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.

Momentum in Crypto

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.

Hypothesis

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*.

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.

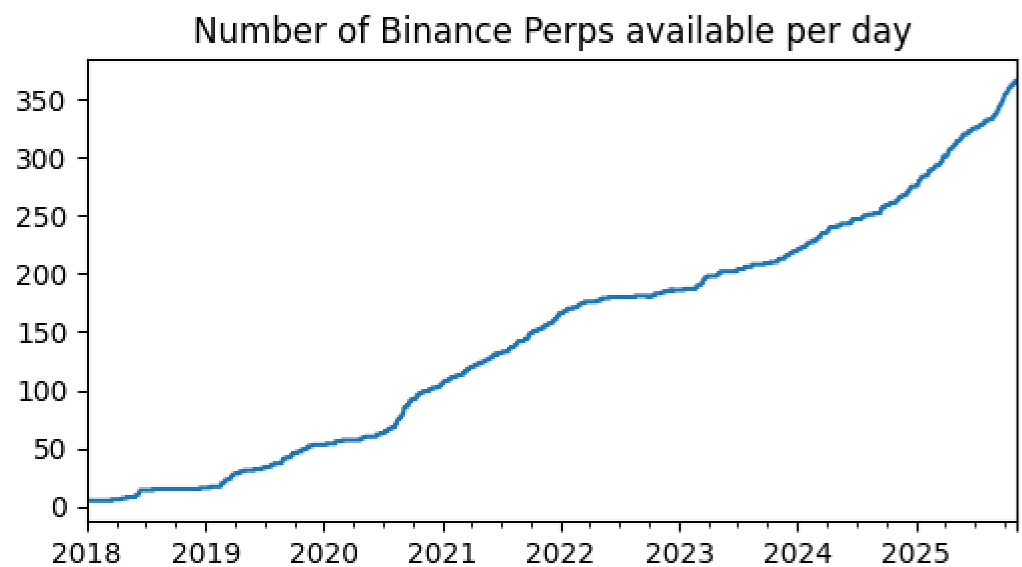
Formally, if a perp **did not exist** at time *t*, then:

```
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)

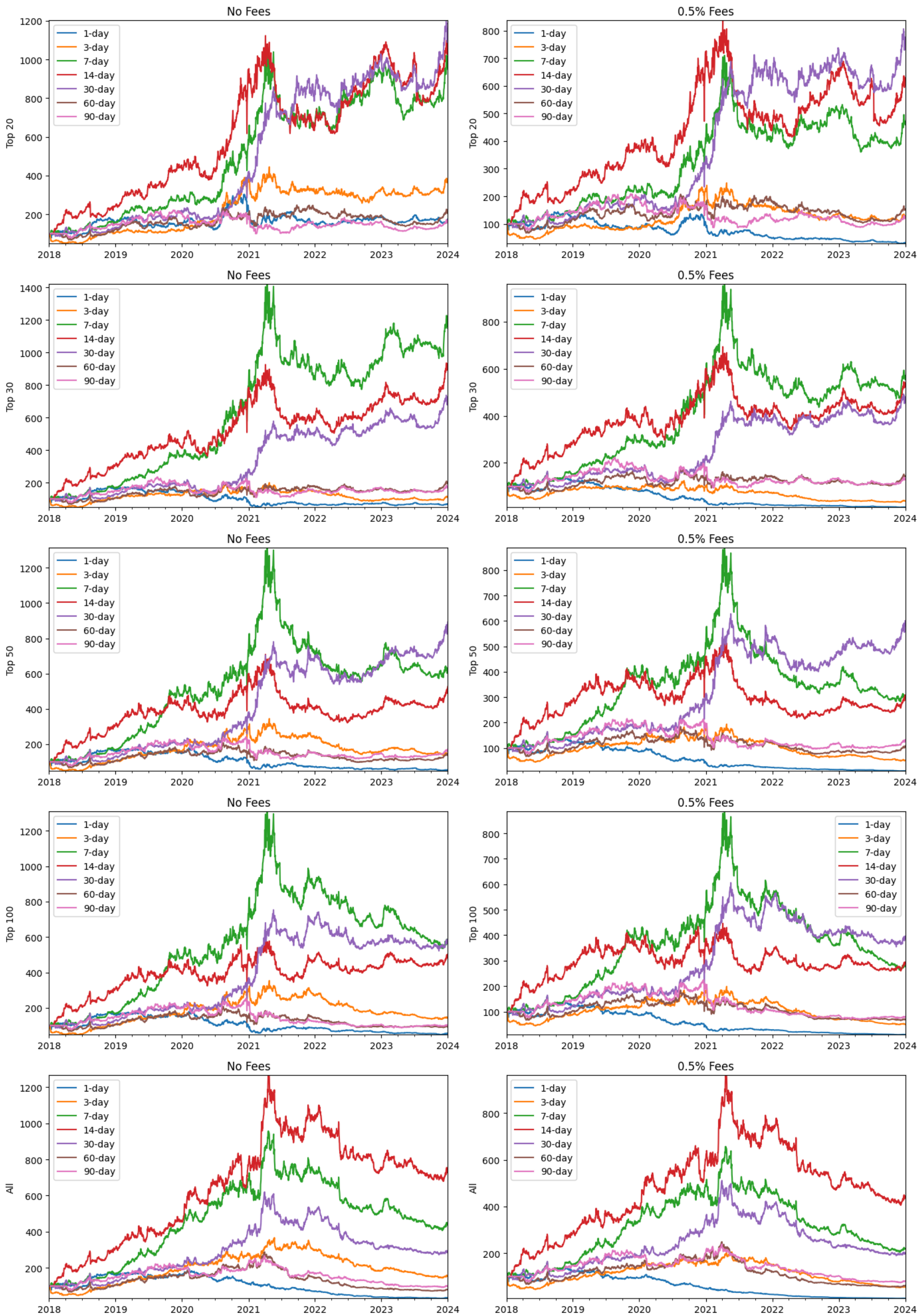
This split highlights the extent to which turnover-driven horizons (especially short lookbacks) are sensitive to execution costs.

Results & Permutation Selection

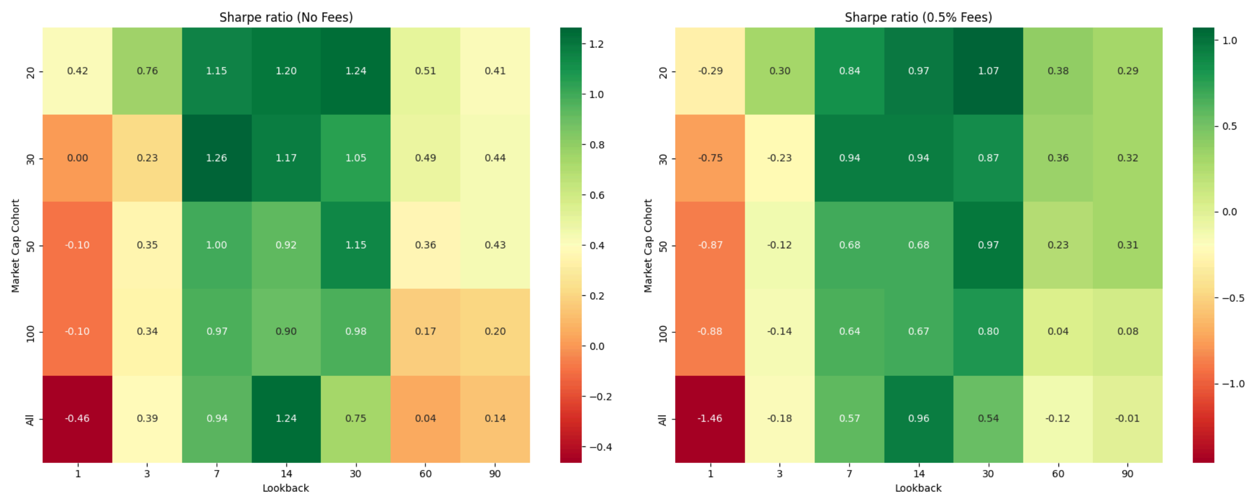
The performance of the Price Momentum factor was evaluated across all daily lookback windows. The figures below report the:

- 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 30
Top 50
Top 100
All
1-day
3-day
7-day
14-day
30-day
60-day
90-day
2018
2019
2020
2021
2022
2023
2024



<u>Observations</u>

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.
4. There is a clear regime shift around Q1 2021, which leads to alpha decay.

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.

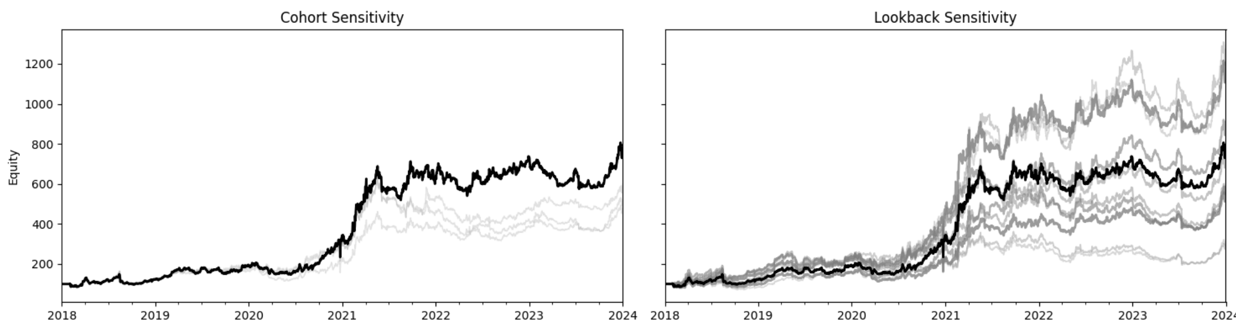
A narrow band of outcomes implies stability; a wide band suggests fragility or overfitting.

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

- **Market-cap cohorts:** 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.

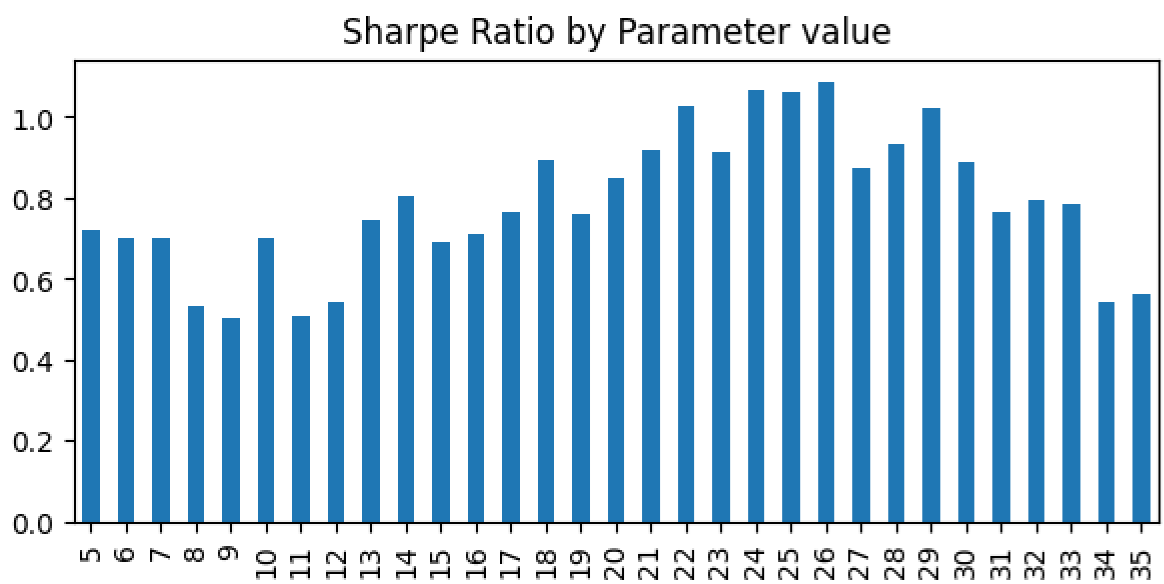
In our case, however, the selected permutation already demonstrates **strong and robust performance both gross and net of fees**, indicating that noise is not a major concern.

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

System Parameter Permutation (SPP)

Earlier analysis showed that the system is **highly sensitive to the choice of lookback window**, increasing the risk of **parameter overfitting**. To mitigate this, we apply **System Parameter Permutation (SPP)** - an ensembling approach that stabilizes performance by **aggregating signals across a neighborhood of similar parameter values**, rather than relying on a single optimized setting.

To define an appropriate permutation range, we first evaluate system performance over a **broad span of lookback windows**.

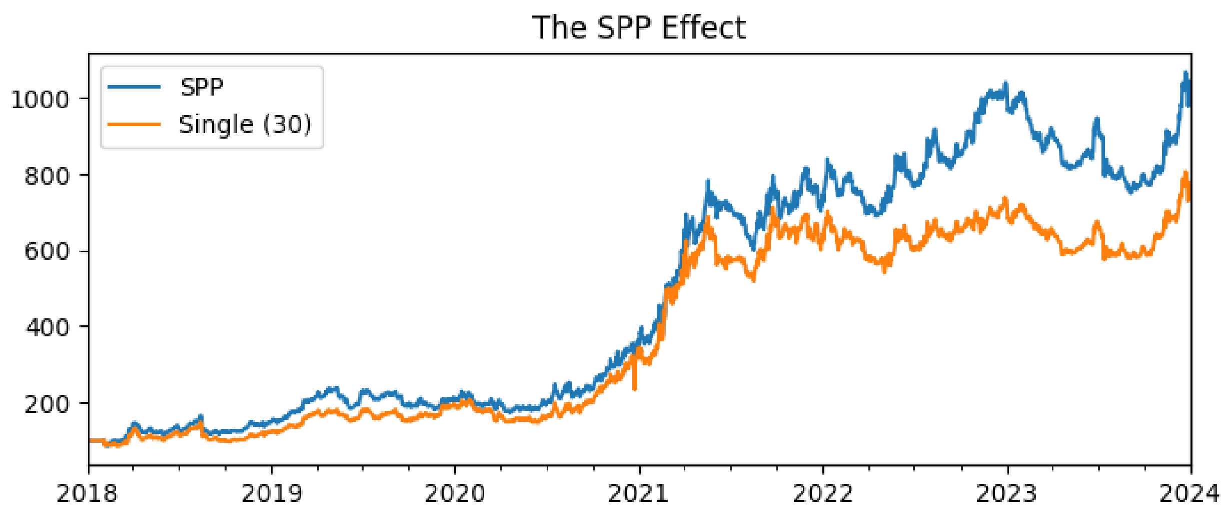


As shown in the Sharpe ratio profile above, performance exhibits a **well-defined plateau** rather than a single sharp optimum. Based on this structure, we select a **contiguous sub-range**

spanning 20 to 30 days, which captures the region of consistently strong performance while avoiding dependence on any single parameter choice.

This SPP range reduces estimation error, improves robustness to regime shifts, and lowers the likelihood that observed performance is driven by parameter-specific noise rather than persistent signal.

For each lookback window within this selected range, we construct a corresponding **sub-factor** and assign each an **equal weight**. The final ensemble factor is obtained by **averaging these sub-factors**, resulting in a composite signal that is less sensitive to any single parameter choice and more robust to estimation noise.



The resulting simulation demonstrates two key improvements:

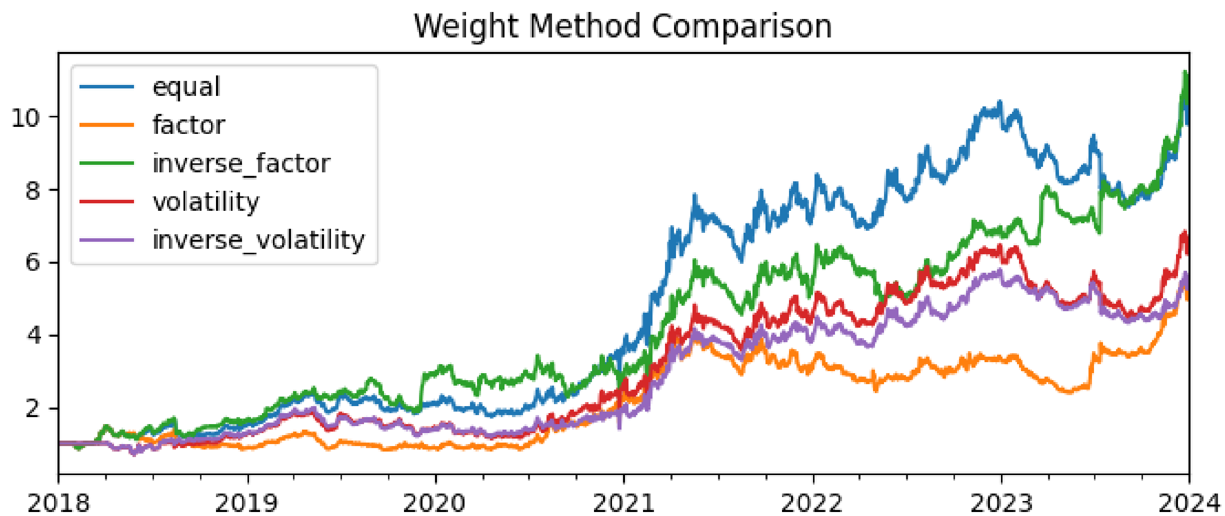
1. **Substantially reduced parameter sensitivity**, allowing us to rely less on the performance of any single lookback choice.
2. **Enhanced overall performance**, with the SPP ensemble outperforming the single-parameter version in both return and stability.

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:

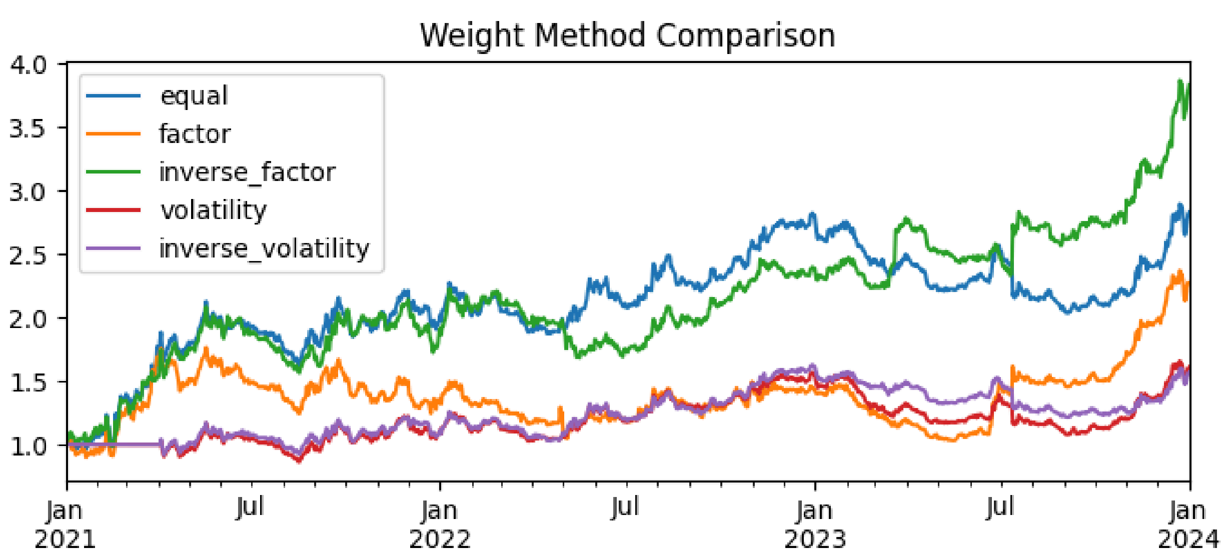
- Factor-weighted
- Inverse-factor weighted
- Volatility-weighted
- Inverse-volatility weighted

(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

At first glance, the **equal-weighted ensemble** appears to outperform all individual parameter choices. However, given the clear **regime shift around 2021**, it is important to evaluate whether this result persists under the post-2021 market environment. We therefore examine system performance **from 2021 onward**.



Weight Method	Sharpe	CAGR [%]	MaxDD [%]
equal	1.18	41.42	-27.89
factor	0.87	31.48	-41.56
inverse_factor	1.44	56.47	-24.91
volatility	0.69	17.21	-31.21
inverse_volatility	0.69	16.23	-25.39

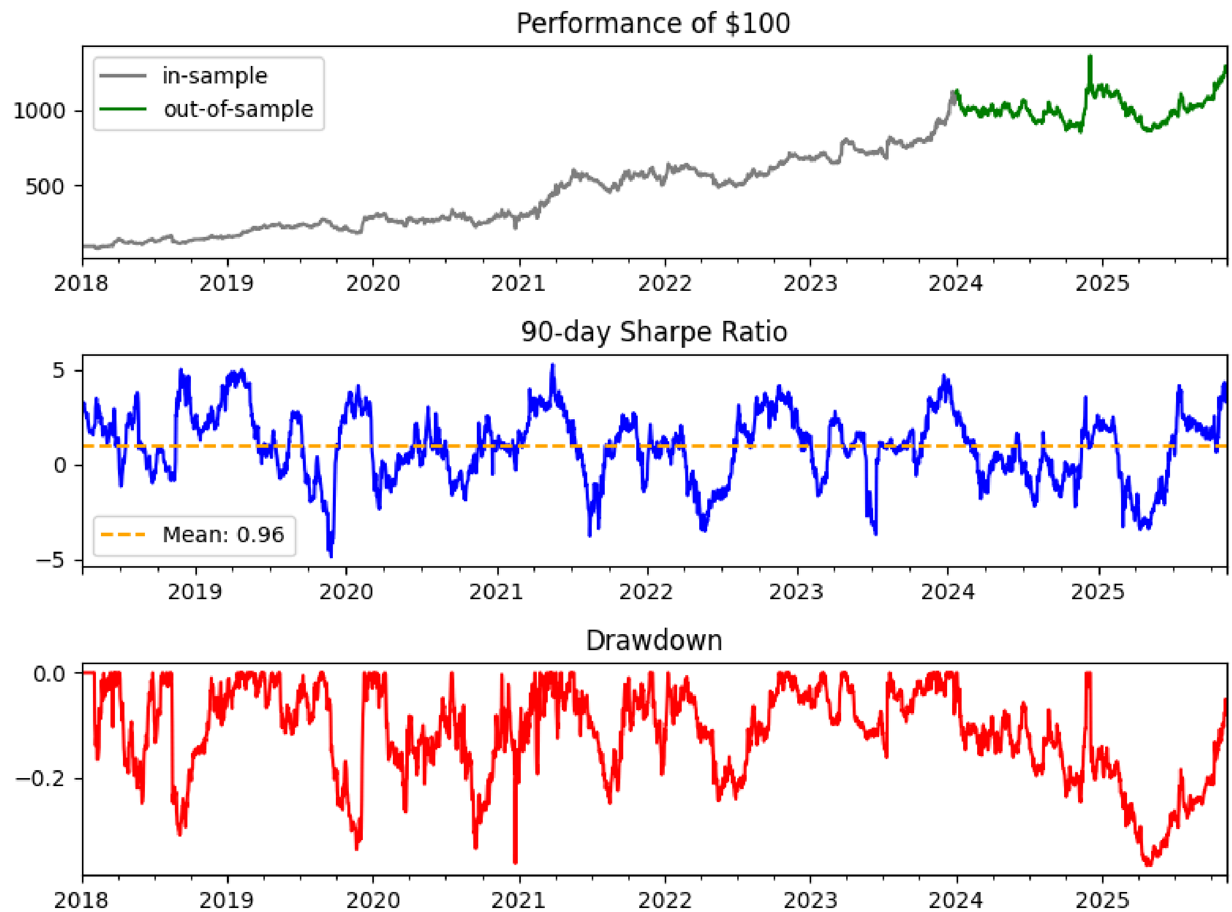
The results now indicate a specification that is **better adapted to the post-2021 regime**. In particular, the **inverse factor-weighted ensemble** consistently outperforms the equal-weighted approach across all evaluation metrics. Given this robustness in the new regime, we adopt the inverse factor-weighted specification going forward.

Out-of-sample Testing

Incorporating all optimizations, the final system configuration is:

- **Market Cap Cohort:** Top 20
- **Lookback Window:** SPP ensemble from 20 to 30 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** : 1.02
- **CAGR** : 37.9%
- **Max Drawdown** : -36.7%

Conclusion

While the out-of-sample period does not deliver monotonic performance, it provides a realistic stress test of the factor across multiple crypto regimes. The strategy demonstrates:

- Sensitivity to macro and microstructure regime shifts (expected for momentum)
- No evidence of terminal degradation or signal collapse
- Recovery following adverse conditions, consistent with a durable factor exposure

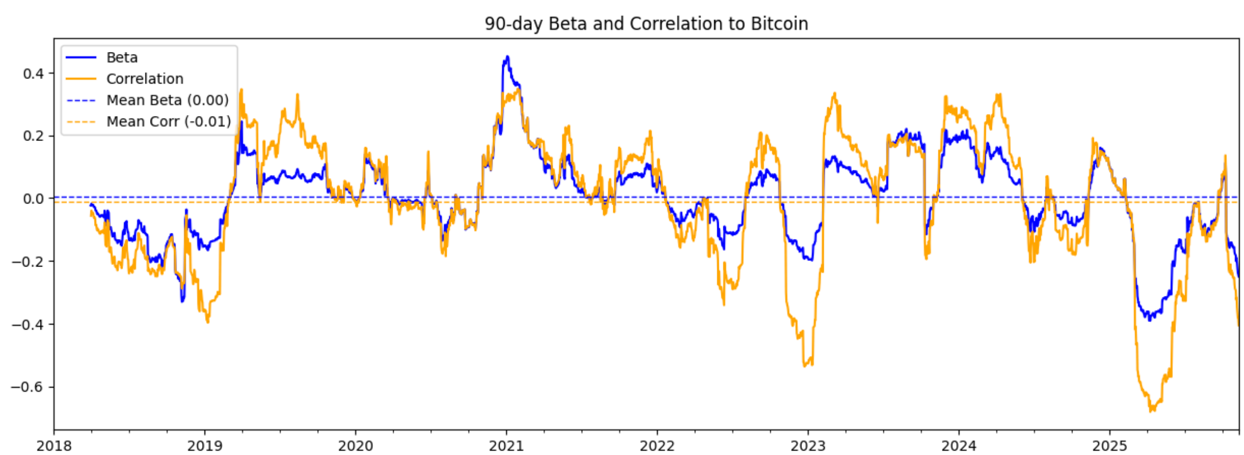
In this context, the out-of-sample results support the interpretation that the system captures a genuine crypto momentum effect, with performance driven by regime suitability rather than overfitted dynamics.

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.



Overall, the strategy exhibits **structurally low market risk** with respect to Bitcoin, with both rolling beta and correlation oscillating around zero over the full backtest horizon. This indicates that returns are not systematically driven by broad market direction, but instead by cross-sectional dispersion within the Top-20 universe. Periodic excursions in beta - both positive and negative - are best interpreted as **regime-induced exposure**, where momentum leadership temporarily aligns with high-beta assets in risk-on phases or inverts during deleveraging and rotation events. Importantly, these exposures are transient and mean-reverting, suggesting that market sensitivity is an emergent property of the factor rather than a structural dependency.

The dominant risk to the system is therefore **regime risk rather than directional market risk**. Performance drawdowns tend to coincide with transitions between trend-dominated and mean-reverting environments, when momentum signals lose persistence and cross-sectional leadership becomes unstable. In these phases, whipsaw risk and factor crowding dominate, particularly within a concentrated large-cap cohort. However, the absence of sustained correlation spikes, combined with the strategy’s ability to recover following adverse regimes, supports the conclusion that risk is primarily factor-specific and episodic, not systemic - positioning the strategy as a diversifying, alpha-oriented allocation rather than a proxy for crypto beta.

Conclusion & Next Steps

This study demonstrates that even a deliberately **naive formulation of price momentum** - based solely on simple *N*-day percentage returns - can produce a **meaningful and economically viable signal** within the Binance perpetual futures universe. Despite its simplicity, the factor shows strong persistence over the **20-30 day horizon** and is most effective within the **Top 20 market-cap cohort**. Sensitivity analysis indicates that while cohort selection is relatively stable, performance is materially more sensitive to the lookback window. This fragility is substantially mitigated through **System Parameter Permutation (SPP)** and further reinforced using an **inverse factor–weighting scheme**, yielding a final system that performs consistently both in-sample and out-of-sample. Overall, the strategy achieves a Sharpe ratio of approximately **1**, a **~38% CAGR**, and maintains **low long-term beta and correlation to Bitcoin**, highlighting strong cross-sectional and diversification properties.

Crucially, the results also reveal the presence of **distinct market regimes**, not only following the structural shift observed post-2021, but more importantly during the **out-of-sample period prior to 2025**, where the system experienced its **largest drawdown to date**. This episode underscores that while cross-sectional momentum remains effective on average, its risk profile can deteriorate sharply during certain market conditions - particularly when correlations spike, dispersion compresses, or market structure becomes temporarily hostile to relative-value signals.

These observations motivate the need for **explicit regime-adaptive logic** as a core component of the framework. Such mechanisms are essential for dynamically scaling exposure, preserving **market neutrality**, and mitigating tail risk when the cross-sectional signal weakens or becomes dominated by common-factor moves. Without regime awareness, even well-ensembled momentum systems remain vulnerable to episodic drawdowns that can dominate long-term risk-adjusted performance.

It is also important to stress that the momentum factor employed here is intentionally basic. More advanced formulations - such as **volatility-adjusted momentum**, **residual (beta-neutralized) momentum**, **delay-adjusted momentum**, or momentum definitions that exclude the most recent *k* days - are natural extensions and may further improve robustness across regimes. When combined with regime-conditioned exposure control, these enhancements offer a clear pathway to reducing unintended directional risk and improving consistency through stressed environments.

Looking ahead, promising next steps include evaluating enhanced momentum variants under **explicit regime classification frameworks**, analyzing complementary and orthogonal signals (e.g., funding-rate premia, open-interest growth, or term-structure features), and constructing **multi-factor ensembles with cross-factor orthogonalization**. Execution-aware refinements, such as volatility targeting and liquidity-adjusted sizing, will further align the system with real-world trading conditions. Finally, deploying the strategy in a controlled live or paper-trading environment will be critical for assessing slippage and liquidity dynamics.