 96.6% of the maximum gross Sharpe; equal 20% weights achieve about 95.2%. Among 100,000 feasible weight vectors, about 40% achieve at least 95% of the maximum Sharpe.

The estimated optimum also moves. In rolling 60-month optimizations, HAA's optimal weight ranges from the 10% floor to the 60% cap; BAA does the same; LAA ranges from the floor to above 50%. Block bootstrap resampling also produces wide ranges for HAA, BAA, and LAA.

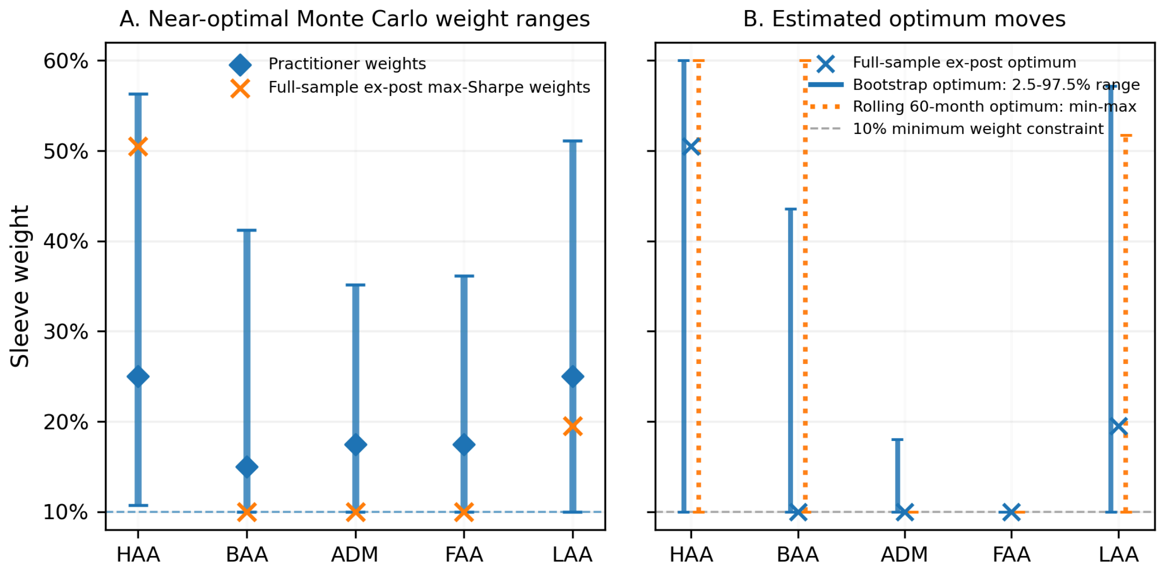

Figure 5. The near-optimal weight region is broad, while the estimated optimum moves. Panel A shows the observed minimum and maximum sleeve weights among the 40,329 of 100,000 feasible Monte Carlo portfolios that retain at least 95% of the full-sample maximum Sharpe. These are sample ranges, not exact boundaries of the feasible set. Panel B shows block-bootstrap 2.5-97.5% ranges (solid blue) and rolling 60-month min-max ranges (dotted orange) for the ex-post optimum. When a rolling range collapses to the 10% floor, it appears as a short orange cap rather than a vertical interval. The dashed horizontal line is the 10% minimum-weight constraint.

The practitioner allocation lies within a broad sampled near-optimal region, while the estimated optimum varies substantially across rolling windows and bootstrap resamples.

> ***Takeaway.*** *The relevant question is the stability of the near-optimal feasible region, not the location of one historical optimum.*

These results do not argue against optimization. They argue against placing too much confidence in a single historical optimum when materially different allocations perform similarly and the estimated optimum shifts across samples. This is a practical portfolio-design principle, not a statistical guarantee.

The evidence here is limited to showing that ADAA's historical-sample performance is relatively insensitive across a broad range of sleeve weights while the estimated optimum moves substantially.

As an exploratory post-hoc check, we also estimate sleeve weights from the previous 60 completed monthly returns, subject to 10%-60% bounds, and apply them in the following month. The rolling optimizer earns slightly more gross CAGR but requires more trading. After a 25-basis-point one-way trading cost, the fixed practitioner allocation has the higher CAGR and Sharpe. Because this analysis was designed after examining the main results, it is exploratory rather than confirmatory and is not used to redefine the portfolio. It does not prove that fixed weights always beat rolling optimization; it shows that chasing a moving optimum is not free.

- Decision Diversification addresses uncertainty about which rule will work best.
- Weight Robustness addresses uncertainty about how precisely those rules should be combined.

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8. What Does Decision Diversification Look Like in the Data?

The main historical sample runs from June 2008 through July 2026 and uses the ETFs in the ADAA portfolio studied here together with the histories required by its lookback rules. The start date is determined by data availability rather than portfolio performance. Because some published strategies and their ADAA adaptations were specified after June 2008, the results are reconstructed over a common historical sample rather than representing live or post-publication track records.

Table 2A compares the practitioner and equal-weight ADAA portfolios with HAA, SPY/IEF 60/40, and SPY over the 218-month sample.

Table 2A. Performance and implementation costs in the historical simulation

Portfolio	Basis	CAGR	Volatility	BIL-excess Sharpe	Maximum drawdown
ADAA (practitioner)	Gross	10.80%	8.97%	1.05	-10.34%
ADAA (practitioner)	25 bps one-way	9.36%	8.97%	0.90	-10.75%
ADAA (equal 20%)	Gross	10.66%	8.97%	1.03	-10.00%
ADAA (equal 20%)	25 bps one-way	9.07%	8.97%	0.87	-10.43%
HAA	Gross	12.97%	10.70%	1.07	-11.68%
HAA	25 bps one-way	11.20%	10.76%	0.92	-12.30%
60/40 SPY/IEF	Gross	8.44%	9.72%	0.75	-27.55%
60/40 SPY/IEF	25 bps one-way	8.38%	9.71%	0.75	-27.61%
SPY	Gross	11.68%	15.73%	0.70	-46.32%

Note: HAA is the strongest standalone sleeve over the full sample, identified ex post. BIL-excess Sharpe uses BIL monthly total return as the cash-rate proxy. Transaction costs are charged on final-account one-way turnover after offsetting sleeve-level trades. SPY is unchanged across the trading-cost assumptions because it is buy-and-hold in this comparison.

Table 2A does not support a simple winner-takes-all interpretation. HAA has the highest gross CAGR, while SPY also earns more than ADAA but with materially greater volatility and drawdown. ADAA is not a return-maximizing strategy. The case for ADAA rests instead on its historical risk-return trade-off and on whether that trade-off remains meaningful after implementation costs and robustness checks.

Trading costs materially reduce ADAA's gross performance. We evaluate one-way cost assumptions of 0, 5, 10, 25, and 50 basis points. At 25 basis points, the practitioner-weighted portfolio falls from 10.80% to 9.36% CAGR and from 1.05 to 0.90 Sharpe; the 60/40 benchmark has 8.38% CAGR and 0.75 Sharpe under the same assumption. Implementation is therefore part of the comparison, not an afterthought.

Table 2B. Uncertainty checks accounting for serial dependence

Comparison	Basis	Annualized mean-return difference	HAC(12) p-value	Bootstrap advantage frequency		
				Mean return	Sharpe	MDD
ADAA vs 60/40	Gross	+2.10 pp	0.205	91.0%	95.2%	97.3%
ADAA vs 60/40	25 bps	+0.83 pp	0.623	67.5%	78.2%	96.0%
ADAA vs HAA	Gross	-2.12 pp	0.057	2.3%	38.5%	86.5%
ADAA vs HAA	25 bps	-1.85 pp	0.111	5.0%	41.4%	84.3%

Note: Bootstrap results use 12-month moving blocks. HAC(12) is a Newey-West heteroskedasticity-and-autocorrelation-consistent mean-return test with 12 monthly lags. Reported advantage percentages are resampling frequencies, not p-values or posterior probabilities. MDD denotes maximum drawdown; an MDD advantage means a shallower maximum drawdown for ADAA. HAA is the strongest standalone sleeve over the full sample, identified ex post.

In the 12-month moving-block bootstrap, ADAA has a shallower maximum drawdown than the 60/40 benchmark in 97.3% of gross resamples, and its gross Sharpe is higher in 95.2%. However, the HAC test does not reject equality of average gross returns at conventional levels. The evidence is therefore stronger for risk-adjusted behavior and drawdown than for a statistically significant mean-return advantage.

ADAA does not outperform the strongest standalone sleeve over the full sample. HAA is the strongest full-sample sleeve, at roughly 13.0% CAGR and 1.07 Sharpe gross. This illustrates the strategy-selection problem directly. The best rule is easy to identify after the fact; the practical allocation problem is that hindsight is unavailable when capital must be allocated.

On 60-month rolling Sharpe, the practitioner-weighted ADAA portfolio ranks above the median standalone sleeve in about 98.7% of windows. Among the five standalone sleeves plus ADAA, it ranks in the top two in about 69% of windows and never falls into the bottom two.

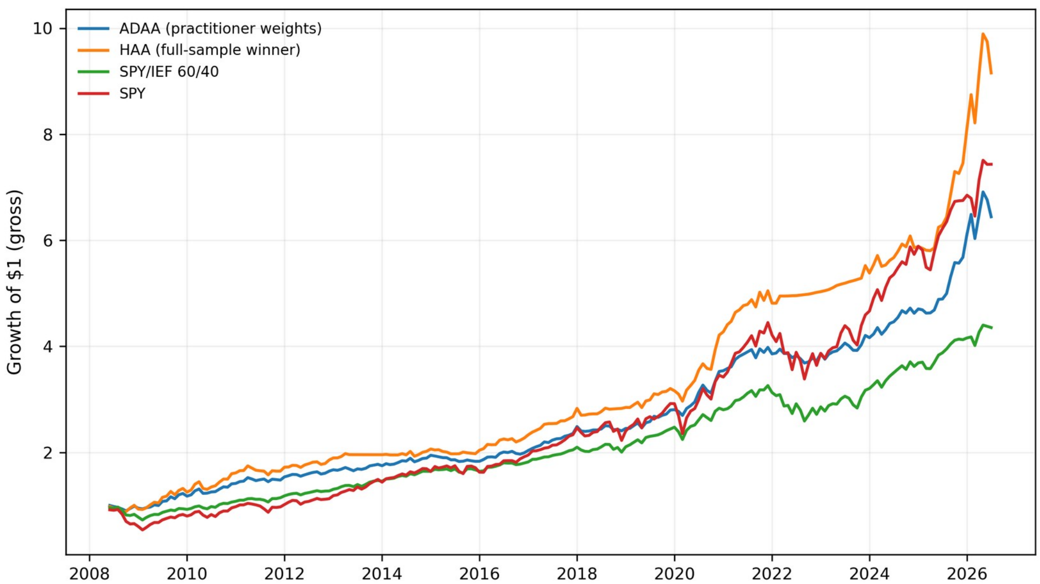

Figure 6. Cumulative wealth in the historical simulation. Growth of $1 is shown for the practitioner-weighted ADAA portfolio, HAA (the strongest standalone sleeve over the full sample, identified ex post), the SPY/IEF 60/40 benchmark, and SPY from June 2008 to July 2026. The chart is descriptive and does not imply that ADAA maximizes terminal wealth.

Drawdown, recovery, and survivable compounding

Drawdown matters because compounding remembers losses. A 20% loss requires a 25% gain to recover; a 50% loss requires a 100% gain. Deep losses therefore create a recovery burden that volatility alone does not show. Research has long treated peak-to-trough loss as a distinct portfolio constraint (Grossman and Zhou 1993; Goldberg and Mahmoud 2017). More recent work treats drawdown duration as a separate dimension of risk (Vedernikov, Liesiö, and Seppälä 2024), while investor-flow evidence suggests that investors respond materially to maximum drawdowns (Riley and Yan 2022).

The goal is not to minimize drawdown at any cost. Too much protection can starve participation in growth, and a shallow-drawdown strategy can still compound poorly. The practical objective is survivable drawdown: losses shallow and recoverable enough that investors can remain invested and compounding can continue.

We measure drawdown from the running wealth peak and treat the initial invested wealth of 1.0 as the first valid peak. This convention matters because the sample begins during the 2008 crisis: an immediate loss should count as a drawdown from the capital initially invested.

Under this convention, the practitioner-weighted ADAA portfolio has a maximum drawdown of 10.34%. Recovering from that trough requires an 11.53% gain. The SPY/IEF 60/40 benchmark has a 27.55% maximum drawdown, requiring 38.03% to recover, while SPY falls 46.32% and requires 86.30%. The longest underwater spell is 18 months for ADAA, 27 months for 60/40, and 32 months for SPY. These are descriptive historical-sample outcomes, not forecasts of future protection.

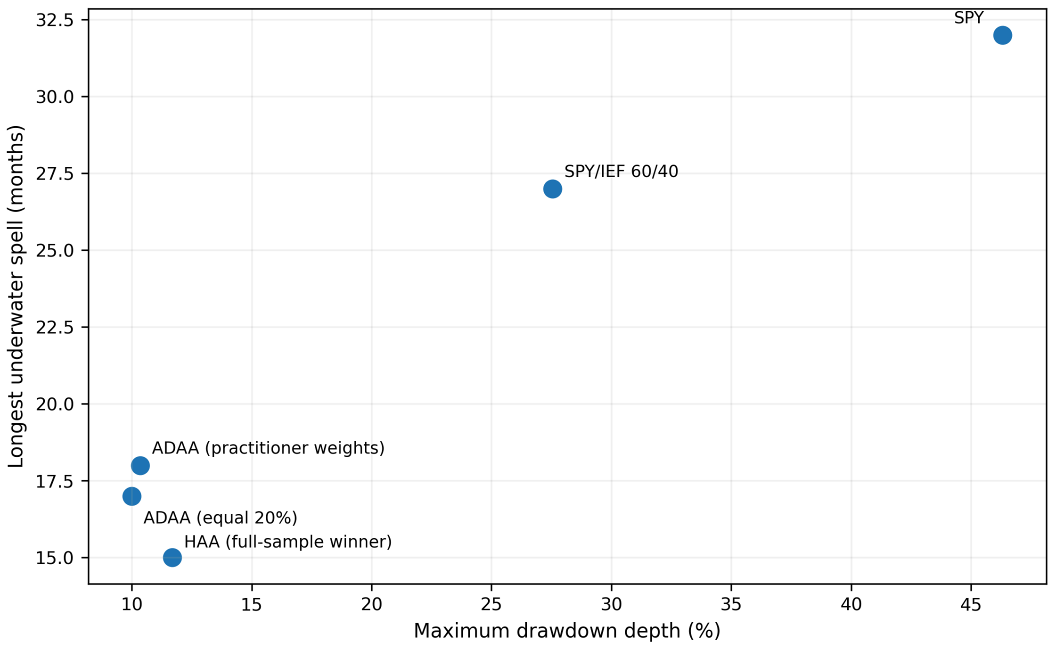

Figure 7. Drawdown has both depth and duration. The horizontal axis shows maximum drawdown depth and the vertical axis the longest period below a prior wealth peak. All values use the same historical simulation and the same initial-wealth convention (W0 = 1) as the text. Neither statistic should be interpreted in isolation.

Table 3. Drawdown and recovery in the historical simulation (gross returns)

Portfolio	Maximum drawdown	Gain required to recover	Longest underwater spell (months)	MDD trough	MDD recovery
ADAA (practitioner)	-10.34%	+11.53%	18	2008-10	2009-05
ADAA (equal 20%)	-10.00%	+11.11%	17	2008-10	2009-05
HAA	-11.68%	+13.23%	15	2008-10	2008-12
60/40 SPY/IEF	-27.55%	+38.03%	27	2009-02	2010-09
SPY	-46.32%	+86.30%	32	2009-02	2011-02

Note: HAA is the strongest standalone sleeve over the full sample, identified ex post.

HAA has the higher CAGR and Sharpe and a shorter underwater period than ADAA, even though its maximum drawdown is slightly deeper. Protection is valuable only if it preserves enough participation for compounding, so drawdown should be considered alongside return, volatility, turnover, and recovery time.

The role of the slow sleeve

LAA illustrates why a sleeve should be judged by its portfolio role rather than headline return alone.

In an equal-weight comparison, removing LAA and rescaling the remaining four sleeves equally slightly raises gross CAGR but also increases volatility and turnover. With a 25-basis-point one-way trading cost, the five-sleeve portfolio including LAA has the higher CAGR and Sharpe in this sample.

Yet LAA does not consistently reduce drawdown. Replacing it with RAA (Keller 2020), another slow-moving rule, produces an even shallower drawdown but slightly lower return in the historical simulation. The comparison shows that the choice of a slow-moving sleeve can materially affect the portfolio's risk-return profile; decision speed can diversify the portfolio without guaranteeing protection.

9. Where It Fails

The evaluation is incomplete without explicit failure modes.

9.1 Rapid reversal and re-entry lag

The clearest recurring failure pattern is a sharp rebound after a weak prior market.

As an exploratory diagnostic, we identify the ten months in which ADAA underperformed the SPY/IEF 60/40 benchmark by the most. Seven coincide with a rapid reversal, defined here as a month in which SPY had fallen over the previous three months and then rose by more than 3%. Examples include March and April 2009, October 2015, January 2019, July and October 2022, and November 2023.

> ***Takeaway.*** *A momentum rule can avoid part of a fall and still miss part of the first rebound.*

That lag is the price of waiting for evidence before taking risk again.

9.2 Not every stress episode favors ADAA

In the historical simulation, ADAA loses about 4.5% during the portion of the Global Financial Crisis covered by the sample, compared with roughly 23.0% for the SPY/IEF 60/40 benchmark and 41.9% for SPY. ADAA also loses less than those benchmarks in the COVID crash and in the 2022 stock-bond stress window. However, 2011 is an important counterexample. ADAA loses about 2.0% over the prespecified May-October window, while SPY/IEF 60/40 is slightly positive. ADAA does not outperform in every risk-off episode.

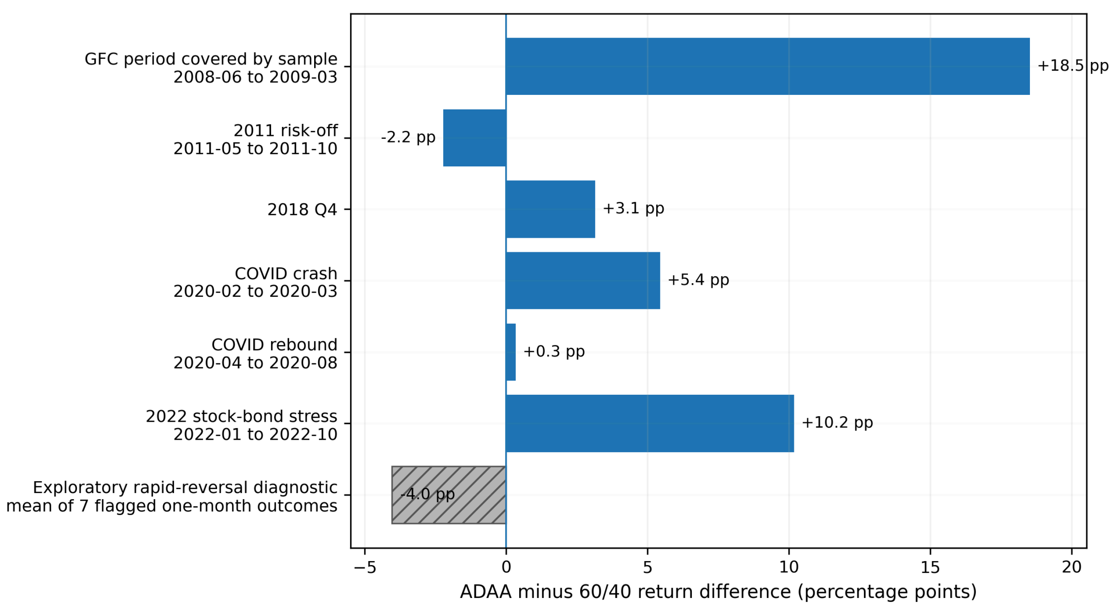

Figure 8. Stress protection is episodic in the historical simulation; rapid reversals remain a failure mode. ADAA has higher cumulative return than 60/40 over the GFC sample period, COVID crash, 2018 Q4, and 2022 stock-bond stress, but not in 2011. The stress-window bars show cumulative return differences; the hatched diagnostic shows the mean one-month return difference across the seven flagged months.

9.3 Slow does not mean safe

LAA loses about 19.6% in the 2022 stock-bond stress window, even though HAA is close to flat and BAA is positive over the same episode.

Slow is a clock, not a guarantee. Sometimes persistence helps; sometimes it means holding the wrong thing for longer.

9.4 Decision diversity does not eliminate common market risk

No prespecified stress episode has all five sleeves changing target weights simultaneously. This indicates differences in transition timing, but not immunity from loss. Different decisions can still produce losses together when the underlying asset opportunity set is broadly unfavorable.

The five sleeves diversify aspects of the decision process, but they do not eliminate common market risk.

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10. Rules for a Portfolio That Must Evolve

The sleeves and their number may change, but the questions used to evaluate the portfolio should remain the same. ADAA is therefore a modular framework rather than a fixed set of strategies.

1. Require a rationale independent of backtest performance. Economic, behavioral, or implementation logic should come first; backtest results can then serve as supporting evidence.
2. Assess decision diversity directly. Strategy labels are not evidence of diversification; evaluate what is held, when allocations change, and how strongly risk is expressed.
3. Use return correlation, but do not stop there. Add holdings overlap, target-weight distance, transition timing, defensive exposure, concentration, and holding persistence.
4. Diversify response horizons. If rules de-risk and re-enter on similar schedules, several strategies can still amount to a single timing exposure.
5. Treat investable substitutions as substantive strategy changes until their effects are evaluated. A broader universe or replacement ETF can make a strategy more investable while also changing its portfolio decisions.
6. Do not assign a slow-moving sleeve the role of universal hedge. Persistence can diversify timing without guaranteeing drawdown protection.
7. Evaluate the stability of the near-optimal weight region. Prefer allocations whose performance remains similar across materially different feasible weights rather than relying on one estimated optimum.
8. Measure implementation costs at the final-account level after netting offsetting trades in the same underlying assets across sleeves.
9. Identify recurring failure patterns. Rapid rebounds after defensive shifts, synchronized de-risking, and persistent exposure to an unfavorable regime are more actionable than a generic list of losing months.
10. Set sleeve-review and replacement criteria in advance. Retain, revise, add, remove, or replace a sleeve using documented tests of role, redundancy, robustness, and implementation feasibility. Define the criteria clearly enough to reduce scope for decisions to be justified only after the results are known.

11. KRW-Based Investor Extension: Currency Exposure

For a KRW-based investor, USD/KRW exposure is practically important even though it lies outside the core Decision Diversification claim.

The currency extension applies a long-horizon USD/KRW z-score to vary the unhedged USD share among 90%, 50%, and 10%. The thresholds and 1,306-trading-day lookback are carried forward unchanged rather than retuned to the present sample.

Table 4. Historical USD/KRW currency-exposure sensitivity

Currency exposure	CAGR	Volatility	Maximum drawdown
Hedged proxy	10.80%	8.97%	-10.34%
Fixed 50% unhedged	11.99%	8.41%	-9.39%
Fully unhedged	12.79%	11.57%	-14.32%
Historical dynamic 90/50/10	13.25%	8.17%	-6.93%

Note: These are historical currency-exposure outcomes on the same gross ADAA path, not a forecast or an executable hedge comparison. The full appendix also reports Sharpe, recovery burden, longest underwater spell, and results under a 25-basis-point underlying trading-cost assumption.

The historical dynamic 90/50/10 path has the highest CAGR, lowest volatility, and shallowest maximum drawdown among the four variants, while full USD exposure raises return and risk together. Figure B1 shows the full cumulative wealth paths. These results provide historical sensitivity evidence, not evidence that the dynamic currency rule is ex ante optimal.

Because the historical thresholds were chosen with past outcomes in view, we focus on sensitivity across nearby settings. Of the 16 threshold combinations specified before this sensitivity check, all produce higher historical-sample CAGR than fixed 50% unhedged and 15 produce a shallower maximum drawdown.

The historical -0.5/+2.0 pair is not the ex-post CAGR maximum, and the 756-, 1,306-, and 1,827-trading-day windows give similar results on their common evaluation period. These checks reduce, but do not eliminate, concern that the finding depends on one narrowly tuned setting. They do not turn a historically chosen rule into evidence about future performance. Appendix B reports the full check.

What the currency analysis does not include

The 'hedged' leg is an exposure proxy, not a traded hedge. It excludes USD/KRW forward or NDF carry, bid-ask spreads, funding and collateral costs, hedge-rebalancing costs, taxes, and account-specific effects. The extension therefore measures sensitivity to currency exposure rather than executable hedged returns and is not additional evidence for the core Decision Diversification claim. Using the same initial-wealth convention ($W_0 = 1$) as in the core analysis, the hedged-proxy path has a maximum drawdown of 10.34%; no forward- or NDF-return mechanics are added.

12. Limitations and Boundaries

Sample and timing

The analysis uses ETF return histories rather than non-ETF proxy series, keeping the historical simulation closer to an investable portfolio but limiting the common sample to about eighteen years. June 2008 is the earliest point at which the required ETF histories support the common analysis; it is not the start of a live ADAA record. Several strategies and ADAA adaptations were specified or published later, so the 2008-2026 headline results are historical simulations rather than post-publication out-of-sample performance.

Strategy-family challenge

The five strategy families in the documented 2023 portfolio were not selected from an exhaustive survey of strategies available at the time. Appendix A compares them with 16 published allocation rules associated with the 2023 analysis. Within that set, the 2023 portfolio ranks 735th of 4,368, around the 83rd percentile. A different combination has the highest Decision-Space score, and BAA Aggressive and BAA Balanced are the closest pair. Four additional published rules were evaluated only after the Decision-Space measure had been defined. Their inclusion modestly reduces concern that the measure was tailored to those four rules, but it is not historical preregistration or out-of-sample validation in market time. An independent implementation reproduced the target weights of the four added rules to numerical precision without using performance data.

From published strategies to investable sleeves

The investable sleeves are adaptations rather than exact replicas of the published strategies. These comparisons show how implementation changes affect portfolio decisions, but they cannot eliminate specification or data-mining risk. They also reveal a practical tension: greater diversification within a sleeve can make the sleeves more similar to one another. The five-sleeve portfolio is therefore one empirical example of a modular design, not a claim that these particular sleeves - or five sleeves in general - should be permanent.

Data, costs, and FX

For LAA, unemployment inputs are aligned to the information historically available at each decision date, including the missing October 2025 observation. However, the analysis relies on a single revised data vintage rather than reconstructing the full sequence of first releases. Trading costs are evaluated under several one-way cost assumptions. Taxes, market impact, fund closure risk, and investor-specific constraints remain outside the model. The USD/KRW appendix studies currency exposure rather than executable hedged returns.

Claim boundary

Decision Diversification is used here as a practitioner term, not as a claim of conceptual novelty. Related precedents include forecast diversity, model averaging, signal diversification, strategy ensembles, model-speed diversification, and position-overlap analysis. The contribution is a practical framework for evaluating diversification across dynamic asset-allocation rules by asking what they hold, when they change, and how much risk they take.

The same framework asks whether each sleeve continues to serve a distinct portfolio role, whether conclusions depend on precise sleeve weights, and what evidence would justify adding, modifying, or replacing a sleeve.

13. Conclusion: What Should Stay When the Strategies Change?

Momentum is useful not because it reveals the next regime, but because it offers a disciplined way to adapt when market evidence changes. Yet one successful idea can be expressed through many reasonable lookbacks, universes, defensive conditions, and portfolio rules. A portfolio can therefore contain several strategies and still depend on much the same decision logic.

This leads to the paper's central proposal: diversification should extend to the decision process, not stop at the asset list. What a rule holds, when it changes, and how much risk it takes can reveal differences that return correlation misses. Comparing published strategies with their investable ADAA adaptations reveals an important complication: making each sleeve broader or more investable can also make different sleeves behave more similarly. Adaptation inside each sleeve and diversification across sleeves therefore have to be considered together.

The empirical evidence does not identify a universally superior rule or weight vector. The practitioner weights were not prespecified for this analysis and are not presented as optimal. In the historical sample, however, they lie within a broad near-optimal region while estimated optimal weights move substantially. ADAA does not outperform the strongest standalone sleeve over the full sample and does not protect in every stress episode. The evidence does not establish guaranteed outperformance, a permanently superior set of sleeves, or a universally optimal allocation rule.

The more durable conclusion concerns portfolio design and maintenance. A multi-rule portfolio should combine sleeves that respond differently, remain reasonably robust across a range of sleeve weights, and use explicit criteria when sleeves are added, modified, or replaced. The framework does not require a fixed set or a fixed number of sleeves.

A robust allocation process should not depend on too many uncertain judgments being exactly right at the same time. The next regime, the future winning rule, the precise weight vector, the useful set of sleeves, and the timing of the next transition are all uncertain.

Drawdown management matters because deep or prolonged losses can interrupt compounding, but minimizing drawdown is not the sole objective. The broader objective is a transparent, implementable process that remains useful as market conditions and portfolio sleeves change, without pretending that uncertainty can be eliminated.

Appendix A. Decision-Space Comparison of 16 Published Allocation Rules

A natural concern is that several ADAA sleeves are adapted from familiar published allocation strategies. The relevant question is whether these shared origins still lead to meaningfully different portfolio decisions. A useful measure should be able to reveal redundancy in the 2023 portfolio rather than simply confirm its original composition.

We compare 16 published allocation rules documented in connection with the 2023 analysis on a common data history: AAA, ADM, BAA Aggressive, BAA Balanced, DAA, DM, EAA, FAA, GPM, GTAA, KDA, LAA, PAA, QSF, RAA, and VAA. For rules implemented in the 2023 analysis with reference to the DB Financial Investment asset-allocation report, we reconstruct the rule logic from the strategy descriptions cited there (Kang 2022).

For each pair of rules, the Decision-Space measure combines three components:

1. **Target-weight distance (What + How Much).** Half the average sum of absolute target-weight differences after equivalent ETF exposures are mapped to common economic buckets.

2. **Holdings disagreement.** One minus the average Jaccard overlap of holdings - the share of the combined holdings that the two rules have in common.

3. **Transition-timing disagreement (When).** One minus the Jaccard overlap of target-change dates - the share of combined change dates that occur in both rules.

Each component ranges from 0 (the same) to 1 (maximally different). The pairwise Decision-Space distance is the simple average of the three components. A five-rule set contains ten pairs, so its overall diversity score is the average of those ten pairwise distances.

Returns, Sharpe ratios, drawdowns, and other performance statistics are not used. A higher score therefore means more disagreement in portfolio decisions under this specific measure; it does not mean higher expected returns or a statistically better portfolio. All Decision-Space scores in this appendix are computed over the common 216-month target-weight history from July 2008 through June 2026. "2023 portfolio" refers to the documented five-family composition in the 2023 analysis, not to a score that could have been computed using only information available at the time.

The Decision-Space measure was specified before four additional rules - DM, AAA, PAA, and KDA - were included in this comparison. Evaluating those additional rules therefore provides a limited robustness check on a measure that had already been defined.

This is not historical preregistration, independent validation of the metric itself, or an out-of-sample test in market time: the market history and the earlier ADAA design were already known.

Among the 4,368 possible five-rule combinations, ADM + DM + FAA + LAA + QSF has the highest Decision-Space score, about 0.895. The 2023 portfolio scores about 0.817 and ranks 735th, around the 83rd percentile. It therefore ranks above most combinations but is not the maximum-diversity set; the 2023 portfolio was not constructed by maximizing this measure.

A notable result is that BAA Aggressive and BAA Balanced are the closest pair among the 16 rules. Because performance data do not enter the measure, this finding identifies redundancy within the original portfolio rather than rewarding strategies that happened to perform differently.

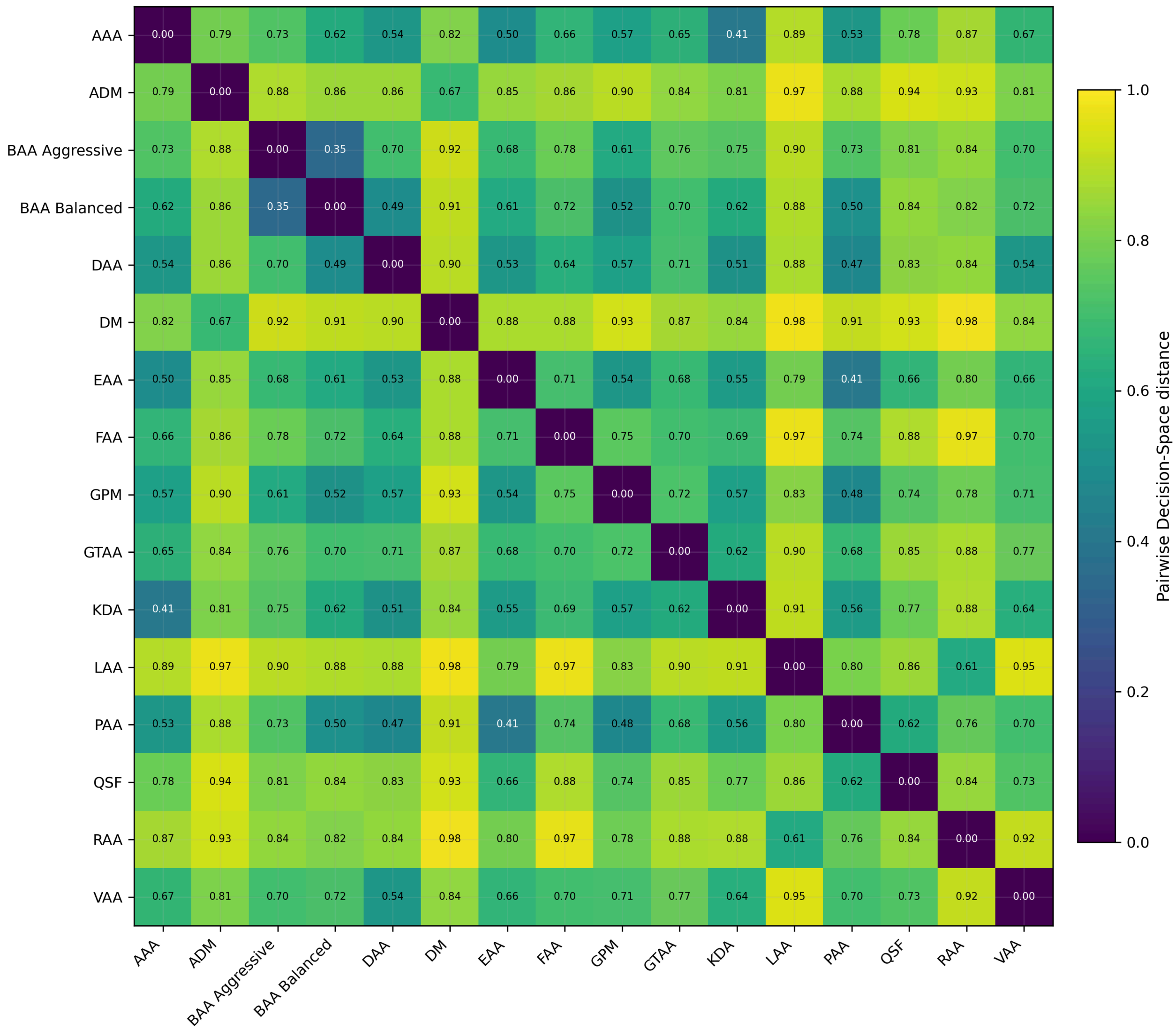

Figure A1. Decision-Space distances across 16 published allocation rules. Lower values indicate more similar portfolio decisions; higher values indicate greater disagreement in target allocations, holdings, and transition dates. Performance statistics do not enter the measure. Distances are computed over the common July 2008-June 2026 target-weight history.

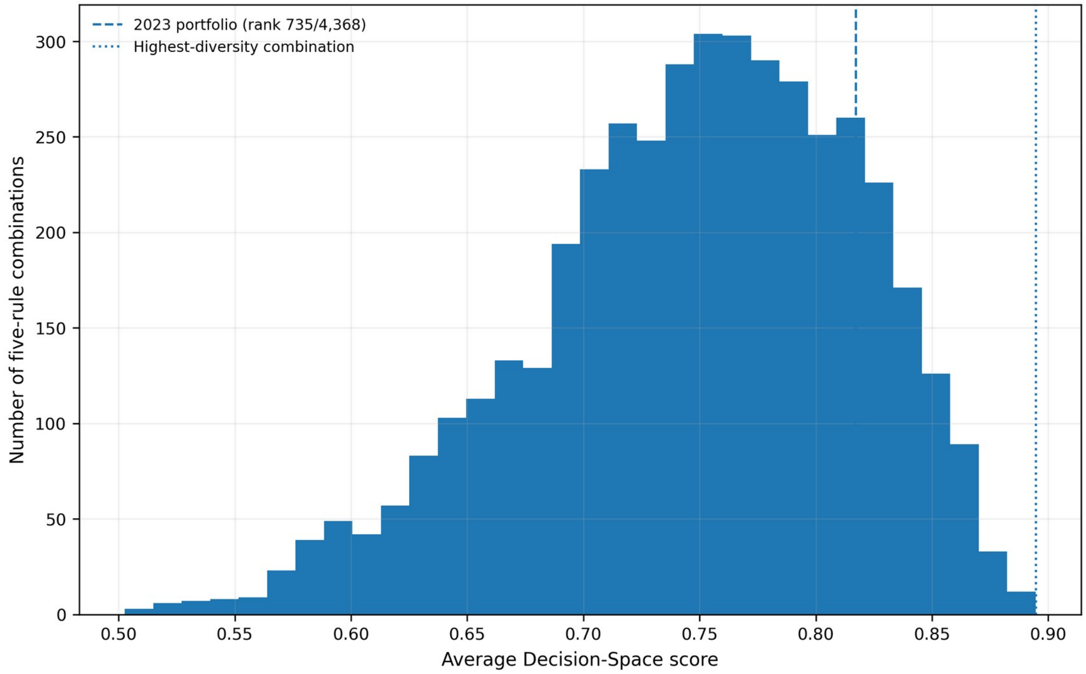

Figure A2. The 2023 portfolio ranks above most five-rule combinations in Decision Space, but not first. Bars show the distribution of Decision-Space scores across all 4,368 possible five-rule combinations. Higher scores mean greater decision disagreement, not better returns; the figure is not a performance test.

The ranking is reasonably stable across the prespecified alternative weightings of the three Decision-Space components. The 2023 portfolio ranks between 622nd and 1,040th, approximately the 76th to 86th percentiles, and remains above the median under every weighting. None ranks it first. This suggests that its above-median position is not driven by one particular component-weighting choice, while leaving open which specification of Decision Space is preferable.

HAA is excluded from the 16-rule comparison because it was not part of the strategy set documented in the 2023 report, although it had been publicly available since February 2023 (Keller and Keuning 2023).

In a separate exploratory comparison that adds HAA to the 16-rule universe, the five-rule combination corresponding to the sleeves studied here ranks around the 96th percentile. Because HAA was not part of the 2023 portfolio, this result is exploratory and does not show that its subsequent inclusion was prespecified or motivated by Decision Space.

A separate implementation reproduced the monthly target weights for DM, AAA, PAA, and KDA to numerical precision (maximum absolute difference $< 3 \times 10^{-15}$), using no performance data and the same Decision-Space definition. The public replication materials document the procedure.

Appendix B. Currency Exposure for a KRW-Based Investor

This appendix examines currency exposure for a KRW-based investor and is separate from the core evidence on Decision Diversification. The extension uses a 1,306-trading-day USD/KRW z-score to vary the unhedged USD share among 90%, 50%, and 10%. The original thresholds are retained rather than reselected using the present sample.

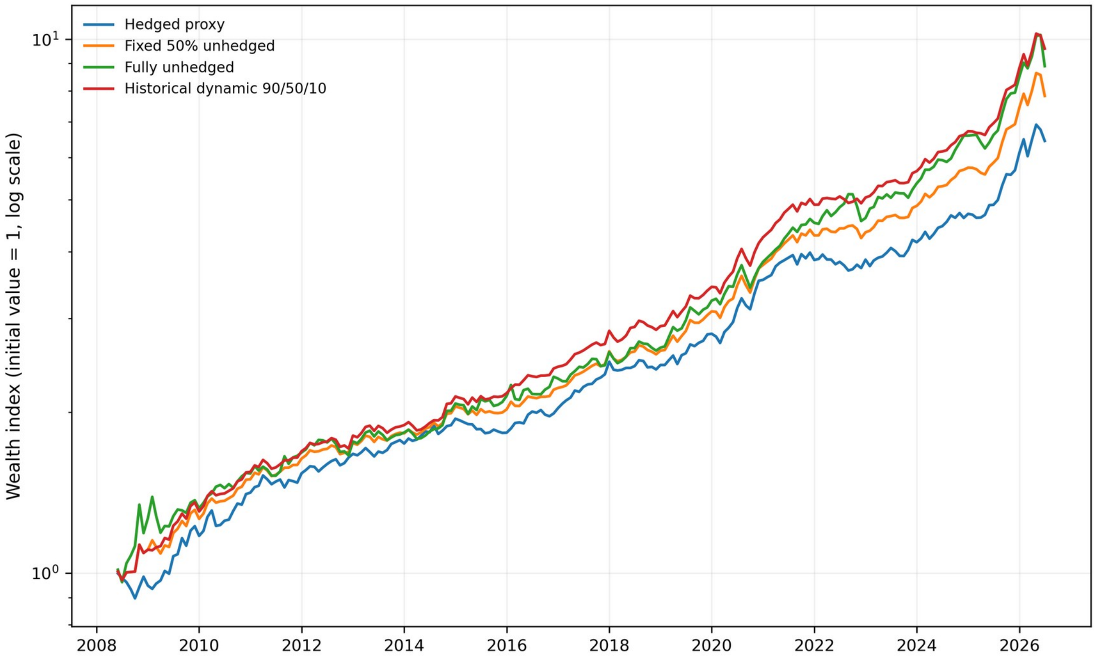

Figure B1. Historical wealth paths under four USD/KRW currency-exposure choices. Each exposure rule is applied to the same gross simulated ADAA return path, with initial wealth set to 1. The hedged proxy assumes zero FX carry and zero hedge-implementation cost and is not an executable forward or NDF return.

Table B1. Historical USD/KRW currency-exposure performance summary

Panel A. Gross ADAA portfolio path

Currency exposure	CAGR	Volatility	Sharpe (0% ref.)	Maximum drawdown	Gain required to recover	Longest underwater spell (months)
Hedged proxy	10.80%	8.97%	1.19	-10.34%	11.53%	18
Fixed 50% unhedged	11.99%	8.41%	1.39	-9.39%	10.36%	12
Fully unhedged	12.79%	11.57%	1.10	-14.32%	16.71%	12
Historical dynamic 90/50/10	13.25%	8.17%	1.57	-6.93%	7.45%	7

Panel B. ADAA portfolio path with a 25-basis-point trading-cost assumption

Currency exposure	CAGR	Volatility	Sharpe (0% ref.)	Maximum drawdown	Gain required to recover	Longest underwater spell (months)
Hedged proxy	9.36%	8.97%	1.05	-10.75%	12.05%	23
Fixed 50% unhedged	10.53%	8.40%	1.24	-9.46%	10.45%	16
Fully unhedged	11.32%	11.56%	0.99	-14.49%	16.95%	16
Historical dynamic 90/50/10	11.78%	8.16%	1.41	-7.03%	7.56%	12

Note: Panel B applies the same 25-basis-point final-account trading-cost assumption used in the core analysis. No FX forward/NDF carry, bid-ask spread, funding, collateral, hedge-rebalancing cost, or other currency-hedging implementation cost is modeled. Sharpe ratios use a 0% reference rate for descriptive comparison within this appendix and should not be compared directly with the BIL-excess Sharpe reported in the core analysis.

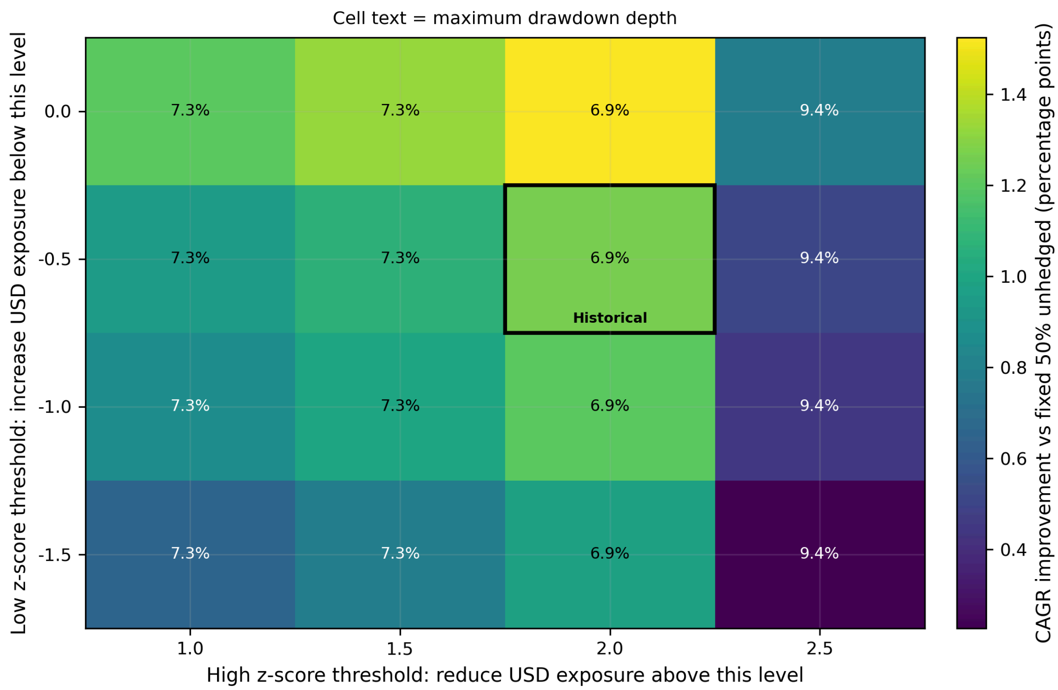

Figure B2. Performance is similar across a broad range of threshold settings. Cell color shows the historical-sample CAGR difference relative to fixed 50% unhedged, while cell text shows maximum drawdown depth. The historical -0.5/+2.0 pair is outlined but not presented as optimal. Across the 16 threshold combinations specified before running this sensitivity exercise, historical-sample gross CAGR ranges from 12.22% to 13.51%, and maximum drawdown depth ranges from 6.93% to 9.39%.

Using a common evaluation period after all three lookback windows are available, gross CAGR ranges from approximately 12.45% to 12.59% across 756-, 1,306-, and 1,827-trading-day windows; each produces a maximum drawdown of 6.93%.

In the paired 12-month block bootstrap, the historical dynamic 90/50/10 rule has a higher CAGR than fixed 50% unhedged in 99.76% of bootstrap samples and a shallower maximum drawdown in about 83.2%. The bootstrap preserves serial dependence within 12-month blocks. These resampling results describe uncertainty within the historical simulation; they do not establish future superiority of the dynamic currency rule.

Two limitations matter. First, the original thresholds were chosen with past outcomes in view, so the stability of results across nearby settings is more informative than the performance of the historical threshold pair alone. Second, an implementable hedging analysis for a KRW-based investor would require forward/NDF carry, bid-ask spreads, funding and collateral mechanics, hedge-rebalancing costs, taxes, and account-specific constraints. Those elements are not modeled here.

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Data and code availability

Public replication materials for this working paper are available through the repository. They include research code, metadata for public data sources, derived exhibit data, figures, and concise reproducibility notes. Raw Yahoo Finance and FRED downloads, non-public research materials, and third-party article files are not redistributed. The repository provides source metadata and retrieval instructions for publicly available inputs.

Research dashboard: https://slackquant80.github.io/adaa-slackquant/
Public replication repository: https://github.com/slackquant80/adaa-decision-diversification
Archival releases and DOI records: see the public replication repository.

Generative AI disclosure

During preparation of this manuscript, the author used OpenAI's ChatGPT for technical and editorial assistance. The author independently conducted and verified the analysis and takes full responsibility for the content of the manuscript.