ORIGINAL ARTICLE

Building a Mini Backtest Engine

Nathan Bruyere[1]

[1]Industrial Engineering & international middle distance athlete Student, `nathan-bruyere@hotmail.com`

ABSTRACT

This notebook builds a minimal backtesting engine in `Python`. The goal is to:

1. Fetch market data (probably via `yfinance`),
2. Generate trading signals for multiple systematic strategies,
3. Simulate portfolios with transaction costs,
4. Compute performance metrics (annualized return, Sharpe, max drawdown),
5. Visually compare them against common baselines (buy & hold and a 6%

I decided to focus on mono-asset portfolio only, testing the mini-engine on simple trend-following strategies. This introduction to backtesting allows me to get into the basics of using `python` for finance research. We will get to more complex projects afterwards.

Contents

Corresponding Author: Nathan Bruyere
Publication Date: November, 1st 2025
Email: nathan-bruyere@hotmail.com

1 | Introduction

This project reconstructs the core architecture of a backtesting engine, enabling systematic evaluation of strategies through modular components - data loading, signal generation, and portfolio simulation.

The objective is to replicate the analytical rigor of professional quantitative tools from ground. Beyond technical design, this work highlights how performance metrics such as Sharpe ratio, drawdown, and annualized return emerge from trading logic.

It illustrates a practical understanding of simple strategy development and risk analysis.

1.1 Engine Architecture

The engine is split into a few small classes :

- `DataLoader` : fetches and prepares historical price data (*e.g.* SPY Close prices) and ensures we work with a clean `pandas.Series` indexed by dates.
- `Strategy` : generic interface for any - automated - trading logic. A strategy turns prices into a trading signal (e.g. 0 = out of market, 1 = invested, -1 = short).
  - `TrendFollowingStrategy` : exemple of a strategy, invest when a fast moving average is above a slow moving average. Parameters: `(fast\_window, slow\_window)`.
  - `BuyAndHoldStrategy` : trivial baseline: always invested (signal = 1 at all times). Used as a benchmark.
  - ...
- `Portfolio` : simulates capital evolution over time given a price series and a trading signal. Handles position entry/exit, fees, portfolio value trajectory.

Let's get into basics strategies of trend following to see how the backtester goes.

2 | Equity trend-following strategies: Long-Only vs Long-Short

In this section, we implement and compare two classical trend-following models. The first one is based on moving-average crossovers (see 2.1), the second one rely on a channel breakout system (see 2.2).

2.1 Moving Average - MA

This strategy rely on a binary signal s_t computed from the relation between a short-term moving average (MA_{short}) and a long-term moving average (MA_{long} of the closing price.

$$s_t = \begin{Bmatrix} 1 & if\ MA_{short} > MA_{long} \\ -1 & if\ MA_{short} < MA_{long} \end{Bmatrix} \tag{1}$$

The Long-Only strategy takes a long position when $s_t = 1$, and remains in cash otherwise.

The Long-Short extension introduces symmetric exposure when $s_t = -1$: it allows the portfolio to benefit from downward market trends.

Both strategies are backtested on the S&P 500 index (SPY) over the period 2000–2025, with an initial capital of $10 000 and transaction costs set at 0.1% of the trade.
Results are compared against a *Buy-and-Hold* benchmark representing passive market exposure (black curve).
The following figure[1] (fig 1) illustrates the cumulative portfolio value of each strategy over time.

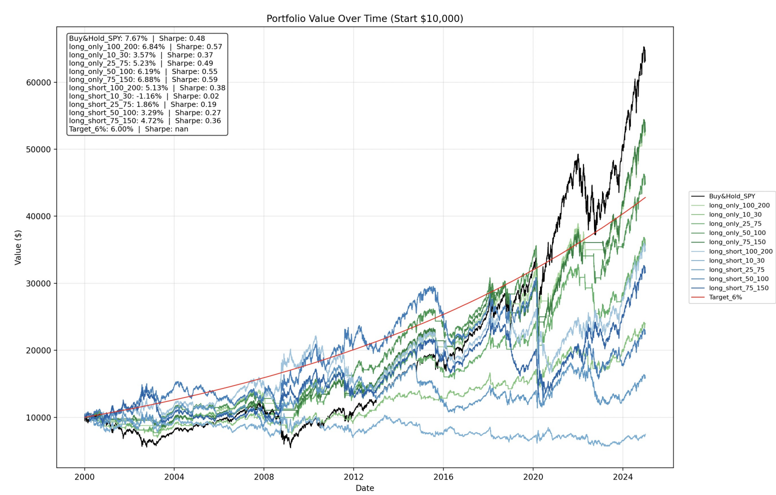

Figure 1: US equity moving average strategies : long only vs long short vs buy&hold (2000–2025).

Results : long-only models deliver consistent positive returns across most parameter sets, with annualized performances between 3.6% and 6.9%, and Sharpe ratios reaching up to 0.59 for the 75/150 configuration. Conversely, long-short

[1] The flat segments in the equity curves correspond to periods where the strategy holds no position (*i.e.* stays in cash).

variants underperform in both absolute and risk-adjusted terms. Negative or marginal Sharpe ratios indicate that the short-side signals introduce excess noise and transaction costs, rather than genuine downside protection. This result aligns with empirical evidence that shorting broad equity indices is structurally disadvantageous in secular bull markets [1].

Overall, the analysis confirms that trend-following is more effective as a risk management overlay than a standalone alpha generator on long-only equity indices.

2.2 Channel Breakout - CB

As a second approach we implement another price-based trend following strategy popularized by R. Donchian [2].
The logic is again purely mechanical : we monitor the asset's highest and lowest prices over a rolling window of N days. A new long position is triggered when the current prices **exceeds** the previous $N - day$ high, while a short position is opened when it breaks **below** the $N - day$ low.
We can define the signal as :

$$s_t = \begin{Bmatrix} 1 \quad\; if\ P_t > max(P_{t-N:t-1}) \\ -1\ if\ P_t < min(P_{t-N:t-1}) \end{Bmatrix} \tag{2}$$

As before, both the long-only and long-short configurations are backtested on `SPY` between 2000 and 2025. Results are benchmarked with a buy-and-hold strategy.

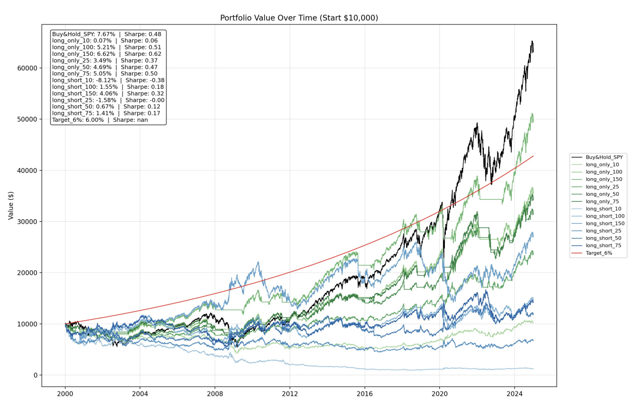

Figure 2: US equity channel-breakout strategies : long only vs long short vs buy&hold (2000–2025)

Results : they reinforce the conclusions drawn from moving-average systems. Long-only variants generate moderate but stable returns ($\approx$ 4–6%) with Sharpe ratios peaking around 0.6, while long-short implementations continue to underperform or even lose money in persistent bull markets. This pattern confirms that directional filters, whether based on averages or price breakouts, capture the same underlying momentum effect.

Overall, breakout signals offer similar exposure characteristics to moving averages, differing mainly in timing sensitivity rather than long-term efficiency. As before, the approach proves more useful as a risk management overlay than as a standalone alpha source.

2.3 Momentum Strength Model: Volatility-Adjusted Trend Following

As a final variant, we implement a continuous version of trend following based on time-series momentum, inspired by T. J. Moskowitz [3] and their **time-series momentum**.
Unlike discrete crossover or breakout rules, this model adjusts its exposure smoothly according to the recent price return normalized by volatility. The resulting signal $s_t \in [-1, 1]$ captures the **direction** (as before) and the **strenght** of the trend.
Formally :

$$s_t = tanh\left(\frac{r_t}{\sigma_t}\right) \quad with \quad r_t = \frac{P_t}{P_{t-L}} - 1 \tag{3}$$

Where L is the lookback period, r_t the raw momentum over L (relative return) normalized by the recent volatility σ_t. The resulting $\frac{r_t}{\sigma_t}$ captures how strong the current price is, relative to its own variability. We then apply the hyperbolic tangent transformation to fit to our backtest engine ($\forall x \in IR \quad tanh(x) \in [-1, 1]$).

As volatility is one nuanced quantitie in finance, let's stop a second here. It can be computed in multiple ways - historical, high-low, exponentially weighted, implied... In the context of this project we use the **rolling historical volatility**, which provides a robust estimate of recent market instability :

$$\sigma_t = \sqrt{\frac{1}{L-1}\sum_{i=1}^{L}(r_{t-i} - \bar{r})^2} \tag{4}$$

Where r_t denotes the daily return.

Long only strategy : again, as s_t indicates a upward momentum, so we'll be long, proportionnal to $|s_t|$.

Long-Short strategy : shorting the position, proportionnal to $|s_t|$.

In this continuous framework, the ‘long-only’ variant is obtained by truncating negative signals at zero. The comparison thus measures the cost of short-selling restrictions rather than a structural difference in trading logic.

To further test the robustness of our backtesting engine, we switch from the U.S. market (`SPY`) to a global equity benchmark (`ACWI`), which better captures cross-country dynamics and diversification effects.

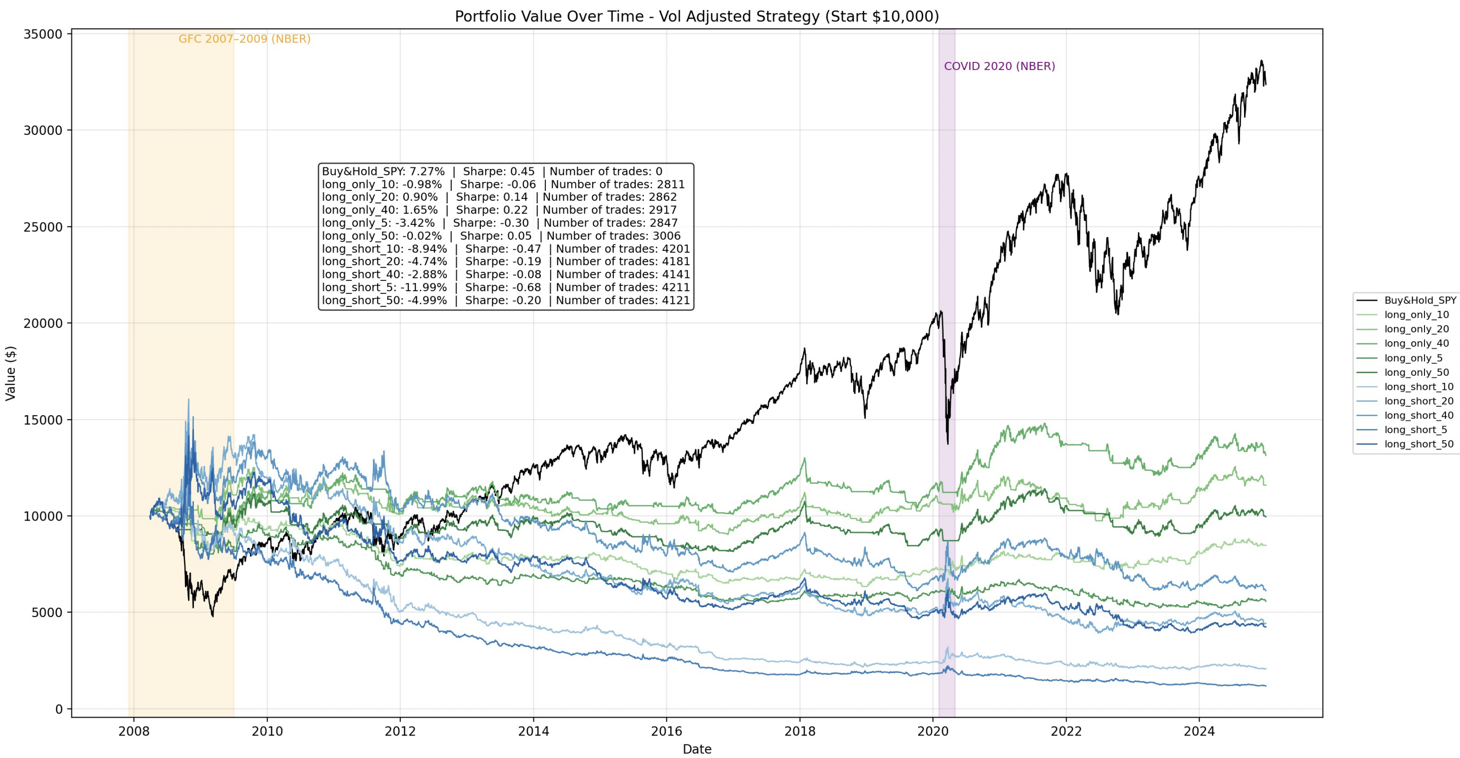

Figure 3: ACWI volatility ajusted strategies : long only vs long short vs buy&hold (2000–2025)

The period from 2000 to 2025 covers several distinct market regimes, including the 2008–2009 Global Financial Crisis (GFC), the 2020 COVID shock, and the post-pandemic rate-tightening phase.

Results : as illustred in Figure 3 , both the long-only and long-short versions of the volatility-adjusted momentum strategy **underperform the benchmark** (here `ACWI`) over the full sample. The long-only variants exhibit smaller drawdowns but limited upside capture, while the long-short models tend to erode value in low-volatility bull markets due to persistent whipsaws.

However, a closer look at high-volatility periods (highlighted in orange and purple on the plot) reveals a striking asymmetry:

During crisis regimes (2008–2009 and early 2020) : long-short strategies outperform their long-only counterparts and the bench by limiting downside exposure or even profiting from negative trends. This behavior aligns with theoretical expectations—volatility-adjusted momentum adapts more quickly to sharp price reversals, effectively shifting exposure away from risky assets when market variance spikes.

In summary, these results confirm that while volatility-adjusted trend-following may lag in prolonged bull markets, it **adds significant convexity and crisis protection**.

2.4 Conclusion

Across all three models the evidence points to a common pattern: equity trend-following performs well in directional or volatile environments but fails to

consistently outperform a passive benchmark over long bull markets.
Overall, these experiments highlight the dual nature of trend-following: not as a standalone alpha engine, but as a **risk-balancing component** that mitigates drawdowns and complements traditional long exposure. In that sense, systematic momentum appears more valuable as part of a diversified or risk-parity allocation than as a pure equity substitute.

3 | Final remarks

While the three families of trend-following strategies explored here offer useful intuition, the results themselves are deliberately modest. Over the last two decades of equity history—characterized by long U.S bull markets punctuated by short but violent crises—shorting broad indices is structurally penalized. With a different universe, another timeframe, or more sophisticated risk filters, the conclusions might very well differ.

But this was never the primary purpose of the study. The objective was to design a functional, modular, and transparent backtesting engine capable of handling realistic trading rules, transaction costs, long/short exposure, and continuous signals.

In short, the value of this work lies less in "finding a strategy that beats the market" than in building a quantitative research tool—a tool that can support future experiments, or academic exploration across a wide range of systematic investment ideas.