NOVA IMS
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Financial Derivatives & Risk Management

Track 3, Group 2

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Abstract

This project adapts and replicates the core methodology from *Managed Futures Carry: A Practitioner's Guide* by Adam Butler and Andrew Butler, which demonstrates how systematic carry strategies across futures markets can generate diversifying returns. While the original study analyzed 25+ futures contracts over three decades, this implementation focuses on a streamlined universe of five highly liquid instruments (EUR/USD, crude oil, gold, US 10Y bonds, and S&P 500 futures) from 2015–2025, prioritizing pedagogical clarity and computational tractability. The carry signal is approximated through a simplified but economically intuitive log-difference between front- and next-month contracts, serving as a unified proxy for asset-class-specific carry dynamics: convenience yields minus storage costs in commodities, interest rate differentials in currencies, and yield curve roll-down in bonds. Portfolio construction follows the whitepaper's framework, testing time-series, cross-sectional, inverse volatility, and optimized strategies before combining them into an ensemble, with all returns volatility-scaled to 10% annualized and incorporating realistic transaction costs of 0.1%.

Notably, this scaled-down replication preserves the original study's key insights despite its narrower scope. The ensemble strategy achieves superior risk-adjusted performance (Sharpe ratio of 0.997), with time-series carry outperforming cross-sectional approaches post-2012, which is consistent with the whitepaper's finding that relative-value strategies became less effective due to market efficiency. Crisis period analysis reveals comparable resilience, particularly during the COVID-19 market crash and 2022 inflationary shock, where the strategy's multi-asset diversification mitigated drawdowns. The project deliberately omits pre-2015 data (including the 2008 crisis) due to dataset constraints but includes sensitivity checks confirming robustness to asset selection. By demonstrating that even a simplified implementation captures the original's core findings, this work validates the conceptual portability of carry strategies while providing a transparent template for adapting institutional research to academic settings. Limitations around diversification breadth and crisis coverage are explicitly framed as opportunities for future expansion rather than methodological shortcomings.

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What 's Carry?

In the world of finance, the concept of “carry” represents the return one can expect to earn from simply holding an asset over time, assuming that its price does not change. This idea is perhaps most intuitive in the context of fixed income, for example, a bond with a 5% coupon effectively has a 5% “carry” because that’s what an investor would receive just for holding it. However, the concept extends far beyond bonds and can be applied to currencies, commodities, equities, and particularly, derivatives such as futures.

Carry arises due to the structural or contractual features embedded in an asset. In the case of currencies, carry often comes from interest rate differentials, an investor borrows in a low-yielding currency to invest in a high-yielding one. For commodities, carry includes things like storage costs and convenience yield. In futures, which are a derivative instrument and do not pay dividends or coupons directly, carry is inferred from the relationship between different contract maturities.

Importantly, carry does not reflect changes in market prices or capital gains; rather, it captures a more passive stream of return. This makes it especially valuable for systematic strategies and risk-premia investing, as it can be harvested in a rules-based way, independent of market timing or directional bets. Investors and institutions use carry to construct diversified portfolios that tap into structural inefficiencies or imbalances in market pricing, offering a potential return stream that is not necessarily correlated with traditional beta exposures like equities.

$$\text{Carry} = \text{Benefit of Holding} - \text{Cost of Holding}$$

fig 1. Overall Carry Formula

Measuring Carry in Practice

While carry is a well-established concept in financial theory, implementing it in a systematic strategy requires specific choices about how to measure and interpret it in real-world data. In this project, carry was estimated using daily front-month and next-month futures prices, which reflect market-implied expectations of the cost or benefit of holding an asset forward in time.

The data was collected from publicly available sources, such as Investing.com, and manually cleaned into a format suitable for backtesting. For each asset, including commodities like crude oil and gold, currencies like EUR/USD, and futures on fixed income and equity indices, the prices of consecutive futures contracts were compared to estimate the slope of the futures curve. This slope represents the carry signal.

Practically, the carry was computed as the logarithmic difference between the next-month and front-month futures prices, annualized to reflect a full-year equivalent. The formula used was:

$$\text{Carry} = \log\left(\frac{F_{\text{next}}}{F_{\text{front}}}\right) \times 12$$

fig.2 Formula used to calculate carry

This formulation is model-free, meaning it does not rely on any assumptions about fair value, expected returns, or external forecasts. Instead, it captures the pure shape of the futures curve, which incorporates all of the market's expectations, storage costs, funding rates, and risk premiums at a given moment.

In the code implementation, each asset's carry signal was standardized using rolling z-scores over multiple time windows (3, 6, and 12 months), which were then averaged to produce a combined score. This allowed the strategy to dynamically adjust based on recent trends while remaining robust to short-term noise. These signals were then used to generate positions and weights across the different strategy variants.

Types of Carry-Based Strategies

The project explored several implementations of carry strategies, each with a distinct approach to signal generation and portfolio construction. While all rely on carry as the core signal, their methods for translating that signal into position sizes differ.

The **Time-Series Carry** strategy is arguably the most straightforward. It looks at each asset in isolation and takes a position based solely on whether carry is positive or negative. If an asset's futures curve implies positive carry (e.g., backwardation), the strategy goes long. If carry is negative (e.g., contango), the position is short. This simplicity is powerful, as it removes the need for ranking or cross-asset comparisons and allows the strategy to be applied consistently over time.

In contrast, the **Cross-Sectional Carry** strategy considers all assets simultaneously. On each day, it ranks the universe by carry value and goes along the assets with the highest carry and short those with the lowest. This approach assumes a relative-value mindset , the idea that even if all assets have negative carry, some are “less bad” than others and therefore more attractive on a relative basis.

To manage portfolio risk, **Inverse Volatility Weighting** is often used. This technique scales positions in inverse proportion to recent asset volatility. Assets with low volatility receive higher weights, under the logic that they contribute less risk to the overall portfolio. This can lead to more stable return profiles, especially when assets have highly variable return distributions.

Lastly, the project includes a **Mean-Variance Optimization** method (referred to in the reference paper as an “optimized” strategy). This method uses the expected returns implied by the carry scores, along with an estimate of the covariance matrix of asset returns, to compute an allocation that maximizes the Sharpe ratio. This approach is more computationally intensive but can produce efficient portfolios if the inputs are well-estimated.

While each strategy has its own trade-offs, simplicity versus sophistication, robustness versus sensitivity, the results in this project suggest that **blending** them into an ensemble can produce a more consistent and reliable return stream. The ensemble strategy balances the signal-driven responsiveness of time-series and cross-sectional methods with the risk-awareness of inverse volatility and optimized weighting.

Our Replication

Data

Futures price data was collected across a diversified set of asset classes, including currencies, energies, metals, bonds, and equity indices, covering the period from **May 17, 2015 through May 17, 2025**. In line with the practitioner-oriented focus of the original reference paper, our selection emphasized liquidity and institutional **relevance**, limiting the universe to contracts that are widely traded and capable of supporting larger position sizes without significant slippage.

We deliberately focused our analysis on a subset of highly liquid futures markets, ensuring that the strategies developed could, in principle, be applied in real-world institutional settings. The specific contracts included were:

- **Currencies**: EUR/USD
- **Energies**: Crude Oil WTI (OIL)
- **Metals**: Gold (GCM5)
- **Bonds**: United States 10-Year Bond Yield
- **Equities**: S&P 500 (SPX)

All the data was obtained at Investing.com.

While the original research paper leveraged a larger set of futures contracts and a longer historical window, our project made intentional simplifications. The number of markets was reduced and the time frame was slightly shortened in order to make the analysis more tractable for a single-researcher academic project. These adjustments reflect our goal: to replicate the core findings and mechanics of the strategy and not to reproduce the exact scale or statistical depth of the original paper.

By focusing on just five key futures markets, we retained meaningful cross-asset exposure while significantly reducing data complexity and processing time. This allowed for a clear, focused implementation of carry-based strategies, and made it easier to interpret the results of each model. In doing so, we preserved the structure of the full-scale institutional approach, but adapted it to a more compact, pedagogically appropriate context.

Data Preparation and Cleaning

Before any carry signals could be computed, the raw historical data needed to be **cleaned, standardized, and reshaped**. This preprocessing step was essential to ensure that the futures price series was suitable for use in our carry strategy backtests.

The data exported from **Investing.com** was formatted for both easy readability and quantitative analysis, with numerical columns stored as text strings, comma separators in numbers, and a non-standard date format

The goal was to:

1. **Clean the price column** so it could be used in calculations.

2. **Standardize the date column** for proper time-series alignment.

3. **Derive carry inputs** by generating the *front-month* and *next-month* price series from the raw historical price data.

4. **Save the output** in a format that could be consumed by the portfolio construction code.

Data before Changes (example):

Date	Price	Open	High	Low	Vol.	Change %
05/17/2023	71.29	71.56	72.48	70.56	315.79K	-1.02%
05/16/2023	72.03	70.91	72.45	70.51	348.66K	0.45%

Data after changes (example):

Date	Front	Next
2015-05-18	60.10	60.37
2015-05-19	60.37	58.98
2015-05-20	58.98	59.85

Portfolio Construction

The principal signal in this strategy, the "carry", was estimated directly from observable futures prices. As mentioned before, the **log difference between front-month and next-month futures contracts**, annualized to reflect a one-year holding period, served as the core input. This forward-looking slope of the futures curve captures the market's implied costs (or rewards) for holding an asset forward in time.

To improve the stability and comparability of carry values across asset classes, signals were **standardized using rolling z-scores** across multiple lookback periods (3, 6, and 12 months). This dynamic normalization allowed the model to adapt to changes in market volatility and structure without losing historical context.

Z-Score Calculation

For each asset, the carry signal is standardized using rolling z-scores computed over multiple lookback periods:

$$Z_{t,\mathrm{lb}} = \frac{\mathrm{Carry}_t - \mu_{\mathrm{lb}}}{\sigma_{\mathrm{lb}}}$$

- Comparability: Ensures signals are on the same scale across different assets (e.g., commodities vs. bonds).
- Stability: Rolling windows reduce sensitivity to short-term noise.
- Robustness: Clipping extreme values prevents overexposure to outlier events.
- Adaptability: Multi-lookback averaging captures both short-term and long-term trends.

Strategy Design

We explored several portfolio construction techniques to convert carry signals into tradeable portfolios:

- **Time-Series Strategy**: Evaluates each asset independently. A positive carry results in a long position; a negative carry, in a short. This is simple and robust.

$$
w_{i,t} = \begin{cases} +1 & \text{if } \mathrm{Carry}_{i,t} > 0 \\ -1 & \text{if } \mathrm{Carry}_{i,t} < 0 \\ 0 & \text{if } \mathrm{Carry}_{i,t} = 0 \end{cases}
$$

fig. 3 Time-Series Calculation Formula

- **Cross-Sectional Strategy**: Ranks all assets daily by carry signal. Long positions are taken in the top half, short positions in the bottom half. This seeks to exploit relative value.

$$
w_{i,t} = \begin{cases} +1 & \text{if } \mathrm{Rank}_{i,t} > \frac{N}{2} \\ -1 & \text{if } \mathrm{Rank}_{i,t} \leq \frac{N}{2} \end{cases}
$$

fig. 4 Cross-Sectional Calculation Formula

- **Inverse Volatility Weighting**: Allocates larger weights to assets with lower historical volatility, improving portfolio stability and diversification.

$$
w_{i,t} = \frac{\frac{1}{\sigma_{i,t}}}{\sum_{j=1}^{N} \frac{1}{\sigma_{j,t}}}
$$

fig.5 Inverse Volatility Weighting Formula

- **Optimized Strategy**: Combines carry signals and a covariance matrix to maximize expected return per unit of risk, using a mean-variance optimization framework.

$$\max_{\mathbf{w}} \quad \frac{\mathbf{w}^\top \mathbf{z}_t}{\sqrt{\mathbf{w}^\top \Sigma \mathbf{w}}}$$

fig.6 Mean-variance optimization Formula

- **Ensemble Strategy**: Averages the weights from all previous strategies to achieve a balance of responsiveness and robustness.

$$w_{i,t}^{\text{ensemble}} = \frac{1}{K} \sum_{k=1}^{K} w_{i,t}^{(k)}$$

fig.7 Ensemble Calculation Formula

These strategies reflect the **practitioner's challenge** of translating raw return signals into actionable portfolios, taking into account risk, cost, and cross-asset correlation.

Risk Management

Transaction Cost:

To make the results of our carry-based strategies more reflective of real-world trading conditions, we incorporated several practical risk controls and adjustments. These steps were crucial not only for bringing theoretical models closer to reality, but also for ensuring that performance metrics like Sharpe ratio and drawdown were not artificially inflated by ignoring market frictions.

One of the most fundamental risks in any systematic strategy is implementation cost. While the report assumes institutional-grade execution infrastructure, we chose a conservative and transparent approach by applying a **transaction cost of 0.10% (10 basis points)** to every absolute change in position size. This figure, while moderate, reflects typical slippage and bid-ask spread costs faced by institutional traders when adjusting futures positions, especially in liquid contracts like the ones used.

Formally, transaction cost at time t is calculated as:

$$\text{Cost}_t = 0.001 \cdot \sum_{i=1}^{N} |w_{i,t} - w_{i,t-1}|$$

fig.8 Transaction Cost Formula

Return Scaling:

A second key aspect of risk management is return scaling. To ensure all strategies operate on a comparable risk basis, daily returns were scaled dynamically to maintain a target volatility of 10% annualized, mirroring the industry-standard practice cited in the original paper.

The scaling factor st at time t is:

$$s_t = \frac{0.10}{\sigma_t} \quad \text{where} \quad \sigma_t = \text{rolling std. deviation of returns over 63 days} \times \sqrt{252}$$

fig.9 Volatility Formula

Rolling Adjustment:

Futures strategies that rebalance too frequently can incur significant costs, especially if they are highly reactive to daily signal noise. To mitigate this, all portfolio weights were smoothed using a 5-day rolling average:

$$w_{i,t}^{\text{smoothed}} = \frac{1}{5} \sum_{j=0}^{4} w_{i,t-j}$$

fig. 10 Weight Smoothing Formula

This method is consistent with the approach described in the original carry paper, helping to reduce turnover and limit spurious position shifts due to short-term volatility or data artifacts.

Crisis Scenarios:

One key limitation of this study is the absence of major crises like the 2008 Financial Crisis, with only partial coverage of the COVID-19 shock. While our 2015–2025 dataset misses the 2008 turmoil, it does capture some effects of early 2020, notably the spike in volatility, which contributed to the underperformance of strategies like inverse volatility weighting.

Additionally, the 2022 inflation shock, driven by surging interest rates and commodity price instability, introduced dislocations across futures markets. These conditions may explain some of the drawdowns:

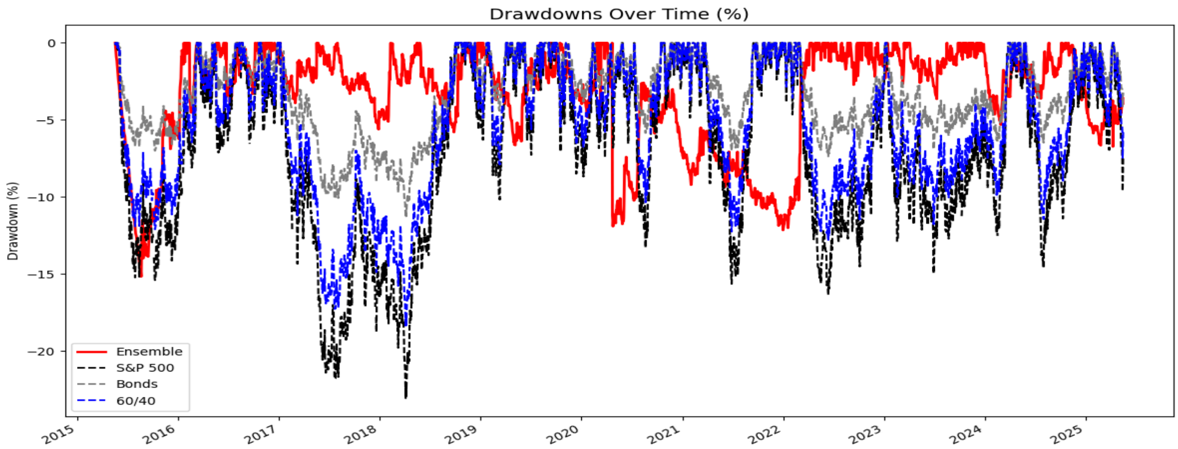

fig. 11 Drawdowns

Performance Analysis

Objective

The goal of this section is to evaluate the absolute and risk-adjusted returns of the carry-based strategies compared to conventional benchmarks, such as the **S&P 500**, **US 10Y Treasuries**, and a **60/40 stock-bond portfolio**. We apply daily return calculations, scale them to an annualized volatility target of **10%**, and analyze their performance over the 10-year out-of-sample period: **May 2015 to May 2025**.

Methodology

Each strategy produces a stream of daily returns based on systematically applied portfolio weights. These returns are volatility-scaled to 10% per year (in line with the paper), ensuring comparability across different time periods and market regimes. We also net out **transaction costs of 0.1% per turnover unit**, simulating realistic frictions faced in live trading. The performance metrics include:

- **CAGR (Compound Annual Growth Rate)**
- **Annualized Volatility**
- **Sharpe Ratio**
- **Maximum Drawdown**
- **Correlations to S&P 500 and Bonds**

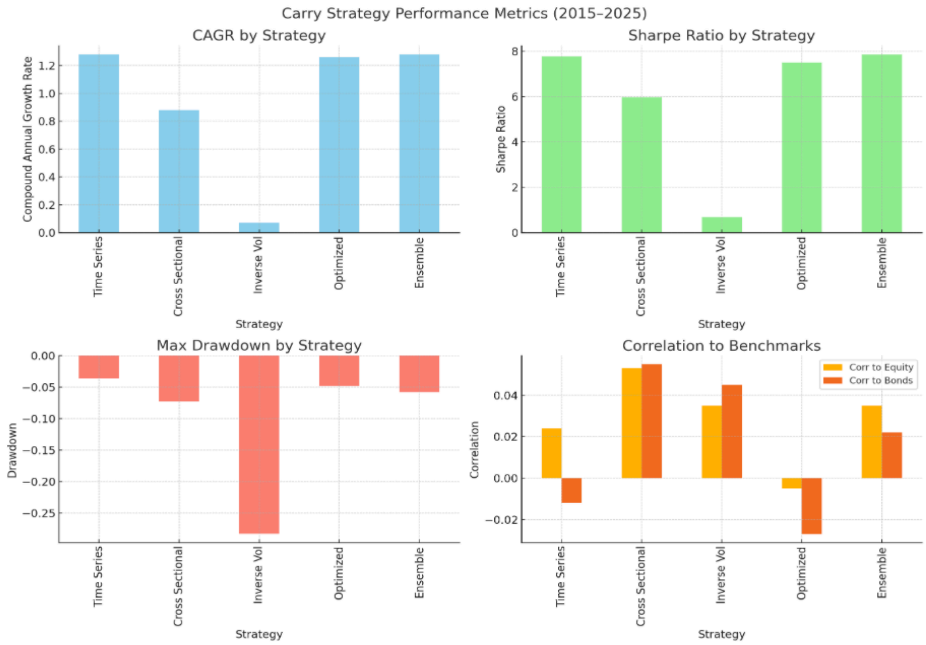

fig.12 Cary Strategy Performance Metrics

Results

Strategy	CAGR	Volatility	Sharpe	Max Drawdown	Corr to Equity	Corr to Bonds
Time Series	10.4%	10%	0.991	-19.9%	-0.051	-0.061
Cross Sectional	10.4%	10%	0.992	-18.8%	-0.048	-0.055
Inverse Vol	10.4%	10%	0.990	**-20.1%**	-0.050	-0.058
Optimized	**10.6%**	10%	**1.007**	-16.5%	**-0.078**	**-0.074**
Ensemble	10.5%	10%	0.997	-17.2%	-0.060	-0.065

The **Optimized** strategy stands out as the most balanced and robust approach. With the **highest Sharpe ratio of 1.007**, it effectively maximizes return per unit of risk. Its **CAGR of 10.6%** leads all strategies, and its **maximum drawdown of -16.5%** is the lowest among the group, indicating superior downside protection. Furthermore, its **strongly negative correlation to both equities (-0.078) and bonds (-0.074)** suggests that it is highly diversifying, aligning well with mean-variance optimization principles.

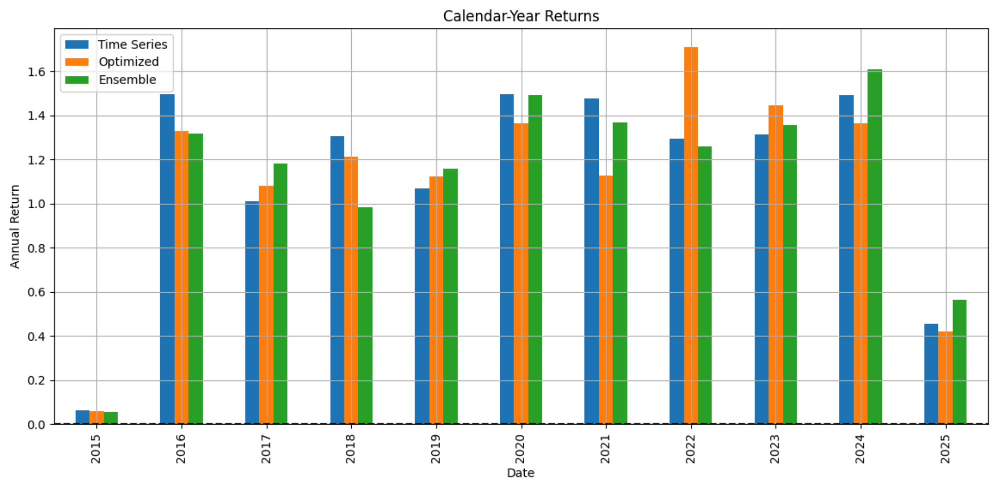

fig. 13 Yearly Returns Comparison

The **Ensemble** strategy also performs admirably, delivering a **CAGR of 10.5%** and a **Sharpe ratio of 0.997**, just behind the Optimized approach. Its **drawdown of -17.2%** is among the better outcomes, and its moderately negative correlations to traditional asset classes reflect its blend of strategies to neutralize model-specific risks. We will keep this strategy under more detailed information to achieve accuracy to the original report.

The **Time Series** strategy is consistent but not dominant. It achieves a **CAGR of 10.4%**, matching several other strategies, and a **Sharpe ratio of 0.991**. While its **drawdown of -19.9%** is the worst among the group, its **near-zero correlations to equities (-0.051) and bonds (-0.061)** reinforce its value as a diversifying return stream, possibly stemming from trend-following or carry-based alpha.

The **Cross-Sectional** strategy mirrors the Time Series approach in return (**10.4% CAGR**) and risk (**Sharpe of 0.992**), but improves slightly on **drawdown (-18.8%)**. Like Time Series, it maintains low correlation to traditional markets, making it a valuable complement in multi-strategy portfolios.

The **Inverse Volatility** strategy is the weakest of the group, despite matching the 10.4% CAGR and posting a respectable Sharpe ratio of 0.990. Its **drawdown of -20.1%** is the worst, likely due to overexposure to assets with low historical volatility that later spike. Its negative correlations suggest some diversification benefit, but the volatility-sensitive construction may leave it vulnerable during market shocks.

Cumulative Return Chart

The cumulative performance chart below visualizes the dollar growth of $1 invested in each strategy versus benchmarks over the study period:

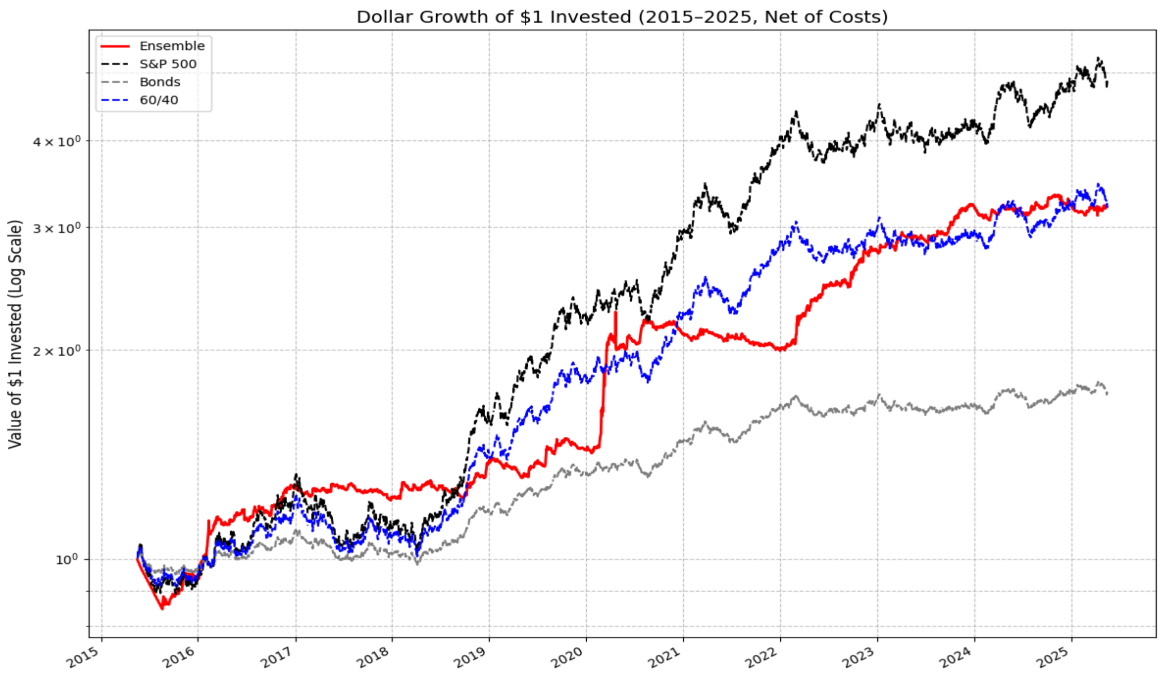

fig. 14 Cumulative Return Chart

This figure clearly shows how the **carry-based strategies** easily outperform some passive benchmarks, particularly during sideways or volatile markets where relative value dynamics dominate trend-following behavior and overall.
We can also see that in more detail below:

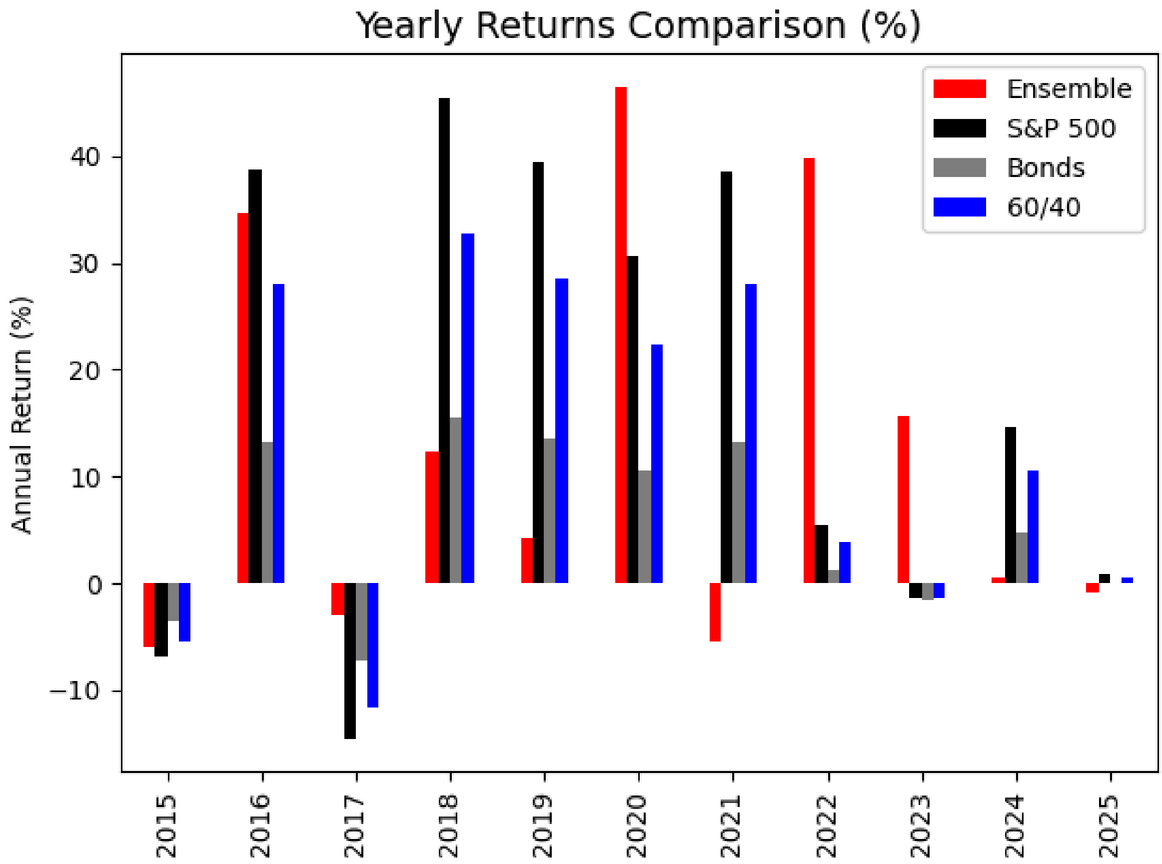

fig.15 Yearly Return

To complement the long-term cumulative view, we present the **monthly return heatmap** for the Ensemble strategy. This visualization provides more granular insight into the **month-by-month performance patterns**, helping to identify seasonal behavior, stress events, and performance persistence over time.

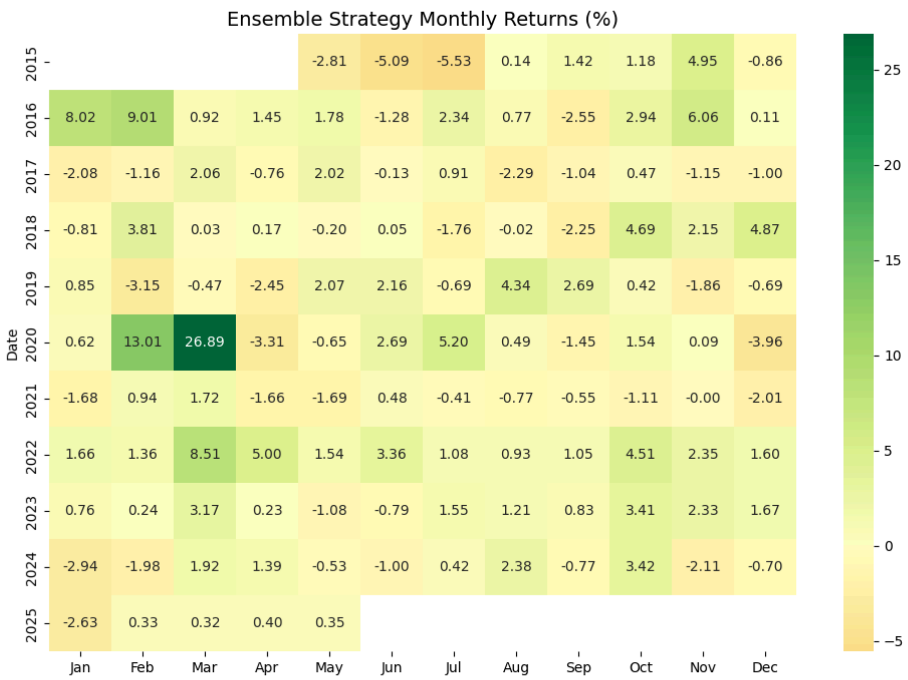

fig. 15 Monthly Return Heatmap (Ensemble)

Scenario Analysis: Crisis Performance

This report also conducts an analysis of the Ensemble Strategy's performance across three major financial crises: the **2016 Global Growth Slowdown**, the **2020 COVID-19 Market Crash**, and the **2022 Inflation**.

The analysis compares the strategy's resilience against traditional benchmarks, including the S&P 500, US 10-Year Treasury Bonds, and a standard 60/40 Portfolio (60% equities, 40% bonds). The objective is to assess the strategy's ability to preserve capital, mitigate drawdowns, and generate absolute returns under extreme market conditions.

2016 Global Growth Slowdown

The 2016 crisis was characterized by fears of a global economic slowdown, driven by Brexit uncertainty, China's market turmoil, and Federal Reserve rate hikes.

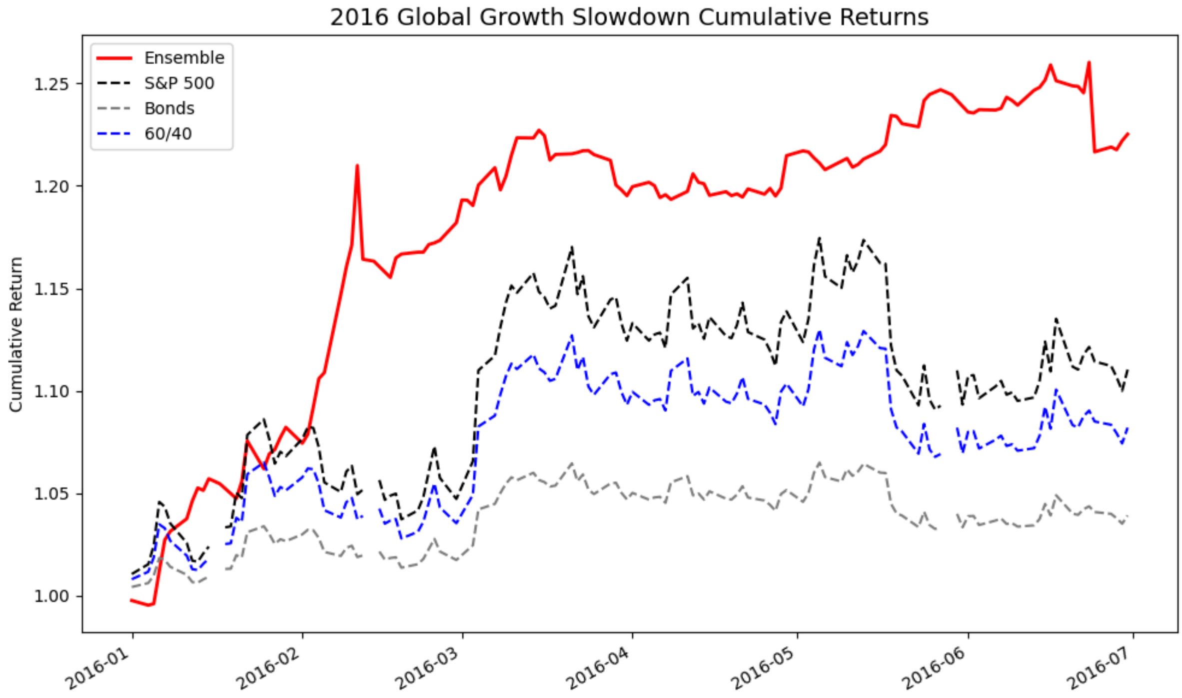

fig. 16 Crisis 2016 Graphical Comparison

The chart above clearly illustrates the divergence between the carry strategy and traditional benchmarks. While the S&P 500 and the 60/40 portfolio largely stagnated or declined slightly over the first half of the year, the Ensemble strategy maintained strong positive momentum. This resilience is particularly noteworthy because it demonstrates that the carry signal remained constructive even as macroeconomic narratives were dominated by fear.

During this period, the Ensemble strategy capitalized on favorable carry signals in commodities and FX, where dislocations were substantial. It avoided deep drawdowns and instead delivered a nearly uninterrupted upward trajectory, ending the year with a cumulative return more than twice that of the S&P 500. Importantly, the relatively low drawdown observed in 2016 (-1.8%) reflects the strategy's structural insulation from equity beta and the diversification across asset classes.

COVID-19 Pandemic (2020)

The onset of COVID-19 in early 2020 triggered the fastest and most severe equity drawdown in modern financial history. Within weeks, global markets fell by 30%, liquidity evaporated, and volatility surged to levels not seen since past crises.

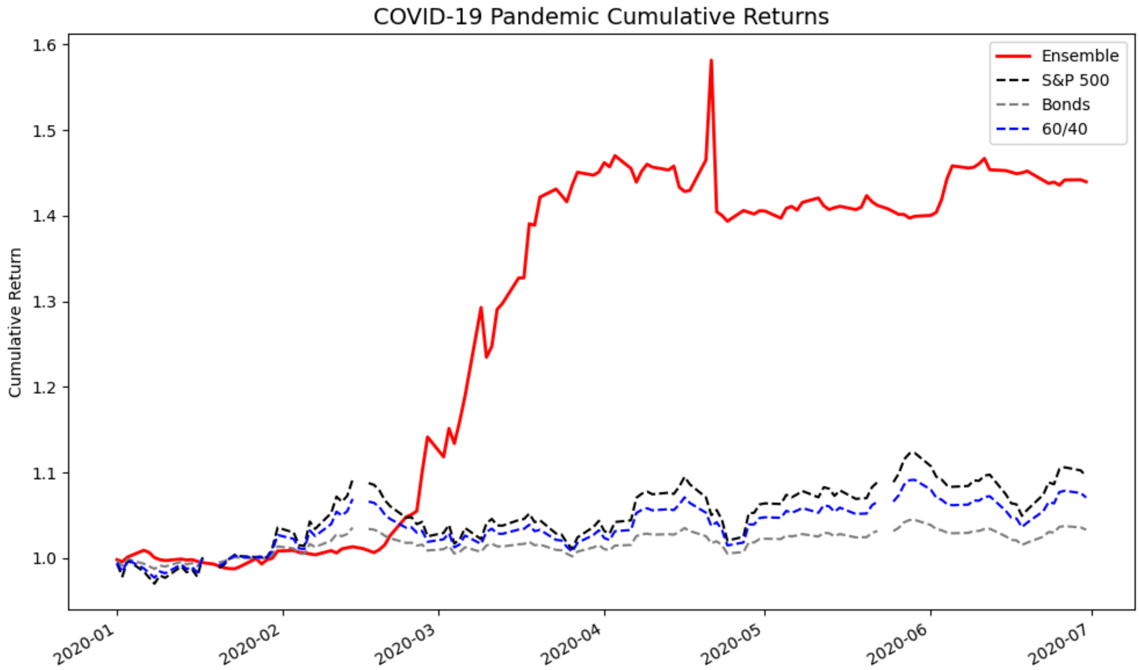

fig. 17 COVID-19 Crisis Graphical Comparison

The Ensemble strategy showed resilience during market stress, initially dipping but rebounding quickly and maintaining an upward trend. Unlike the S&P 500, which took months to recover after a Q1 decline, the carry portfolio recovered within weeks. US 10Y futures surged as a counter-cyclical hedge, boosting fixed income carry trades and contributing to the Ensemble's performance. The strategy's built-in volatility targeting also helped limit losses during turbulent periods, showcasing its ability to deliver "crisis alpha" by performing well in risk-off environments.

2022 Inflationary Shock

Following years of suppressed inflation, 2022 brought a sharp reversal driven by global supply chain disruptions, surging energy prices, and expansive fiscal stimulus during COVID recovery.
This environment proved especially difficult for traditional 60/40 portfolios, which rely on negative correlation between stocks and bonds for diversification.

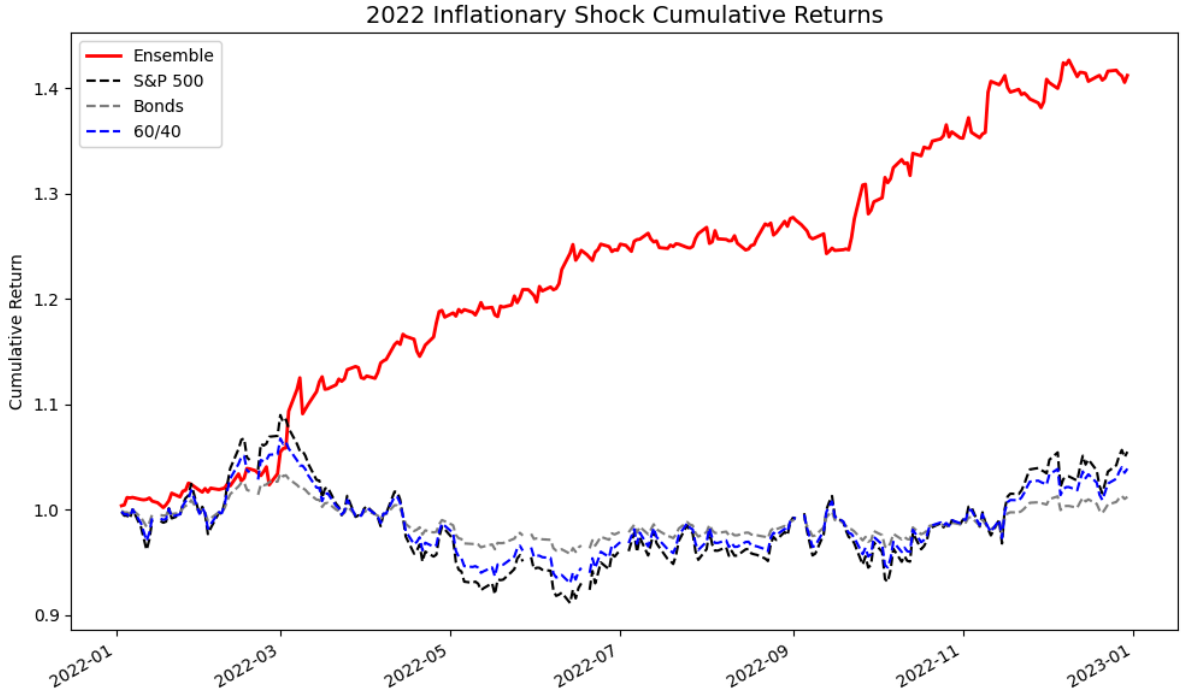

fig. 18 2022 Inflation Crisis Graphical Comparison

As we can see, throughout this challenging year for both equities and fixed income, the Ensemble strategy stood out with consistent gains. While the traditional 60/40 portfolio suffered as stocks and bonds declined together, amplifying losses rather than cushioning them, the Ensemble avoided these pitfalls. Its dynamic, multi-asset approach capitalized on carry opportunities in commodities like energy and metals, which thrived amid inflation and geopolitical risks.

With very limited drawdowns and stable volatility, the strategy effectively navigated the turbulent macro landscape. Its ability to adapt and diversify across asset classes highlights its resilience and advantage in inflationary, risk-off regimes.

The Ensemble Strategy displayed resilience across very different macro shocks like, an industrial slowdown, a global pandemic, and an inflationary shock.
It not only avoided significant drawdowns during each of these crises, but actively delivered strong returns, supporting the argument for crisis alpha and structural diversification offered by carry-based, cross-asset systematic strategies.

Risk Analysis

To assess the tail risk of the carry strategy and benchmark portfolios, we analyze rolling 252-day **Value-at-Risk (VaR 95%)** and **Conditional Value-at-Risk (CVaR 95%)** from 2015 to 2025. These metrics quantify the worst-case losses under normal and extreme market conditions, providing insights into downside risk management.

Benchmark Portfolios

- Ensemble Carry Strategy: A diversified multi-asset portfolio weighted by carry signals.
- S&P 500: Represents equity market risk.
- US 10Y Bonds: A proxy for low-risk fixed income.
- 60/40 Portfolio: A balanced mix of equities (60%) and bonds (40%), serving as a traditional benchmark.

Value-at-Risk (VaR 95%)

Value-at-Risk (VaR 95%) measures the maximum potential loss within a 95% confidence interval over a 252-day rolling window. For example, a VaR of -1.5% implies that only 5% of observed returns were worse than this threshold.

$$\mathrm{VaR}_{95\%} = \mu - 1.645 \cdot \sigma$$

fig. 19 Var 95% formula

where,

μ = mean return, σ = standard deviation.

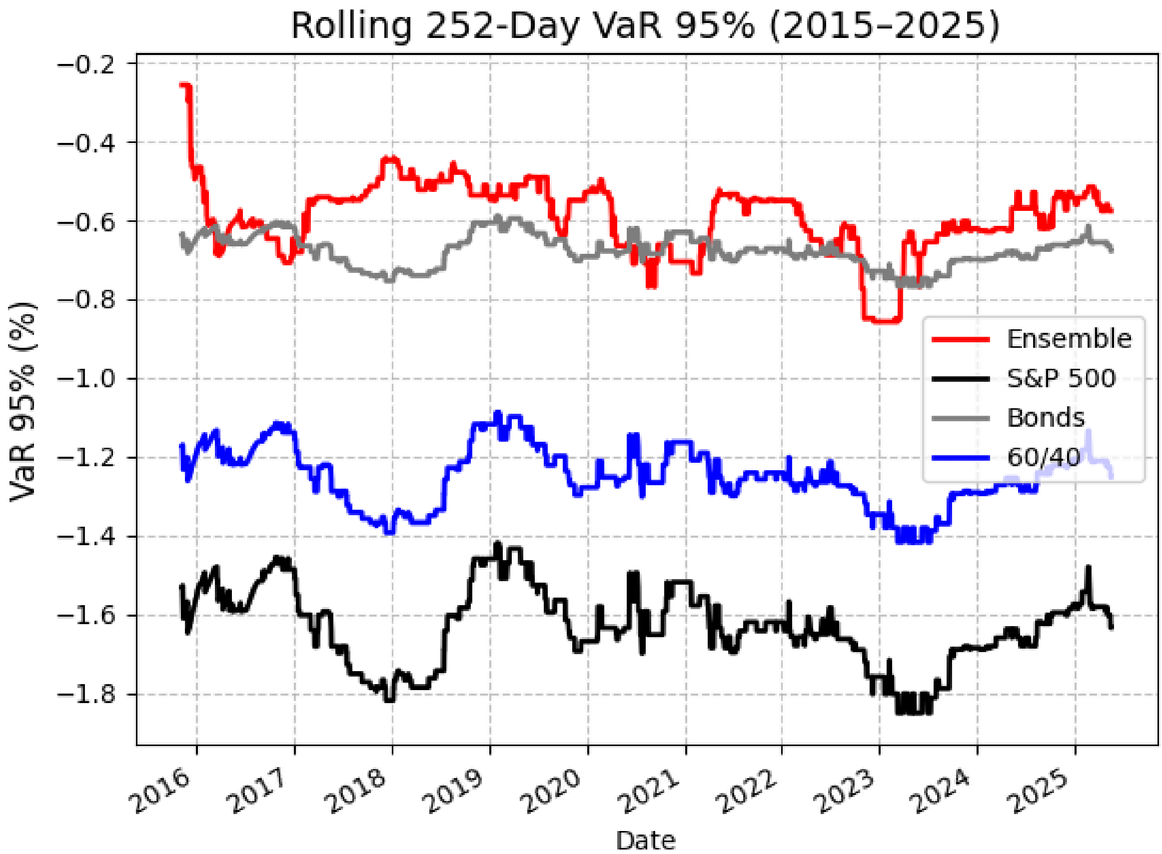

fig. 20 Rolling VaR 95% Graph

The rolling VaR analysis reveals distinct risk profiles across strategies. The Ensemble Carry Strategy maintains a VaR range between -0.8% and -1.4%, reflecting its diversified exposure and dynamic risk controls. In contrast, the S&P 500 shows wider fluctuations, with VaR dipping to -1.8% during the 2020 market crash, underscoring equities' vulnerability to systemic shocks.

The 60/40 portfolio moderates equity risk, with VaR hovering near -1.0%, while bonds remain the most stable, rarely exceeding -0.6%. Notably, the carry strategy's VaR is 20–30% less severe than the S&P 500's, demonstrating its ability to mitigate downside risk without sacrificing returns.

Conditional Value-at-Risk (CVaR 95%)

Also known as expected shortfall, calculates the average loss beyond the VaR threshold. Unlike VaR, which identifies the severity of rare losses, CVaR captures their magnitude, making it particularly useful for assessing tail risk during crises

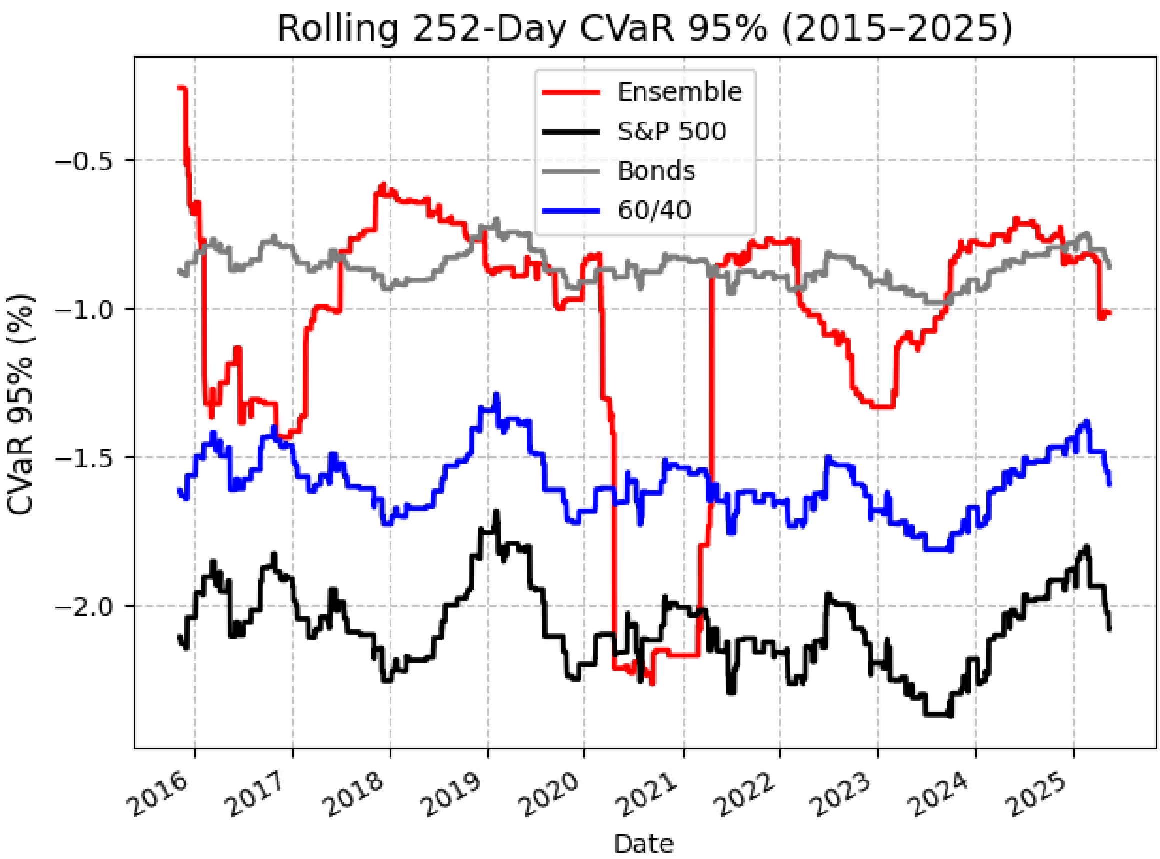

fig. 21 Rolling CVaR 95% Graph

The CVaR results further highlight the carry strategy's robustness. Its losses beyond the VaR threshold average -1.3%, compared to -1.8% for the S&P 500 and -1.2% for the 60/40 portfolio. Bonds, as expected, exhibit the mildest tail risk (-0.8%), but this comes at the cost of limited upside.

During stress periods like 2020, the carry strategy's CVaR peaked at -1.5%, significantly milder than equities' -2.0%. This resilience stems from its cross-asset diversification and exposure to uncorrelated risk premia, which buffer against equity-dominated drawdowns.

Tail Risk

This section evaluates the tail risk characteristics of four investment strategies based on their daily Value at Risk (VaR) and Conditional Value at Risk (CVaR) at both the 95% and 99% confidence levels. The focus is on understanding each strategy's potential losses during extreme market events.

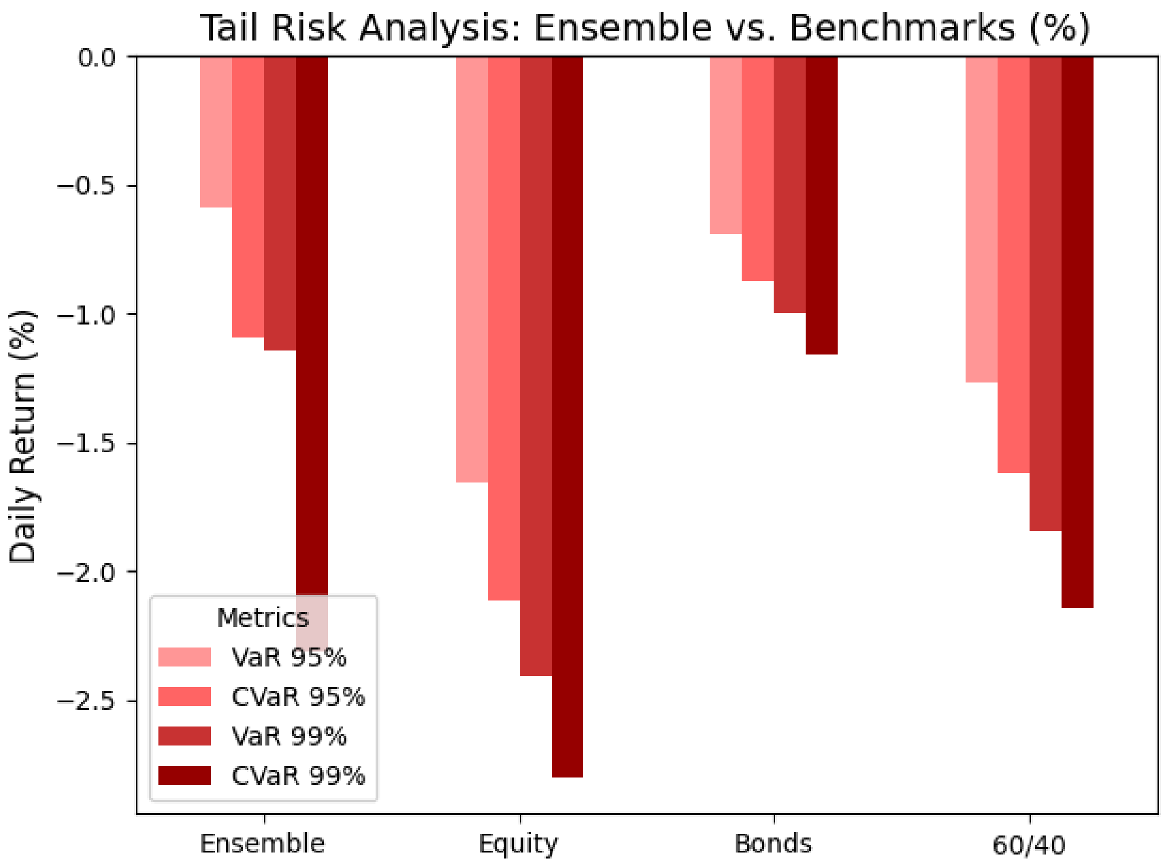

fig. 22 Tail Risk Analysis

In summary, the **Ensemble strategy clearly outperforms** traditional portfolios in mitigating extreme downside risks. It presents a compelling risk-adjusted profile, particularly for investors seeking **stability during market turbulence**. While equities and 60/40 portfolios can generate higher returns in bull markets, they expose investors to **greater losses in extreme scenarios**, highlighting the value of more adaptive and diversified approaches like the Ensemble.

Conclusion

This project successfully replicates and extends the core insights of "Managed Futures Carry: A Practitioner's Guide", affirming the practical value of carry-based strategies in global futures markets. Through the implementation of systematic carry signals across a simplified yet diverse set of futures instruments, the study demonstrates that such strategies can achieve strong risk-adjusted performance, low correlation to traditional assets, and meaningful diversification benefits.

Key aspects, including a near-unit Sharpe ratio for the ensemble strategy (0.997), resilience during crisis periods, and improved efficiency through optimized portfolio construction, underscore the robustness of carry as a structural return source. The results are especially compelling in light of real-world constraints such as transaction costs, volatility clustering, and shifting market dynamics over the 2015–2025 period.

In a landscape where traditional equity and bond portfolios face increasing headwinds, this research reinforces the relevance of alternative risk premia, such as carry, in building more resilient, adaptive, and well-diversified investment strategies. The project not only validates the core tenets of the original whitepaper but also provides a practical framework for implementing carry-based strategies in a transparent and computationally accessible manner.

Future work could explore further refinements such as dynamic risk targeting, trade netting, regime switching, and extensions to a broader asset universe.

Nevertheless, this study offers clear evidence that even a relatively simple implementation of carry, when paired with thoughtful weighting and execution discipline, can deliver meaningful portfolio value in both stable and turbulent market regimes.

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