Price Momentum

Factor Overview

Price momentum is one of the most widely studied and persistent anomalies in financial markets. At its core, the momentum effect captures the empirical tendency for assets that have recently outperformed to continue outperforming, and for recent laggards to continue underperforming, over intermediate horizons.

<u>Momentum in Crypto Markets</u>

Cryptocurrencies are uniquely prone to behavioral and structural forces that can reinforce momentum:

- **Behavioral Underreaction:**
  Information diffuses unevenly across global participants, often reinforcing price trends over several days or weeks.
- **Reflexivity & Market Structure:**
  Liquidation cascades, leverage flows, and funding rate dynamics can amplify directional moves, especially in perpetual futures markets.
- **Retail-Dominated Order Flow:**
  The presence of momentum-chasing retail traders leads to trend persistence and delayed mean reversion compared to traditional markets.
- **High Volatility & Thematic Rotations:**
  Crypto exhibits frequent sector-wide rotations (e.g., L1s, meme coins, AI tokens), which often manifest as momentum across the cross-section.

Given these characteristics, momentum is a natural first-factor to evaluate in a systematic crypto framework.

<u>Hypothesis</u>

The working hypothesis is:

> *Assets with stronger recent returns will, on average, continue to outperform in the near future, while recent underperformers will continue to lag*.

We test this hypothesis across:

- **Daily frequency** using daily OHLCV data
- **Hourly frequency** using hourly OHLCV data

This dual-frequency approach allows us to contrast:

- Short-horizon vs medium-term continuation
- High-turnover momentum vs slower, more persistent trends
- Impact of transaction costs and liquidity constraints at different trading speeds

The aim is to determine whether momentum is a meaningful, robust, and economically viable factor within the Binance perpetual futures universe, and under what lookback horizons it is most effective.

Universe & Data

This study uses the full universe of **Binance USDT-margined perpetual futures ("USDT Perps")**, which represents one of the deepest and most liquid derivatives markets in the cryptocurrency ecosystem. The universe naturally evolves over time as new contracts are launched and delisted; this property is preserved in the dataset to avoid survivorship bias and to accurately reflect real-world tradeability conditions.

All market data were obtained directly through the **Binance public API**, namely, **Daily OHLCV candles.**

We are also using **Daily Market Cap** data from **Coingecko**. The symbol mapping between Binance and Coingecko was done using a semi-automated method, where for all duplicate symbols that exist on Coingecko, we processed the mapping manually.

Survivorship-Bias-Free Construction

To ensure the universe reflects actual historical availability, the dataset explicitly encodes missing prices as **NaN** for periods before an instrument was listed or during times it was inactive. This approach prevents the common pitfall of implicitly assuming all current instruments existed throughout history.

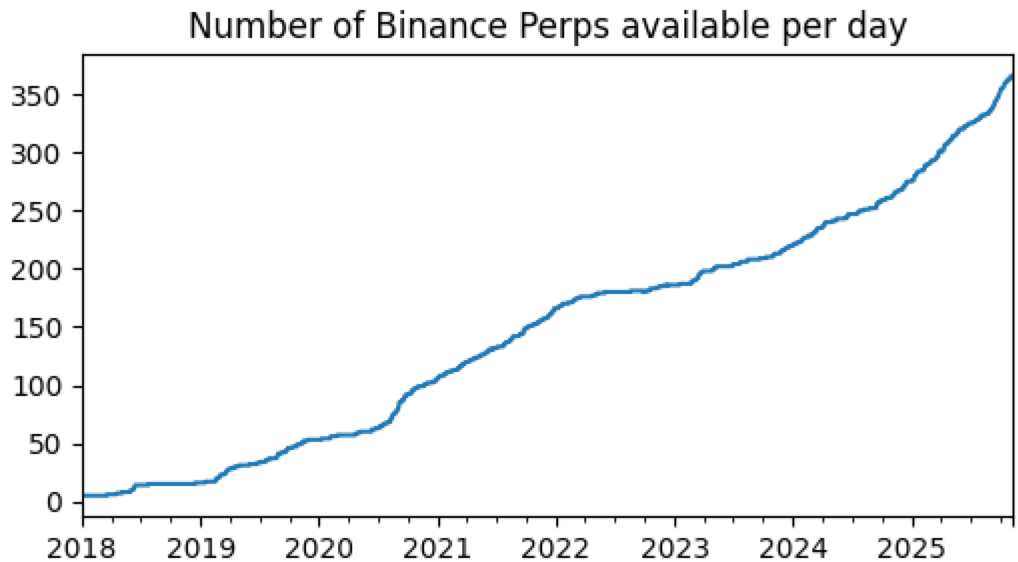
Formally, if a perp **did not exist** at time *t*, then:

```
price[t] = NaN
```

This ensures:

- Correct universe expansion over time
- Fair comparison of factors that rely on return histories
- No look-ahead or hidden survivorship distortions

We can also observe the daily universe size by counting the non-NaN prices per day, as follows:



In-Sample / Out-of-Sample Split

For all empirical analyses, the dataset is partitioned into a training (in-sample) period and a validation (out-of-sample) period, with the **split set at January 1st, 2024**.

All parameter selection, factor calibration, stability testing, and optimization procedures are performed exclusively on the in-sample period (from the first available date up to 2023-12-31). The interval from 2024-01-01 onward is held out entirely for forward performance evaluation, providing an unbiased assessment of out-of-sample robustness across structural regime changes—including the post-ETF environment, liquidity shifts, and variation in market participation.

This method ensures a clean separation between model development and validation, preventing inadvertent look-ahead bias and allowing the results to reflect genuine predictive and cross-sectional utility.

Factor Definition

The **Price Momentum Factor** is constructed using a simple and widely adopted formulation based on past returns. For each asset *i* at time *t*, the momentum signal is defined as the *N-period percentage change in closing prices*, which is equivalent to the following pandas-style notation:

```
factor = close.pct_change(N)
```

This formulation captures the asset's relative performance over the chosen lookback window N. A positive momentum value indicates that the asset's price has increased over the preceding N periods, while a negative value indicates an underperformer.

Lookback Horizons

To evaluate momentum across multiple trading speeds and market regimes, the following lookback windows *N* are used:

Lookbacks : 1, 3, 7, 14, 30, 60, 90 days

These horizons span:

- Extremely short-term continuation (1–3 days)
- Medium-term trend (7–30 days)
- Longer-term persistence (60–90 days)

Using structured and comparable horizons allows us to test how the momentum effect behaves under different levels of noise, turnover, and persistence.

Simulation & Performance Results

Backtest Methodology

The factor is simulated as a **market-neutral long/short portfolio** constructed at each rebalancing timestamp, following the signal definition in the previous section. The methodology is designed to be simple, transparent, and replicable.

Portfolio Construction

At each timestamp:

1. Compute the factor values
2. Rank assets cross-sectionally
3. Select:
    - **Top quantile** (long leg)
    - **Bottom quantile** (short leg)
4. Assign **equal weights** within each leg
5. Ensure dollar neutrality, such as the **sum(long_weights) = abs(sum(short_weights))**

Rebalancing Frequency

Rebalancing occurs at the same frequency at which the factor is computed (i.e. daily). This ensures each momentum signal is fully incorporated into the portfolio construction at the corresponding horizon.

Transaction Costs & Trading Assumptions

To reflect realistic execution conditions, we incorporate **a uniform transaction cost of 5 bps (0.05%) per trade**, applied to every position entry and exit.

This captures:

- Exchange taker fees (≈5 bps for many accounts)
- Minor slippage and spread effects
- The cost of turnover inherent in high-frequency rebalancing

Thus, the **round-trip cost** (close old position + open new one) is effectively 10 bps.

Two versions of results are presented:

1. **Gross performance**
   (no transaction costs)
2. **Net performance**
   (after 5 bps per trade costs)

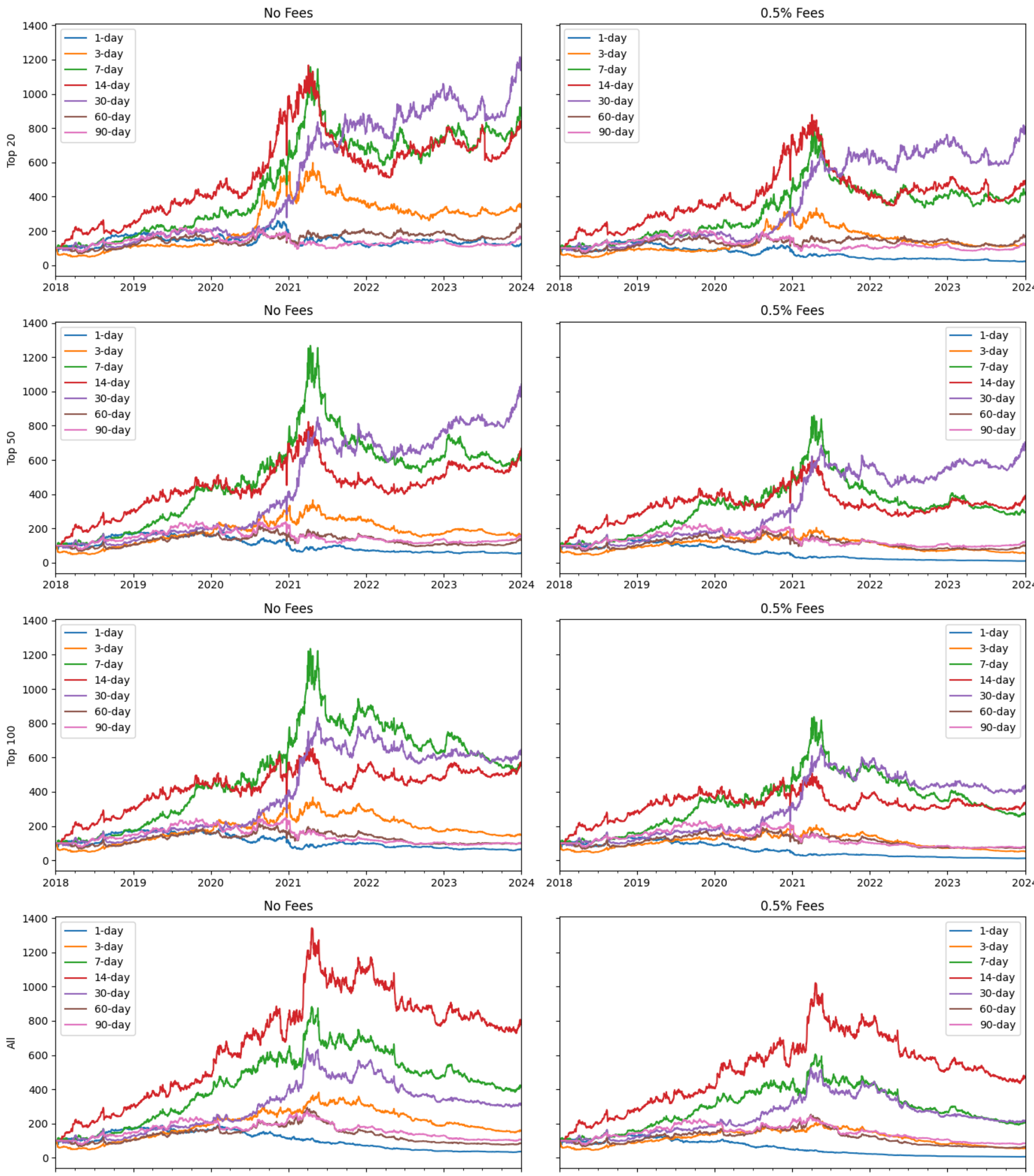
This split highlights the extent to which turnover-driven horizons (especially short lookbacks) are sensitive to execution costs.

Results & Permutation Selection

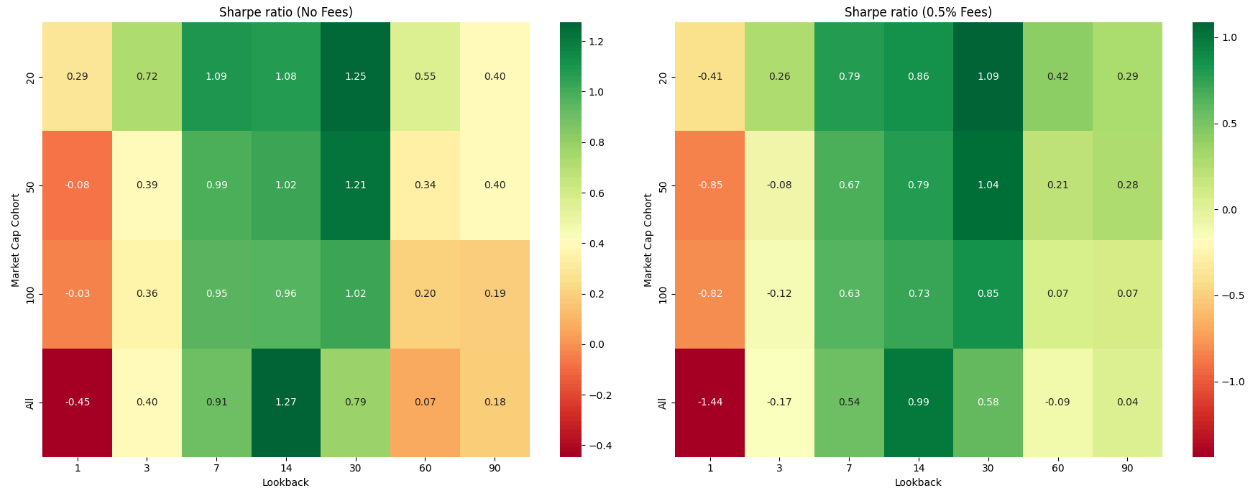
The performance of the Price Momentum factor was evaluated across all daily lookback windows. The figures below report the:

- Cumulative performance of $100 initial investment
- Heatmap Grid of the Sharpe Ratio

for each **market cap cohort x lookback window**, both **gross of fees** and **net of a 0.5% transaction cost per trade**.



No Fees
0.5% Fees
Top 20
Top 50
Top 100
All
1-day
3-day
7-day
14-day
30-day
60-day
90-day
0
200
400
600
800
1000
1200
1400
2018
2019
2020
2021
2022
2023
2024



Observations

1. **Short-term lookbacks (1–3 days) consistently produce weak or negative Sharpe ratios**, reflecting **mean-reversion dynamics rather than momentum** at very short horizons.
2. **Momentum becomes reliable in the 7–30 day range**, where Sharpe ratios are consistently strong and remain **robust even after applying trading fees**, indicating true trend-following behavior.
3. **Expanding the universe increases mean-reversion effects**—as lower-cap, higher-volatility tokens frequently retrace after sharp moves.
   Since the factor does not distinguish between sustainable momentum and volatility-driven spikes, this effect becomes more pronounced in broader cohorts.

Overall, the **Top 20 market-cap cohort with a 30-day lookback** emerges as the **most effective and fee-resilient permutation**, offering the strongest and most stable momentum performance across all tests.

Parameter Sensitivity Analysis

Once a candidate permutation is selected, the next step is to assess how **robust** it is. We do this by examining its **sensitivity to key parameters**, namely the **market-cap cohort** and the **lookback window**.

The idea is simple:
simulate an equity curve for each parameter variation and compare them to the chosen configuration.

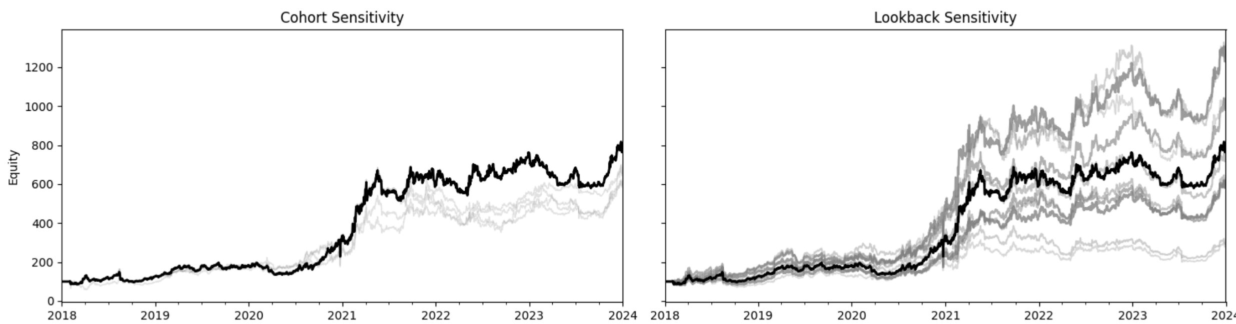
A narrow band of outcomes implies stability; a wide band suggests fragility or overfitting.

For this permutation (Top 20, 30-day), we define the sweep ranges as:

- **Market-cap cohorts:** 10, 20, 30, 40, 50 (with 20 being the chosen value)
- **Lookback window:** 26–35 days (with 30 being the chosen value)

The lookback sweep is intentionally tight. While this may seem too narrow, it still reveals meaningful behavior—specifically, how sensitive the system is around a local neighborhood of parameter choices.

As illustrated in the sensitivity plots:



- **Cohort Sensitivity:**
  The outcomes across different market-cap cohorts cluster fairly tightly. This indicates that the system is **robust at the cohort level**, with performance not overly dependent on selecting precisely the Top 20 set.
- **Lookback Sensitivity:**
  In contrast, the range of outcomes across lookback windows is **significantly wider**, showing substantial dispersion.
  This indicates that the system is **highly sensitive to the exact lookback parameter**, and even modest deviations from 30 days can materially change performance.

This degree of lookback sensitivity raises the possibility of **overfitting** to a specific time horizon. At this stage, one could either:

- **Abandon** the system due to its parameter fragility, or
- **Mitigate** the sensitivity through an approach designed to reduce dependence on any single parameter setting.

We choose the latter by introducing an **ensembling method known as SPP**, which aims to stabilize performance by blending signals across parameter choices.

The following section explores this ensembling approach in detail.

Optimizing the Selected Permutation

Factor Smoothing

A common first step in factor optimization is **smoothing**, typically via a simple or exponentially weighted moving average. This is especially effective for high-turnover factors, where noise can overwhelm signal.

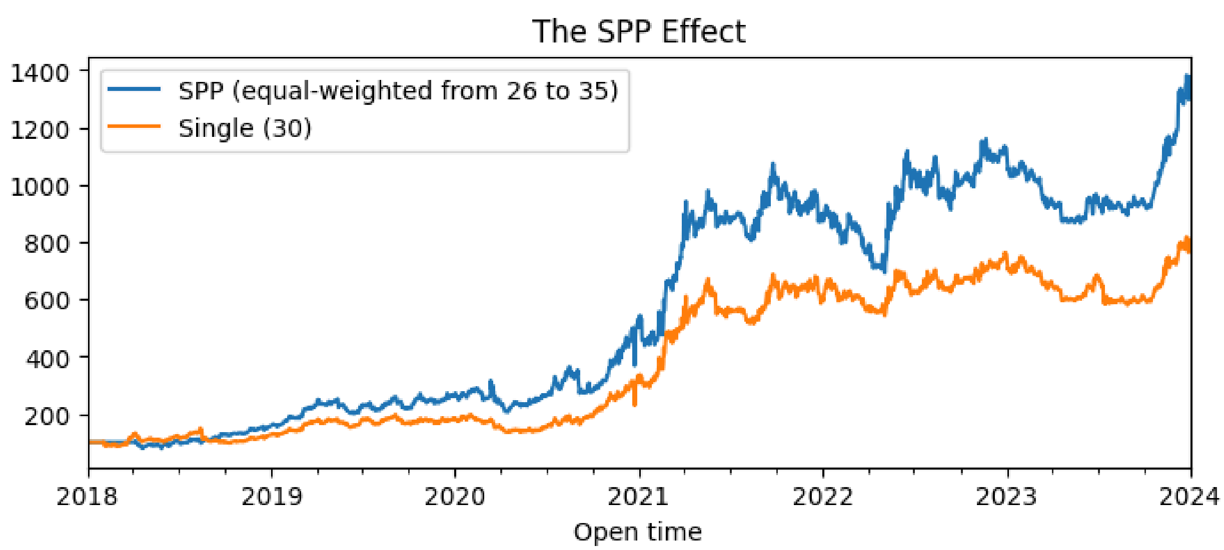
In our case, however, the selected permutation already demonstrates **strong and robust performance both gross and net of fees**, indicating that noise is not a major concern.

Because of this, we elect **not** to apply smoothing, and instead preserve the raw momentum structure.

System Parameter Permutation (SPP)

Earlier we observed that the system shows **notable sensitivity to the lookback window**, which raises the risk of parameter overfitting. To address this, we employ **System Parameter Permutation (SPP)**—an ensembling technique designed to stabilize performance by aggregating signals across a range of nearby parameter values.

For this system, we define a sweep from **26 to 35 days**. For each lookback window in the range, we compute its individual sub-factor and assign it an equal weight (10%). The final ensemble factor is then simply the average of all sub-factors.



The resulting simulation demonstrates two key improvements:

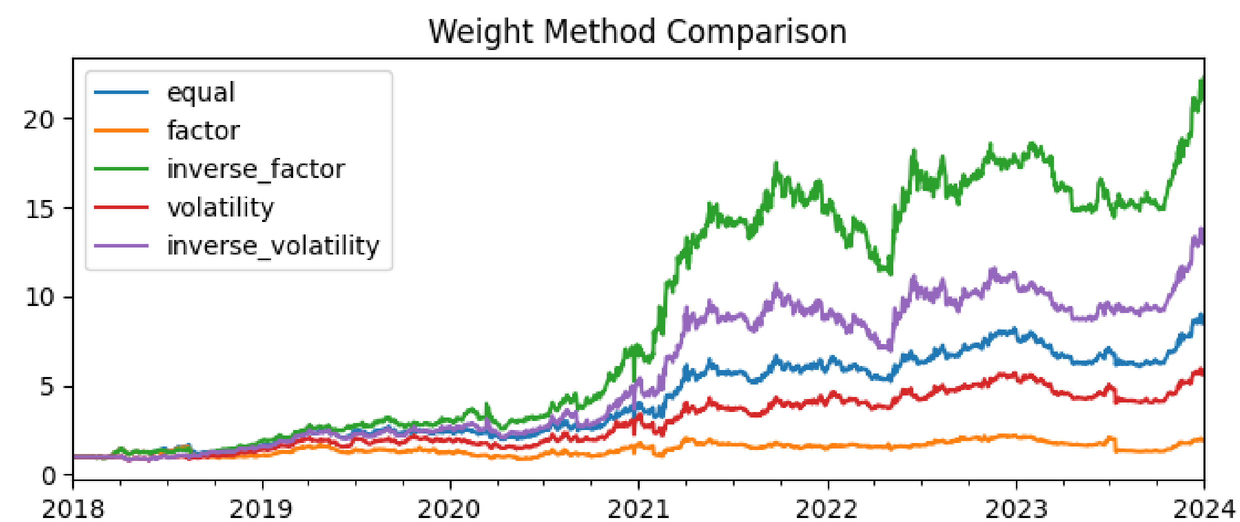
1. **Substantially reduced parameter sensitivity**, allowing us to rely less on the performance of any single lookback choice.
2. **Enhanced overall performance**, with the SPP ensemble outperforming the single-parameter version in both return and stability.

Alternative Weight Methods

All preceding tests relied on **equal-weighted asset allocation**, which is ideal for isolating factor efficacy but not necessarily optimal for maximizing portfolio performance. To explore potential improvement, we test several weighting schemes:

- Factor-weighted
- Inverse-factor weighted
- Volatility-weighted
- Inverse-volatility weighted

(With volatility defined as the annualized 90-day rolling standard deviation.)



Weight Method	Sharpe	CAGR [%]	MaxDD [%]
equal	1.13	43.93	-30.72
factor	0.49	12.13	-48.57
inverse_factor	1.39	67.72	-36.03
volatility	0.92	34.23	-35.63
inverse_volatility	1.22	54.78	-35.59

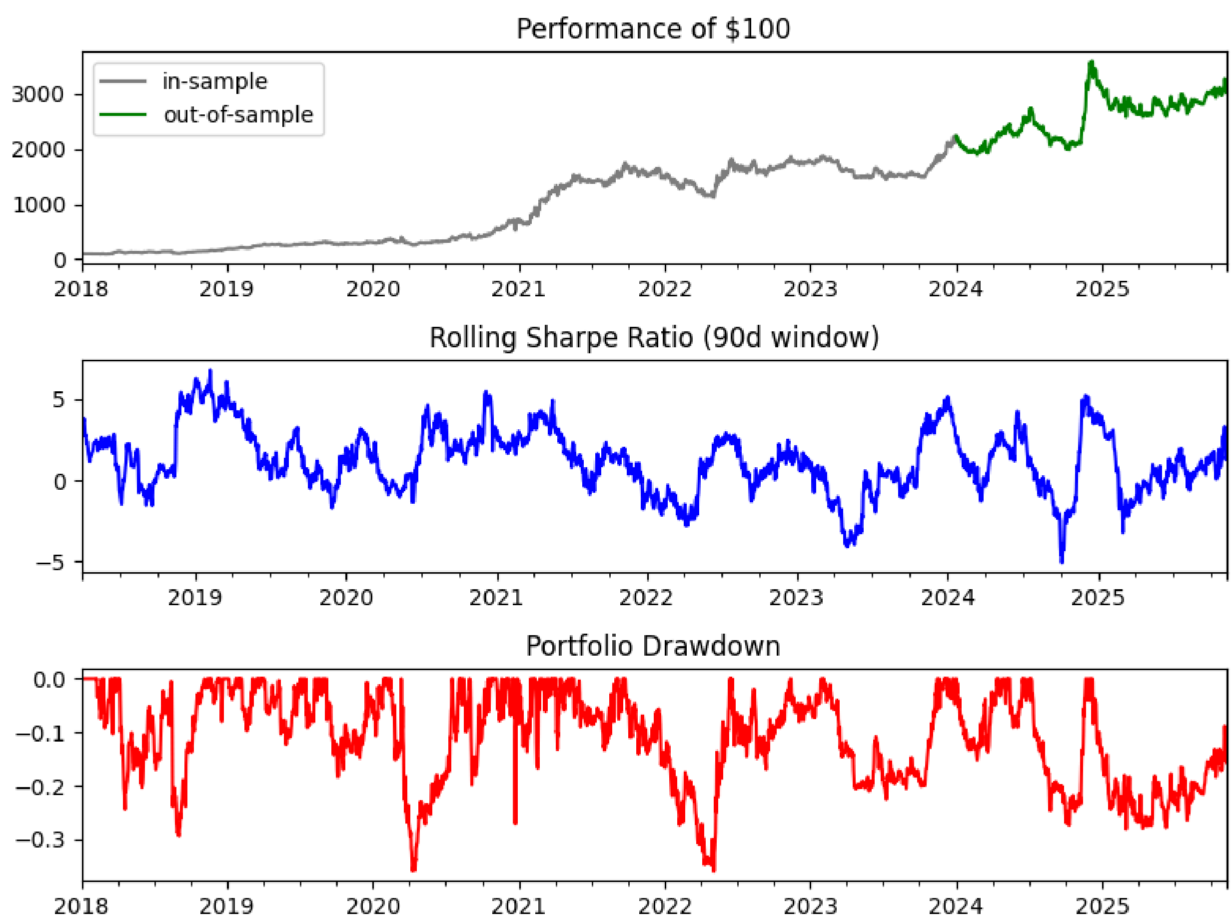
The comparison reveals a clear pattern: **inverse-based methods outperform**, with **inverse-factor weighting** delivering the strongest results. It achieves the highest Sharpe ratio, the highest CAGR, and does so while keeping drawdowns within a reasonable range. This suggests that down-weighting assets with extreme factor values or excessive volatility leads to a more balanced and efficient portfolio.

Out-of-sample Testing

Incorporating all optimizations, the final system configuration is:

- **Market Cap Cohort:** Top 20
- **Lookback Window:** SPP ensemble from 26–35 days
- **Weight Method:** Inverse Factor

We then evaluate this system on the out-of-sample dataset. The results show a continuation of strong performance, with an equity curve that behaves consistently relative to the in-sample phase, a stable rolling Sharpe profile, and controlled drawdowns.



Final Performance Summary

- **Sharpe Ratio** : 1.24
- **CAGR** : 54.3%
- **Max Drawdown** : -36%

Conclusion

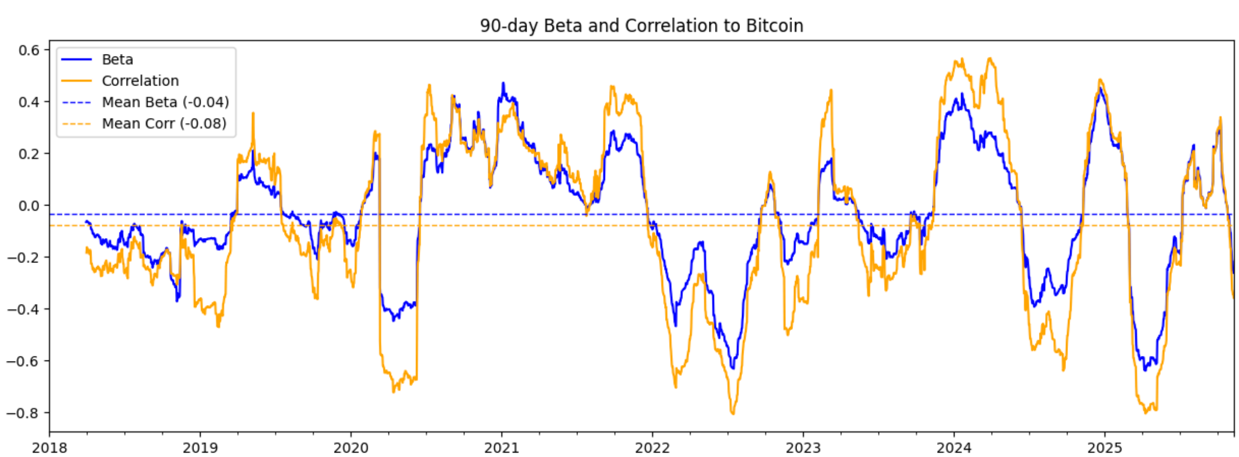
The out-of-sample results reinforce the system's robustness: performance remains strong without significant degradation, the Sharpe ratio stays consistently positive across market regimes, and drawdowns remain manageable relative to return potential. The combination of SPP ensembling and inverse-factor weighting materially improves both stability and efficiency, transforming a sensitive single-parameter system into a more resilient, adaptive momentum strategy suitable for live deployment.

Risk Exposures

To understand the systematic risks embedded in the strategy, we examine its relationship to the broader crypto market—represented by Bitcoin—through two key measures:

1. **90-day rolling correlation**, capturing co-movement.
2. **90-day rolling beta**, capturing directional sensitivity and market-scaled volatility exposure.

The chart below illustrates the evolution of both metrics over time, along with their long-run averages.



Correlation

The rolling correlation fluctuates meaningfully across market regimes, oscillating between strongly negative and strongly positive readings. This variability indicates that the strategy does **not maintain a persistent directional co-movement with Bitcoin**. Instead, its correlation structure adapts to the prevailing regime—sometimes benefiting from decoupling during market stress, and other times participating more fully in broad uptrends.

The mean correlation over the full test period is approximately **–0.08**, suggesting **no material long-term correlation to Bitcoin**, and even a slight tendency toward anti-correlation.

Beta

Similarly, rolling beta exhibits substantial variation, ranging from negative to moderately positive values. This reinforces the idea that the strategy's Bitcoin exposure is **not stable**, nor consistently long or short. The average beta is roughly **–0.04**, effectively indicating **no sustained directional dependence** on Bitcoin's returns.

Periods with mildly positive beta tend to coincide with trend-driven expansions in risk appetite, whereas negative beta episodes emerge during corrective or rotational phases—consistent with a cross-asset momentum framework.

Interpretation

Overall, the results highlight that the strategy carries **minimal long-term market risk to Bitcoin**, with both beta and correlation anchored near zero on average. This is a favorable property: it suggests the system's performance is driven primarily by **idiosyncratic cross-sectional momentum effects**, rather than by exposure to broad crypto-market direction. In practical terms, this makes the system a potentially effective diversifier within a portfolio that is already Bitcoin-heavy or otherwise directionally exposed to the crypto market.

Conclusion & Next Steps

This study shows that even a **naive definition of price momentum**—based solely on simple N-day percentage returns—can produce a meaningful and economically viable signal in the Binance perpetual futures universe. Despite its simplicity, the factor exhibits strong persistence within the **7–30 day horizon** and is most effective within the **Top 20 market-cap cohort**. Parameter sensitivity analysis reveals that cohort selection is relatively stable, while lookback sensitivity is significantly higher. This fragility is largely mitigated through **System Parameter Permutation (SPP)**, and further strengthened with an **inverse-factor weighting scheme**, producing a final system that performs consistently both in-sample and out-of-sample. The resulting strategy delivers a Sharpe of **1.24**, a **54% CAGR**, and **limited long-term beta/correlation to Bitcoin**, suggesting strong cross-sectional and diversification properties.

It is important to stress, however, that the momentum factor used here is *intentionally basic*. More sophisticated formulations—such as **volatility-adjusted momentum**, **residual (beta-neutralized) momentum**, **delay-adjusted momentum**, or **momentum excluding the most recent k days**—are widely documented in academic and practitioner literature to deliver superior performance and stability. These alternatives are natural extensions for future iterations and may overcome some of the structural limitations inherent in simple pct-change(N) definitions.

Looking ahead, promising next steps include testing these **enhanced momentum variants**, integrating **complementary factors** (e.g., funding-rate premia, open-interest growth, or term-structure signals), and exploring **multi-factor ensemble models** with cross-factor orthogonalization. Incorporating execution-aware improvements—such as volatility-targeting, adaptive position sizing, or turnover-aware optimization—will further align the system with real-world trading conditions. Finally, deploying the strategy in a controlled live or paper-trading environment will provide deeper insight into slippage, liquidity dynamics, and overall operational robustness.