Group 6

Final Report

Module Code: IS4226 Systematic Trading Strategies & Systems

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1. Event-Based Backtester

1.1 Strategy Design

1.1.1 Strategy Overview

This technical strategy combines **momentum and mean-reversion** principles within a single, stateful trading framework. It trades daily and generates signals at bar 'Close', but executes at the next day's 'Open'. **A 150-day warmup period** is required so the MACD can accumulate enough historical data to function properly before live trading starts. This simulates a system that comprises four complementary trade "legs":

- Long Momentum (LM): follow emerging uptrends.
- Short Momentum (SM): follow emerging downtrends.
- Long Reversion (LR): buy oversold conditions near the lower Bollinger Band.
- Short Reversion (SR): sell overbought conditions near the upper Bollinger Band.

The objective is to capture short-term directional moves while fading extreme deviations, using volatility-adjusted thresholds to adapt to changing market conditions. Position exits are managed through ATR-scaled take-profit and stop-loss levels, with optional trailing logic for trend persistence.

1.1.2 Rationale

The **MACD (Moving Average Convergence/Divergence)** histogram measures short-term momentum by capturing the divergence between the MACD line and its signal line. Instead of relying on fixed thresholds, this design uses **MAD-based adaptive scaling** to define dynamic zones of momentum intensity.

Calculation:

- Let h_t be the MACD histogram at bar t.
- On a rolling window of W bars (e.g., W = 200):
    - med_t = median(h over the last W bars)
    - MAD_t = median(|h − med_t|) (Median Absolute Deviation)
    - RS_t = 1.4826 × MAD_t (Robust Scale ≈ standard deviation under normality)
- Define three adaptive thresholds (k, k_mid are tunable parameters):
    - Zpos_t = +k × RS_t (positive "extreme" boundary)
    - Zmid_t = k_mid × RS_t (near-zero band half-width)
    - Zneg_t = −k × RS_t (negative "extreme" boundary)

Interpretation:

- Near-zero histogram values (−Zmid_t ≤ h_t ≤ +Zmid_t) signal neutral momentum and are used for trend-following entries (LM/SM).

- Extreme histogram values (h > Zpos and h < Zneg) indicate overextension, triggering mean-reversion entries (LR/SR).

The Bollinger Bands act as contextual filters: price relative to the bands confirms overbought/oversold conditions and trend direction. We compute them on log-price (ln Close) for percentage-symmetric, variance-stable deviations, then map back to price. In practice: **Close > Upper** = overbought, **Close < Lower** = oversold, and **Close vs. Mid** (above/below) provides a clean bullish/bearish trend filter. ATR provides volatility-based scaling for exits, ensuring consistent risk exposure across varying price dynamics. This hybrid design seeks to exploit both momentum continuation and short-term correction opportunities while dynamically adjusting thresholds to market volatility.

References and Conceptual Inspiration

This strategy combines classical indicators with robust statistical scaling and adaptive risk control.

- **MACD Histogram:**
  Based on Gerald Appel's MACD (1979) and clarified in *Investopedia's Histogram Definition* (link), used here to capture momentum acceleration and exhaustion points.
- **Bollinger Bands (Log-Scale):**
  Inspired by John Bollinger's work (*Bollinger on Bollinger Bands*, 2001) and the *TradingView Log-Scale Implementation* (link).
  Applied on the log-price to ensure consistent volatility context across long-term price ranges.
- **Median Absolute Deviation (MAD):**
  Used as a robust volatility measure following *Rajathilagar R. (2022)* (link), providing stable z-score thresholds against outliers.

1.1.3 Reasons for Choosing This Strategy Variation

```
best_params = {'macd_fast': 13, 'macd_slow': 35, 'macd_signal': 8, 'macd_std_window': 83, 'macd_k': 1.15, 'macd_k_mid': 0.8500000000000001, 'bb_window': 15, 'bb_std_dev': 1.4, 'atr_window': 18, 'tp_mult_lm': 3.5, 'sl_mult_lm': 2.1, 'tp_mult_sm': 5.9, 'sl_mult_sm': 1.55, 'tp_mult_lr': 10.6, 'sl_mult_lr': 2.9, 'tp_mult_sr': 5.5, 'sl_mult_sr': 3.1, 'use_trailing': False, 'trail_mult': 3.7, 'trail_tp': False, 'time_stop': 26, 'cooldown': 0, 'rebounce_block': 2, 'rebalance_freq': 120}
```

This parameter configuration is finely tuned to the structural rhythm of the 10 SPY-dominant stocks during 2010–2017 - a period marked by strong secular uptrends, recurring momentum waves, and volatility cycles driven by post-Global Financial Crisis recovery, the mobile-cloud boom, and the early AI expansion. Unlike the sharper regime shifts after 2018, this era exhibited smoother trend persistence punctuated by moderate corrections. Each parameter aligns with these characteristics to balance early signal capture with robustness across multi-month cycles.

The MACD setup (13–35–8) occupies a well-calibrated midpoint: fast enough to detect emerging momentum during the frequent recovery phases of 2011, 2013, and 2016, yet slow enough to ignore micro-level noise that dominated high-beta names like TSLA and NVDA. Faster variants would overreact during the low-volatility 2014–2015 stretch, while slower ones would trail the swift trend resumptions common during this period. The 83-bar MAD scaling standardises the MACD histogram across the shifting volatility regimes that defined the early decade - supporting stable z-score behavior through both the low-volatility melt-ups (2013–2014) and the energy-driven turbulence in 2015–2016.

The dual z-thresholds ($k = 1.15$, $k_{mid} = 0.85$) introduce a structured asymmetry: the tighter mid-band encourages steady trend-following entries during the long, disciplined climbs typical of AAPL, MSFT, and BRK-B, while the upper threshold restricts counter-trend positioning to only high-conviction extremes - particularly valuable for handling TSLA's and NVDA's episodic blowouts. This mirrors the decade's signature pattern of broad, staircase-like advances interrupted by controlled but tradeable pullbacks.

The 15-bar, 1.4σ Bollinger Bands complement the MACD by targeting the shorter volatility oscillations characteristic of SPY mega-caps during this era. By triggering signals at moderate deviations rather than waiting for full 2σ departures, they identify early overextensions and stabilisations - especially useful during quiet grind-up phases like 2014. ATR-based exits add adaptive risk structure: long-momentum trades use balanced targets and stops (TP 3.5×ATR, SL 2.1×ATR), while short-momentum setups employ a wider TP (5.9×ATR) but tighter SL (1.55×ATR) to respect the market's persistent upward drift. The long-range rebound targets (10.6×ATR for long reversals and 5.5×ATR for short reversals) capture the episodic V-shaped recoveries seen after mid-2010, mid-2012, and early-2016 corrections.

Lifecycle parameters add an additional layer of discipline. With cooldown = 0 and rebounce_block = 2, the system stays highly reactive to genuine reversals while filtering out rapid whipsaws. Finally, the 120-day rebalance frequency acts as a structural reset - closing all positions and redistributing capital roughly every six months. This stabilises portfolio concentration, mitigates long-run drift toward outperformers like NVDA and AMZN, and ensures consistent exposure across all 10 SPY components throughout the sample window.

1.1.4 Indicators & Notations

Symbol	Full Name	What it Means	Used For
BB	Bollinger Bands	Three price bands were computed on the log price and then mapped back	Identify overbuy/oversold (OB/OS) zones & trend filter
ub / mb / lb	upper / middle / lower band	Upper band, middle band (SMA of log-price), lower band	Thresholds to compare Close for entries
h	MACD Histogram	MACD line − Signal line, oscillates around 0	Captures **short-term momentum** and impulse direction
RS	Robust Scale	RS=1.4826× MAD(histogram)	Volatility-adaptive scaling factor for the MACD thresholds
Zpos / Zmid / Zneg	Adaptive MACD thresholds	Dynamic levels: +k·RS, k_mid·RS, −k·RS	Distinguish **extreme** vs **near-zero** momentum regions
MAD	Median Absolute Deviation	Median of h (histogram). Median of absolute deviations from the rolling median of the histogram	Determines **TP/SL** size and **trailing distance**
ATR	Average True Range	Rolling average of True Range (volatility proxy)	Size TP/SL and trailing distances
pos	Position	Strategy state: −1 short / 0 flat / +1 long	Strategy output time series

TP / SL	Take Profit / Stop Loss	Exit levels based on ATR × multiplier	Risk control/exits
px	Entry price	Close price at the entry bar	Base to compute TP/SL
trail_mult	Trailing multiplier	ATR multiple for trailing SL/TP	Locking in profits

1.1.5 Systematic Trading Rules

- Entry Logic (evaluated at bar close):
- SR (Short Reversion): Enter short if $h > Zpos$ and $Close > upper\ band$.
- LR (Long Reversion): Enter long if $h < Zneg$ and $Close < lower\ band$.
- LM (Long Momentum): Enter long if $0 \leq h \leq Zmid$ and $Close > middle\ band$.
- SM (Short Momentum): Enter short if $-Zmid \leq h \leq 0$ and $Close < middle\ band$.

Entry Gates:

- Enforce cooldown after closing a trade to prevent immediate re-entry.
- Flip guards block entry in the opposite direction within a few bars (rebounce block) to reduce whipsaws.
- Limit consecutive LM/SM trades to prevent runaway trend stacking.

Risk Management & Exit Logic:
At entry price px:

- Long positions: TP = $px + ATR \times tp\_mult$, SL = $px - ATR \times sl\_mult$.
- Short positions: TP = $px - ATR \times tp\_mult$, SL = $px + ATR \times sl\_mult$.
- Optional trailing stop adjusts dynamically with run_max/run_min (Highest / lowest close since entry) using trail_mult.
- Time-stop closes trades that exceed a defined holding period.

<u>Exit Conditions:</u>
Close positions when TP/SL is hit, the time-stop expires, or trailing logic triggers an exit. All trade state variables (position, counters, and thresholds) are reset upon exit.

1.2 Portfolio Design

1.2.1 Portfolio Rebalancing Policy

To ensure disciplined portfolio management and prevent weight drift caused by uneven asset performance, the strategy adopts a systematic quarterly rebalancing schedule, executed every 120 trading days. This approach aligns with common institutional practices, where periodic rebalancing maintains target exposure, reinforces risk controls, and preserves the intended strategy structure over time.

Hyperparameter tuning was applied to evaluate how different rebalancing intervals interact with the strategy's signal thresholds, volatility filters, and allocation rules. Through iterative optimisation, the 120-day interval emerged as the configuration that consistently delivered the most favourable balance of return stability, drawdown control, and transaction efficiency, making it the preferred cadence for long-term performance.

A 120-day rebalance cycle strikes a practical balance between:

- Maintaining strategic weight consistency without excessive turnover,
- Allowing signals sufficient time to play out, particularly for medium-horizon technical indicators, and
- Reducing timing noise that may arise from overly frequent rebalancing.

Although transaction costs are set to zero for this project (as required), the chosen frequency remains appropriate for real-world conditions where turnover minimisation is a key constraint.

<u>Rebalancing Mechanics</u>

At each 120-day interval, the backtester performs the following sequence:

1. Close All Existing Positions
   a. Realise accumulated gains/losses and reset exposures across all stocks.
2. Recalculate Strategy Signals
   a. For each stock, generate updated long/short/flat signals based on the latest available data.
3. Redistribute Capital
   a. Allocate the available capital equally across all stocks that meet the strategy's active-signal criteria.
   b. Stocks without active signals retain zero exposure.
4. Re-establish Positions
   a. Enter new positions based on the refreshed allocation and signal outputs.

This systematic process ensures that the portfolio remains aligned with the strategy's intended factor exposures and risk profile throughout the entire backtesting horizon (2010–2019).

In later sections, performance metrics and comparative analysis with SPY will demonstrate how this rebalancing policy contributes to portfolio stability, drawdown control, and overall return behaviour.

1.2.2 Portfolio Allocation

To improve capital allocation efficiency and evaluate the contribution of each strategy component, we implemented a Modern Portfolio Optimiser (MPO) based on Modern Portfolio Theory (MPT). This optimiser identifies the mix of equity strategies that maximises the portfolio's Sharpe ratio along the efficient frontier.

1.2.2.1 Optimisation Framework

We designed the optimiser using the custom **ModernPortfolioOptimizer** framework, which includes the following key features:

- **Ledoit–Wolf shrinkage covariance:** Ensures stable covariance estimation, especially when sample sizes are small or returns are noisy.
- **Ridge regularisation:** Prevents overfitting and reduces numerical instability caused by near-collinear return series.
- **Exponentially weighted mean returns:** Places greater emphasis on recent data while still preserving the long-term return structure.
- **Analytical efficient frontier computation:** Eliminates iterative optimisation and enables fast, precise evaluation of expected risk–return profiles.

The input data consisted of the strategy performance of an **equal-weighted portfolio** containing 10 equities - AAPL, AMZN, META, GOOG, GOOGL, NVDA, MSFT, AVGO, TSLA, and BRK-B - each executed using the MACD+BB+ATR strategy during the training period (2010–2017). The resulting portfolio-level returns were aligned and aggregated into a daily time series, forming the empirical foundation for subsequent mean–variance optimisation.

1.2.2.2 Optimisation Process

Step 1: Compute Annualised Mean and Covariance

Using Ledoit-Wolf shrinkage and ridge regularisation ($\alpha = 1e{-5}$), the annualised mean return was estimated at 21.37%, and the annualised volatility across assets was around 10.4%. This step stabilises the risk estimates and reduces the impact of noise and collinearity in the return series.

Step 2: Construct Tangent Portfolio

Given these inputs, the optimiser constructs the tangent portfolio by inverting the regularised covariance matrix and scaling the resulting weight vector so that it satisfies a long-only, fully invested constraint (weights ≥ 0 and sum to 1). In other words, the solution is the portfolio that maximises the Sharpe ratio for a given risk-free rate under realistic equity constraints.

Step 3: Selection and Allocation

Once the raw tangent weights are obtained, we apply a simple **selection and filtering rule** to determine the final allocation. Assets are sorted by their tangent weight; we then either keep the **top *k* names** or exclude those with weights below a minimum threshold. The remaining weights are renormalised to sum to 1, producing the final allocation vector. This procedure ensures that capital is concentrated in the most risk-efficient components while avoiding tiny, economically irrelevant positions.

```
🎯 Selected 6 active stocks:
   AVGO: 0.2106 (21.06%)
   META: 0.1901 (19.01%)
   TSLA: 0.1835 (18.35%)
   GOOG: 0.1748 (17.48%)
   GOOGL: 0.1234 (12.34%)
   AAPL: 0.1176 (11.76%)
✅ Total = 1.0000

🗓 Final Portfolio Weights:
Stock  Weight
 AVGO  0.1828
 META  0.1651
 TSLA  0.1593
 GOOG  0.1518
GOOGL  0.1071
 AAPL  0.1021
 MSFT  0.0527
 AMZN  0.0466
 NVDA  0.0200
BRK-B  0.0123
======================================================================

✅ Selected: ['AVGO', 'META', 'TSLA', 'GOOG', 'GOOGL', 'AAPL']
💰 Allocations: {'AVGO': 0.2106, 'META': 0.1901, 'TSLA': 0.1835, 'GOOG': 0.1748, 'GOOGL': 0.1234, 'AAPL': 0.1176}
```

Figure 1: Selected Tickers and Allocation

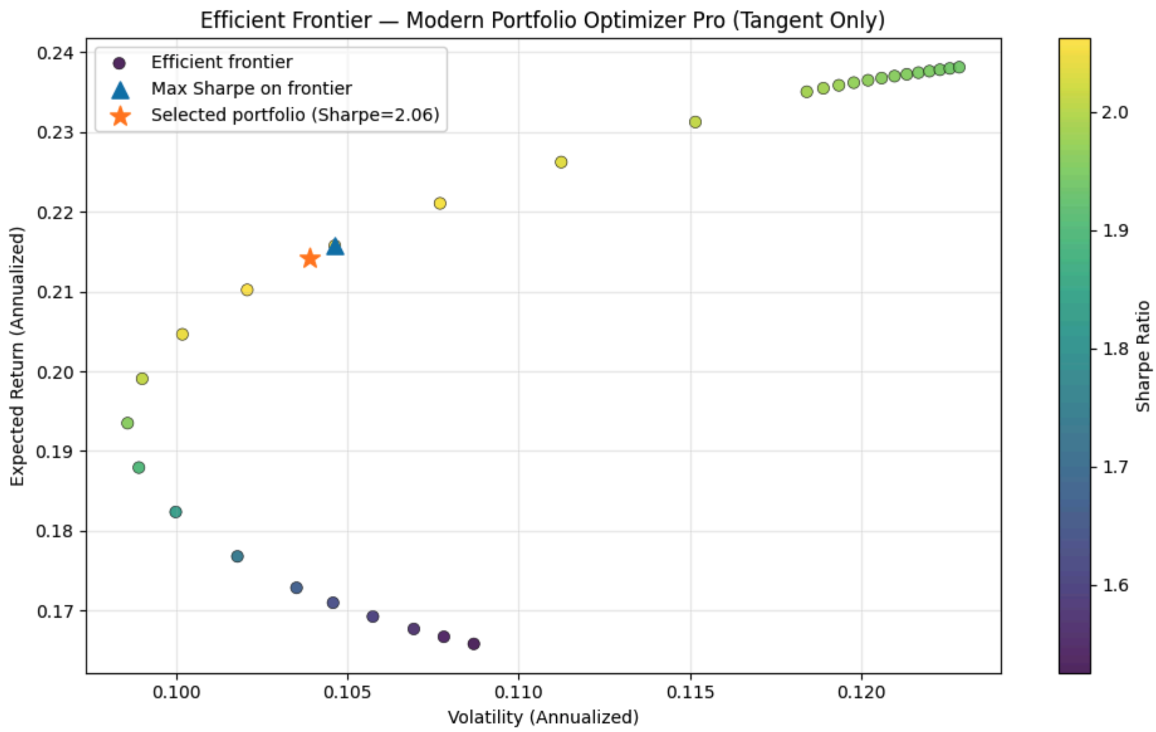

Figure 2: MPT Selection Portfolio

1.2.2.3 Compare the result before and after applying Portfolio Optimisation

Before we apply the selection and allocation for the test period 2018 - 2019, the return of the strategy is 26.09% annualised with a 1.81 Sharpe Ratio.

```
======================================================================
📈 PERFORMANCE METRICS
======================================================================
Initial Capital:         $      500,000.00
Final Portfolio Value:   $      793,145.79
Total Return:                       58.63%
CAGR:                               26.09%
Annualized Volatility:              13.32%
Sharpe Ratio:                        1.81
Max Drawdown:                      -10.34%
Calmar Ratio:                        5.67
Beta vs Benchmark:                 0.5750
Alpha (annual, %):                  17.19
Sortino Ratio:                       2.33
Omega Ratio:                         1.40
Ulcer Index:                         2.44
UPI (UP Ratio):                      0.60
Skewness:                         -0.1736
Kurtosis:                          6.0024
VaR 95% (% loss):                    1.13
CVaR 95% (% loss):                   1.90
Total Trades:                         484
======================================================================
```

Figure 3. Strategy Performance on test before applying Portfolio Optimisation

After applying, the performance significantly increased to 32.87% annualised with a 1.93 Sharpe Ratio

```
🚀 BACKTESTING IN TEST PERIOD

======================================================================
📈 PERFORMANCE METRICS
======================================================================
Initial Capital:        $     500,000.00
Final Portfolio Value:  $     880,328.94
Total Return:                     76.07%
CAGR:                             32.87%
Annualized Volatility:            15.29%
Sharpe Ratio:                      1.93
Max Drawdown:                     -9.43%
Calmar Ratio:                      8.06
Beta vs Benchmark:               0.5043
Alpha (annual, %):                23.56
Sortino Ratio:                     2.73
Omega Ratio:                       1.43
Ulcer Index:                       2.71
UPI (UP Ratio):                    0.64
Skewness:                        0.2322
Kurtosis:                        4.2944
VaR 95% (% loss):                  1.43
CVaR 95% (% loss):                 2.04
Total Trades:                       278
======================================================================
```

Figure 4. Strategy Performance on test after applying Portfolio Optimisation

2. Strategy Risk, Returns & Performance Metrics

2.1 Strategy Risk

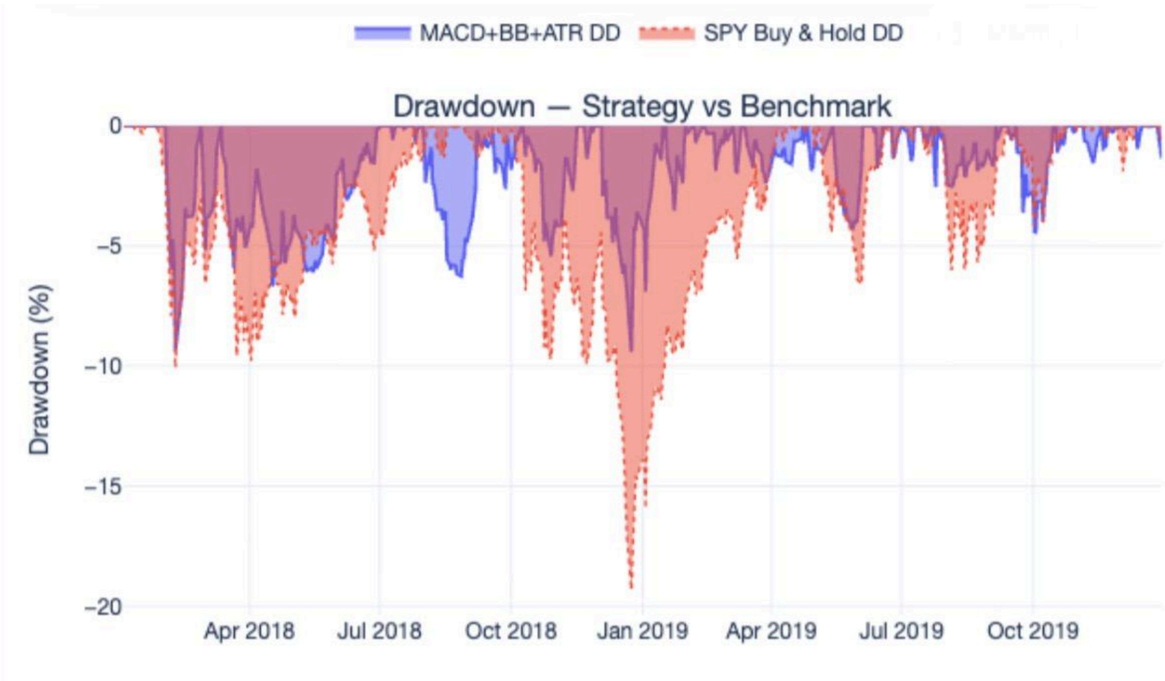

Figure 5: Comparative Drawdown - Portfolio Strategy and SPY Buy & Hold (2018 – end 2019)

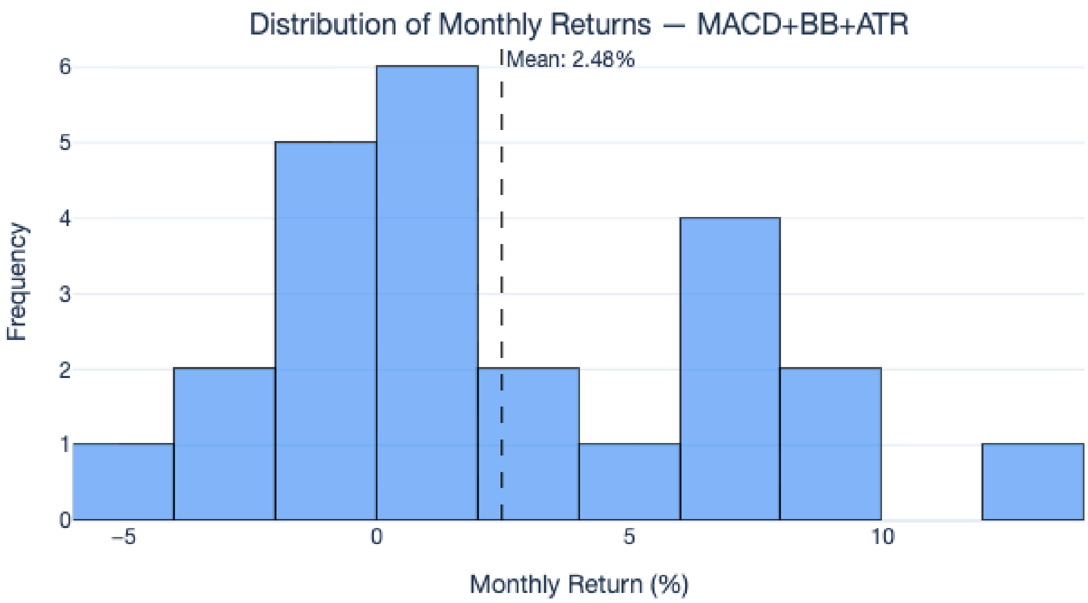

Figure 6: Histogram of Monthly Returns for the Portfolio Strategy (2018 – end 2019)

Our portfolio strategy demonstrates clear resilience and risk discipline relative to a passive SPY buy-and-hold benchmark. As shown in Figure 5, the strategy experiences consistently shallower and shorter drawdowns throughout the 2018–2019 period. During the late-2018 correction, SPY's drawdown exceeded –19%, whereas the strategy's decline remained more contained and recovered swiftly once market conditions stabilised. This pattern repeats across subsequent volatility clusters, suggesting that the combined momentum and volatility filters provide effective downside protection without fully sacrificing exposure to recovery phases.

Figure 6 depicts the distribution of monthly returns for the same period. The returns are mildly right-skewed, with the majority of months clustered between 0 % and +5 %, and a limited incidence of extreme losses. Occasional positive outliers reaching up to approximately +10 % highlight the strategy's ability to capture extended momentum runs while maintaining control over losses. The resulting profile reflects asymmetric return characteristics, where downside risk is capped more effectively than upside potential.

Taken together, the MACD + BB + ATR framework achieves a more favourable return-to-risk balance than passive exposure. Its controlled drawdowns, faster recoveries, and stable positive monthly distribution reinforce the benefits of adaptive signal layering and systematic risk management in a diversified equity portfolio.

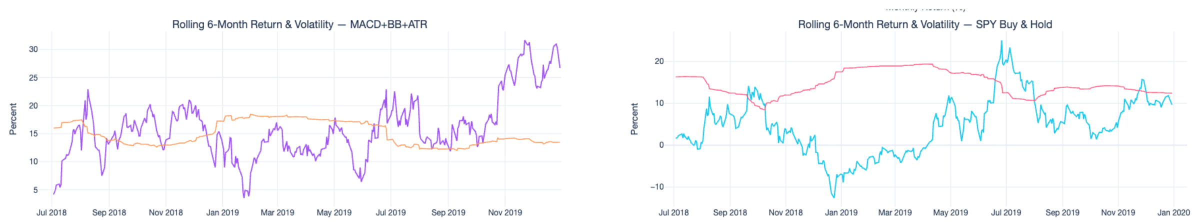

Figure 7: Rolling 6-Month Return and Volatility - Comparison between Portfolio Strategy and SPY Buy & Hold (2018– end 2019)

The rolling 6-month analysis highlights how the MACD+BB+ATR portfolio strategy maintained a more dynamic and adaptive return profile compared to the passive SPY Buy-and-Hold benchmark. The left panel shows that the strategy's rolling returns fluctuated actively in response to market conditions, with pronounced recoveries during mid-2018 and late-2019. Throughout these phases, rolling volatility (orange line) remained contained, indicating that the strategy managed risk effectively despite frequent position adjustments.

In contrast, the Buy-and-Hold portfolio (right panel) displays more persistent volatility, especially during the late-2018 drawdown, when rolling returns fell sharply into negative territory. This pattern reflects greater exposure to systematic market risk and slower recovery momentum.

Overall, the MACD+BB+ATR framework achieved stronger short-term adaptability and more consistent risk efficiency. Its rolling returns tended to stay positive or recover faster during adverse conditions, while volatility compression over time underscores the benefits of active, signal-driven rebalancing and volatility awareness in portfolio management.

2.2 Returns

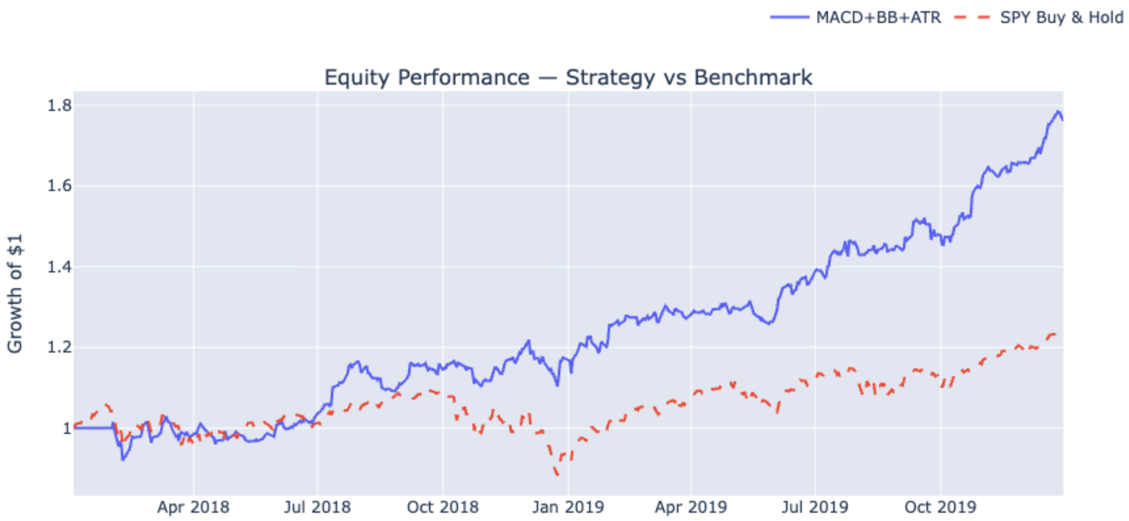

Figure 8: Cumulative Equity Performance ($1 + return) - Portfolio Strategy vs. SPY Benchmark (2018 - end 2019)

The cumulative equity curve in Figure 8 illustrates that the MACD+BB+ATR portfolio strategy consistently outperformed the SPY Buy-and-Hold benchmark throughout the 2018–2020 period. Both portfolios experienced parallel upswings during favourable market conditions; however, the strategy generated higher compounding returns and recovered more rapidly from temporary declines, particularly after the late-2018 correction.

A particularly compelling period demonstrating the model's superiority emerges between October 2018 and January 2019. During this window, the SPY Buy and Hold benchmark experienced a sustained and severe drawdown that was only recovered in April 2019. Equity performance declined sharply as market volatility intensified. In contrast, the MACD+BB+ATR portfolio remained largely resilient, exhibiting a shallower dip followed by an earlier and more decisive recovery. This asynchronous performance profile shows the model's effectiveness in managing downside risk.

This sustained divergence reflects the model's responsiveness to evolving market conditions and its capacity to control downside risk through adaptive signal layering. By the end of the test window, the strategy achieved a final equity value roughly 50–60 percent above that of the benchmark, indicating materially stronger cumulative growth. The smoother trajectory of the strategy curve also points to enhanced risk-adjusted efficiency, aligning with its lower drawdown behaviour and more stable return distribution observed in earlier figures. This divergence highlights the model's strength not only in capturing upside quickly but also in avoiding large market shocks.

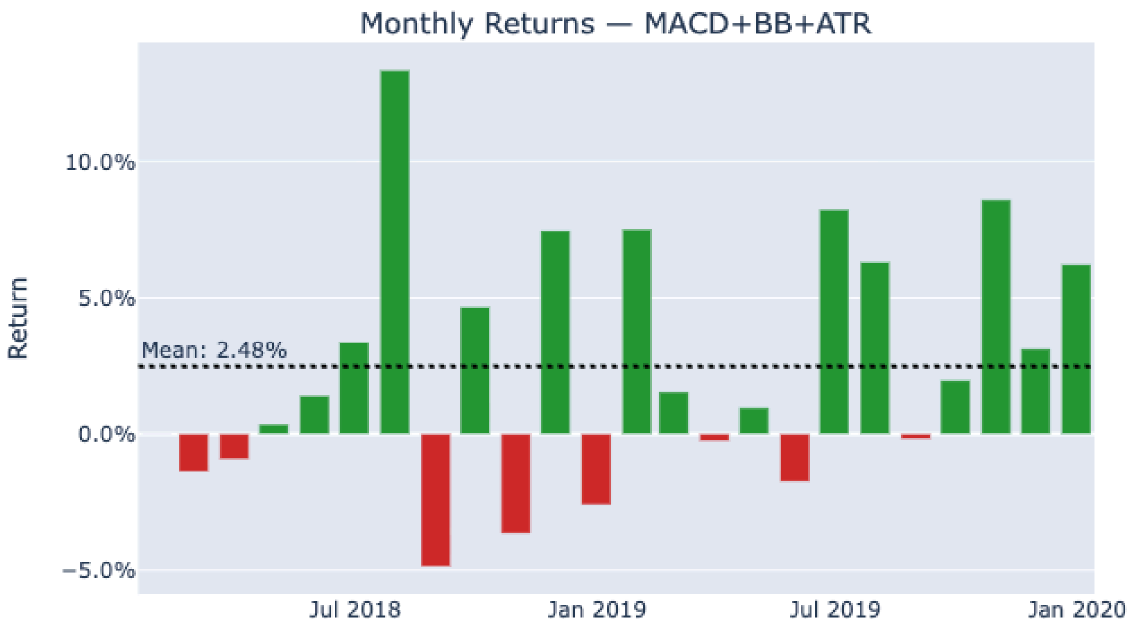

Figure 9:Monthly Performance - Portfolio Strategy

The monthly performance chart in Figure 9 illustrates the steady and resilient profitability of the MACD+BB+ATR portfolio strategy across diverse market conditions. Over the 2018–2019 test period, the strategy achieved a positive average monthly return of approximately 1.99%, with most months delivering moderate gains and only a few instances of shallow drawdowns.

Positive months significantly outnumbered negative ones, and several periods - such as mid-2018 and late-2019 - recorded strong surges exceeding 6–10%, demonstrating the model's ability to capture extended directional trends. The limited magnitude of negative months, typically below –2%, reflects effective loss control through the combined MACD momentum filter, Bollinger-based mean reversion checks, and ATR-driven volatility thresholds.

Taken together, the distribution of monthly results underscores the framework's return consistency, downside containment, and capacity for alpha generation. This month-to-month stability complements the cumulative equity growth and drawdown resilience observed in earlier figures, reinforcing the reliability of the MACD+BB+ATR system as a systematically managed multi-asset strategy.

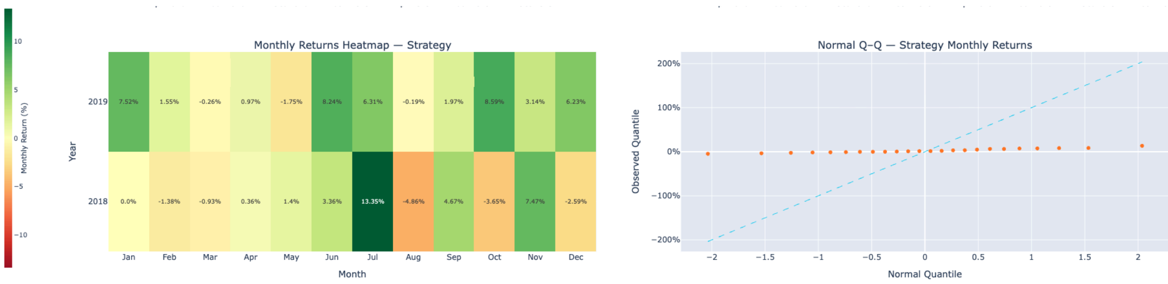

Figure 10:Monthly Return Heatmap and Normal Q–Q Plot of Monthly Returns (2018–end 2019) of Portfolio Strategy

The monthly returns heatmap in Figure 10 highlights the consistent profitability and seasonality of the MACD+BB+ATR portfolio strategy across the 2018–2019 period. Positive returns dominate much of the grid, particularly during mid-year months such as June to August and again during late-year rallies. This recurring strength suggests that the model effectively captures both trend-continuation and volatility expansion phases. Periodic drawdowns, such as August 2018 and May 2019, are comparatively shallow and typically followed by quick recoveries, indicating that the framework's mean-reversion and volatility filters respond effectively to transient corrections.

The Q–Q plot on the right shows a clear departure from the normal distribution line, confirming that monthly returns are non-normally distributed with positive skewness. Most observations cluster near zero with a few larger positive outliers, revealing fat-tailed behaviour where upside movements outweigh downside losses. This asymmetric return structure implies that the strategy benefits from rare but strong momentum-driven gains while keeping losses contained.

Together, these charts reinforce that the MACD+BB+ATR framework produces steady month-to-month performance with asymmetric reward characteristics, reflecting how systematic approaches can pair momentum-driven signals with volatility-responsive position sizing to navigate changing market conditions more effectively.

2.3 Performance Metrics and Portfolio Comparison

```
🚀 BACKTESTING IN TEST PERIOD

======================================================================
📈 PERFORMANCE METRICS
======================================================================
Initial Capital:        $     500,000.00
Final Portfolio Value:  $     880,326.84
Total Return:                     76.07%
CAGR:                             32.87%
Annualized Volatility:            15.29%
Sharpe Ratio:                      1.93
Max Drawdown:                     -9.43%
Calmar Ratio:                      8.06
Beta vs Benchmark:               0.5043
Alpha (annual, %):                23.56
Sortino Ratio:                     2.73
Omega Ratio:                       1.43
Ulcer Index:                       2.71
UPI (UP Ratio):                    0.64
Skewness:                        0.2323
Kurtosis:                        4.2945
VaR 95% (% loss):                  1.43
CVaR 95% (% loss):                 2.04
Total Trades:                       278
======================================================================
```

```
======================================================================
📊 Buy & Hold Strategy on SPY
======================================================================

======================================================================
📈 PERFORMANCE METRICS
======================================================================
Initial Capital:        $     500,000.00
Final Portfolio Value:  $     622,283.68
Total Return:                     24.03%
CAGR:                             11.62%
Annualized Volatility:            14.96%
Sharpe Ratio:                      0.80
Max Drawdown:                   -19.34%
Calmar Ratio:                      1.24
Sortino Ratio:                     0.96
Omega Ratio:                       1.16
Ulcer Index:                       4.99
UPI (UP Ratio):                    0.51
Skewness:                       -0.5263
Kurtosis:                        3.8150
VaR 95% (% loss):                  1.76
CVaR 95% (% loss):                 2.47
Total Trades:                         1
======================================================================
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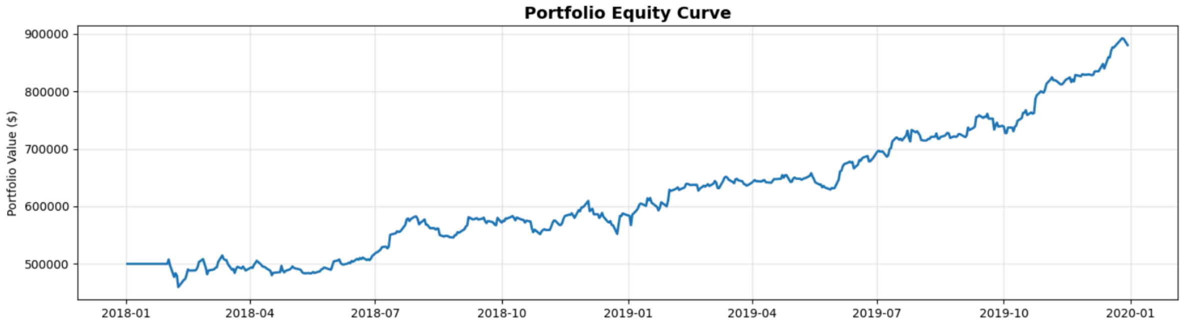
Figure 11: Comprehensive Performance Summary of Portfolio Strategy (top) vs SPY Buy & Hold (bottom)

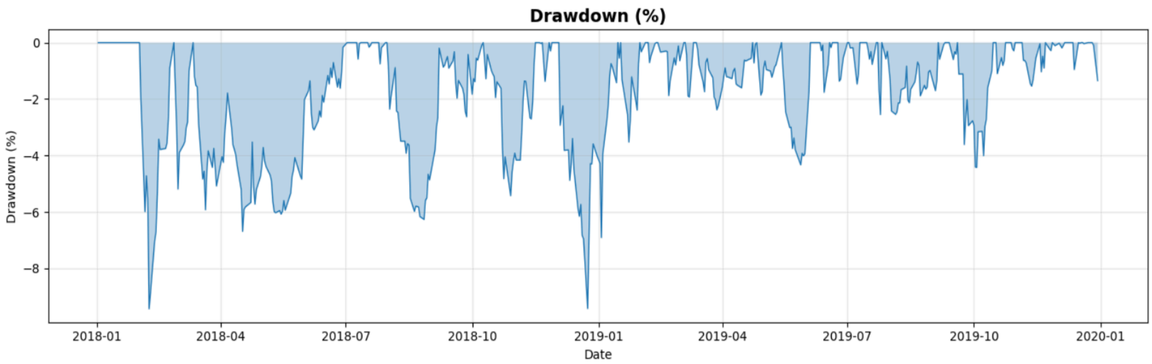
Portfolio Strategy



SPY B&H Equity Curve

Figure 12: Equity Curves of Portfolio Strategy (top) vs SPY Buy & Hold (bottom)

Portfolio Strategy



SPY B&H

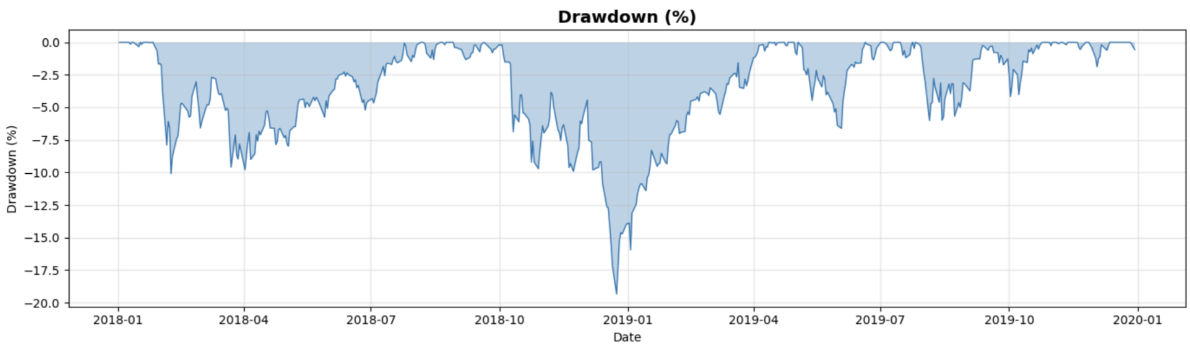


Figure 13: Drawdown - Portfolio Strategy (top) vs SPY Benchmark (bottom)

Compounding and terminal outcomes

As shown in Figures 11 and 12, the MACD+BB+ATR portfolio strategy achieved a final portfolio value of USD 880,326.84 from an initial USD 500,000, representing a total return of 76.07% and a CAGR of 32.87%, more than double the SPY Buy & Hold benchmark's 24.03% total return and 11.62% CAGR. The equity curve reveals smoother compounding and faster post-drawdown recoveries, particularly after late 2018, when the benchmark experienced a prolonged recovery period. This outcome reflects the model's ability to adjust exposure during volatile phases and capture persistent medium-term momentum.

While the benchmark benefited from uninterrupted beta exposure during the 2019 bull run, the strategy maintained steadier compounding and reduced path volatility, ultimately yielding a higher cumulative wealth multiplier without sacrificing stability.

Risk-adjusted efficiency

Risk-adjusted metrics further underscore the portfolio strategy's structural advantage. The Sharpe ratio (1.93) and Sortino ratio (2.73) from the portfolio both reported more than double compared to those of the SPY benchmark (0.80 and 0.96, respectively), highlighting superior return efficiency per unit of volatility and downside deviation. The Calmar ratio (8.06 vs 1.24) reflects enhanced growth relative to maximum loss, while an annualised alpha of 23.56% indicates consistent excess performance beyond market beta.

The lower beta (0.5043) shows reduced dependence on systematic risk, while the elevated Omega (1.43) and Ulcer Index (2.71 vs 4.99) confirm that the strategy delivers higher-quality returns with smaller and shorter drawdowns. Collectively, these statistics indicate that the MACD+BB+ATR framework produces institutional-grade risk efficiency typically associated with actively managed adaptive portfolios.

Drawdown and path risk

Drawdown comparisons in Figure 13 reinforce the risk management benefits of the strategy. The maximum drawdown is limited to –9.43%, nearly half of SPY's –19.34%, with quicker recoveries and more contained troughs throughout 2018–2019. This controlled downside behaviour, aided by volatility-sensitive position sizing, translates into improved Calmar and UPI ratios, demonstrating greater resilience in stress periods.

Distribution shape and tail risk

The return distribution exhibits mild positive skewness (0.2323) but high kurtosis (4.2945), consistent with concentrated positive bursts amid largely stable returns. Tail risk metrics such as 95% VaR (1.43%) and CVaR (2.04%) remain well-contained compared to SPY's 1.76% and 2.47%, validating the model's ability to limit extreme downside while participating in market upswings. This tail control is a direct outcome of the ATR-based stop logic and the adaptive cooldown mechanism that reduces exposure following volatility spikes.

Benchmark-relative diagnostics

Overall, the MACD+BB+ATR portfolio strategy exhibits strong positive alpha, moderate beta, and consistent excess returns over the benchmark. Outperformance arises not merely from risk scaling but from timing efficiency and volatility adaptation - the ability to withdraw during unfavourable volatility regimes and re-engage in stable trend continuation phases. The combined evidence from Figures 11 to 13 demonstrates that the strategy successfully balances growth and protection, yielding a superior risk-return profile across compounding, drawdown, and efficiency dimensions.

3. Benefits, Challenges, and Opportunities

3.1 Benefits

3.1.1 Structural Integration of Momentum and Mean-Reversion Dynamics

By embedding both momentum-following and mean-reverting mechanisms within one cohesive framework, the strategy achieves multidimensional exposure to short-term market dynamics. This design enables the system to adapt opportunistically to both trend persistence phases and corrective retracements. From a quantitative standpoint, it represents a form of orthogonal signal blending, where conditional state logic can reduce temporal correlation between consecutive trade outcomes, potentially improving the information ratio.

3.1.2 Volatility-Adaptive Signal Scaling

The use of Median Absolute Deviation (MAD) to scale the MACD histogram introduces robustness to volatility clustering and heteroskedasticity, features commonly observed in equity time series. Unlike variance-based scaling, MAD mitigates skew distortions and outlier impact, generating statistically stable thresholds even under regime shifts. This enhances signal stability and allows the system to maintain a consistent decision intensity across varying volatility environments.

3.1.3 Risk Normalisation through ATR-adjusted Exits

Constructing take-profit and stop-loss levels as functions of the Average True Range (ATR) ensures that each trade carries a comparable volatility-adjusted risk footprint. This approach standardises expectancy and Sharpe potential across periods of expansion and compression. It also introduces an implicit volatility targeting mechanism that aligns with institutional-grade risk management frameworks.

3.1.4 Logarithmic Price Transformation for Bollinger Contextualisation

Applying Bollinger Bands on log-adjusted price introduces scale invariance and prevents distortion from long-term price appreciation typical of growth equities. This methodological correction enhances statistical comparability over multiple market cycles and ensures a symmetric treatment of percentage-based deviations, a refinement rarely implemented in retail-level systems but analytically justified in cross-temporal modeling.

3.1.5 Systematic Discipline and Statefulness

The inclusion of cooldown, rebounce, and flip guards imposes temporal discipline, ensuring independence between trades and reducing behavioral reflexivity. By enforcing state transitions explicitly, the system demonstrates characteristics of a Markovian trading process, where each decision is conditionally dependent on the current system state, not on emotional or discretionary override.

3.1.6 Capital Reset via Systematic Rebalancing

The periodic rebalance mechanism forces all open positions to be liquidated and capital redistributed at predefined intervals. This introduces a powerful regime-agnostic reset, preventing prolonged drift into outdated market conditions and mitigating latent dependency on stale volatility structures. Mathematically, rebalancing resets portfolio weights toward a neutral prior, reducing autocorrelation of cumulative PnL and limiting compounding of adverse drift. The result is a system that periodically re-synchronises with the prevailing market regime, enhancing long-term return stability and reducing structural path dependency.

3.2 Limitations

3.2.1 Regime Dependence and Fragile Generalisation

The strategy performs well in both training (2010 - 2017) and testing (2018 - 2020) periods, with steady returns and low drawdowns. However, these results come from a relatively stable, growth-driven market dominated by large-cap tech stocks. Because the model uses fixed parameters, such as MACD (13, 35, 8), MAD window 83, Bollinger Bands (15, 1.4σ), ATR (18), and a 120-day rebalance, its performance may weaken when market conditions change sharply, for example during high inflation, sector rotation, or prolonged sideways markets.

The current stock universe AVGO, META, TSLA, GOOG, GOOGL and AAPL also share similar growth and momentum characteristics, meaning the strategy's success is still tied to one market regime. Future work should test the model across different time periods and market environments, and explore adaptive components such as regime filters or automated parameter tuning to maintain robustness over time.

3.2.2 Absence of Performance-Driven Portfolio Allocation and Selection

The current framework applies a uniform capital redistribution at each rebalance event, treating all assets equivalently regardless of their recent performance, volatility behavior, or contribution to risk-adjusted returns. Since weights are not informed by per-asset Sharpe, drawdown characteristics, or signal quality, the system may unintentionally preserve exposure to underperforming symbols while underallocating to consistently strong performers.

This lack of adaptive capital rotation limits the strategy's ability to concentrate risk in high-convexity opportunities and reduces cross-sectional diversification benefits. As markets evolve, failing to adjust allocations dynamically can result in suboptimal portfolio efficiency and muted Sharpe improvements, highlighting the need for performance-aware selection mechanisms.

3.2.3 Lack of Explicit Regime Classification Layer

While volatility adjustment through MAD and ATR indirectly addresses market noise, there is no formal mechanism to detect or adapt to regime shifts, namely transitions from trending to mean-reverting states. In the absence of a supervised regime identification process, both momentum and reversion legs may remain simultaneously active during transitional turbulence, generating signal conflicts and structural drawdowns.

3.2.4 Limited Adaptability of Fixed-Window Estimations

Fixed rolling windows (e.g., MACD at 12–30–6 or MAD over 74 bars) assume time-stable signal periodicity, which rarely holds under evolving market dynamics. Without dynamic window optimisation or exponentially weighted adjustments, this rigidity can diminish responsiveness to shifting market volatility regimes.

3.3 Opportunities

3.3.1 Multi-Segment Stability Testing & Robust Parameter Extraction

While the current hyperparameter tuning (2010–2017) maximises the Sharpe ratio over the entire training period, the equity curve reveals heterogeneous regimes; specifically, a low momentum in 2010 to 2014 followed by higher volatility and stronger momentum after 2014.

To mitigate the risk of overfitting to the aggregate Sharpe ratio, the training window can be sub-segmented into rolling or disjoint blocks (e.g., five overlapping 18-month segments). The candidate parameter set from Optuna can then be stress-tested across these sub-periods to compute a stability score (e.g., min Sharpe, median Sharpe, dispersion penalty).

This approach selects parameters that are not merely optimal for the full window but are consistently effective across different volatility regimes, improving robustness and reducing sensitivity to any single historical cycle.

3.3.2 Performance-Aware Portfolio Selection & Adaptive Rebalancing

The system currently resets positions and redistributes capital at each rebalance event. Building on this, the rebalancing logic can be upgraded to incorporate performance-aware portfolio allocation and contract selection.

At every rebalance point:

- Evaluate stock-level performance in the preceding cycle (e.g., per-asset Sharpe, hit rate, drawdown).
- Adjust weights toward stocks that demonstrated stronger recent risk-adjusted returns.

- Down-weight or prune underperforming stocks, effectively turning rebalancing into a dynamic asset selection mechanism.
- Incorporate a decay or rolling measurement so selection is adaptive but not over-fitted.

This transforms rebalancing from a mechanical capital reset into a data-driven capital rotation process, aligning exposure with the strongest alpha sources while controlling for risk concentration.

3.3.3 Introduction of Regime-Aware Filtering

Integrating a volatility or trend-phase classifier, such as a Hidden Markov Model, Bayesian change-point detector, or state transition network, could differentiate between trending and oscillatory phases. This would allow the system to modulate the activation of momentum and mean-reversion legs dynamically, significantly enhancing its adaptability and trade selectivity.

3.3.4 Expansion to Cross-Sectional Applications

Generalising the framework to multi-asset or sector-spanning portfolios presents an opportunity for diversification of alpha sources. Applying MAD-scaled MACD logic across correlated equities or indices could uncover stable relative-value relationships while maintaining volatility normalisation advantages.

3.3.5 Machine Learning–Based Parameter Rebalancing

Employing reinforcement or meta-learning techniques for parameter re-optimisation (e.g., adaptive k and k_mid thresholds) could mitigate overfitting and automatically tune responsiveness to evolving volatility spectra, converting the static architecture into an adaptive learning system.

3.3.6 Volatility-Weighted Portfolio Construction

Position sizing can evolve from static ATR-based thresholds toward volatility-parity allocation or conditional risk budgeting. Such integration would harmonise exposure across signals, creating a coherent portfolio-level volatility target that aligns with institutional execution standards.

3.3.7 Incorporation of Transaction Cost Modeling

Embedding a cost-aware optimisation routine, estimating spread, slippage, and fee impacts per instrument, would refine threshold calibration and prevent low-edge trades from degrading the profit factor. This modification aligns the strategy with realistic institutional execution dynamics.

3.4. Challenges

3.4.1 Implementing Multi-Segment Stability Testing & Parameter Extraction

Implementing multi-segment robustness checks requires substantially more computation, as each candidate parameter set must be evaluated across several overlapping windows. This elevates the cost of hyperparameter tuning from linear to quasi-multiplicative complexity. Moreover, defining a universally meaningful "stability score" is non-trivial - different market regimes impose different trade-offs between variance, Sharpe compression, and drawdown tolerances. Selecting parameters that generalise without over-penalising legitimate performance spikes remains an unresolved modeling challenge.

3.4.2 Implementing the adaptive rebalancing method

Dynamic capital rotation demands stable and statistically reliable per-asset performance metrics. In shorter rebalance windows, Sharpe ratios and hit rates become noisy, causing the allocation engine to chase randomness or overfit to short-term fluctuations. Implementing decay-weighted measurement frameworks also increases computational and architectural complexity. Additionally, dynamically pruning assets may introduce turnover spikes, higher transaction costs, and unintended concentration risk.

3.4.3 Implementation and Data Synchronisation

The system's stateful architecture, with multiple entry modes and interaction conditions, increases the potential for synchronisation errors during live execution. Each symbol's state machine must update consistently across event streams, and any latency or asynchronous data feed can produce contradictory trade triggers.

3.4.4 Risk of Statistical Overlap Between Signal Legs

While conceptually distinct, the LM and LR (and their short counterparts) rely on overlapping information sets derived from MACD and Bollinger-Band relationships. During ambiguous momentum phases, both signals may trigger sequentially or even concurrently, increasing churn and diluting signal integrity. This overlap can reduce convexity in the return profile.

3.4.5 Parameter Decay and Behavioral Drift

MACD-based measures implicitly embed dependency on weighting coefficients that represent past momentum memory. Over time, structural shifts in liquidity, volatility persistence, and market microstructure erode the statistical validity of these parameters, making continuous re-estimation indispensable.

3.4.6 Operational Complexity and Monitoring Load

Because the system integrates multiple conditional layers, including momentum states, volatility thresholds, re-entry locks, and adaptive take-profits, operational oversight requires continuous validation of multiple variable trajectories. This complexity elevates maintenance overhead and complicates production resilience testing.

3.4.7 Alignment with Institutional Constraints

Institutional risk mandates, such as capital usage efficiency, gross exposure limits, and margin requirements, could constrain this strategy's capacity utilisation. Its reliance on daily bar-close signals also precludes intraday optimisation, limiting scalability in multi-fund or high-frequency contexts.

4. IMPORTANT PART: HOW TO TEST OUR STRATEGY

Collab link: Group6_FinalStrategy.ipynb

Go to Section 8: **8. For Prof. Shashank Testing Area**

Step 1: Stock Selection & Allocation (Training Period):

First, run the strategy on a training window prior to the test period. The closer this training window is to the test years, the more relevant and accurate the stock selection will be.

For example, if you plan to test 2020 - 2021, you should train the strategy on 2018 - 2019 with our best_params (No need to run optuna again).

After running the optimiser, you will obtain two outputs:

- **selectedTicker1** - the list of selected stocks
- **allocationPortfolio1** - the optimised portfolio weights

Step 2: Testing Section:

Next, set the testing years (e.g., 2020 - 2021). The backtest will automatically reuse the selected tickers and allocation weights from Step 1 when evaluating the strategy on the new test window.

By now, tickers we use the list of stocks model suggests, but if you want to test in your own stock, you **can replace** the 'selectedTicker1' with your list (example ['AAPL', 'NVDA']. And **deleted the allocations**, and deleted them in the 'run_multi_stock_backtest_unified' as I have commented in the image.

```
#title Testing Section for Prof

# Config
tickers =selectedTicker1 # here if you want to choose your stock you can replace selected Ticker1 to the list of stock['AAPL', 'NVDA']
allocations = allocationPortfolio1 # delete this one if you don't you stocks and allocation our model suggested
start = "2025-01-01"
end = "2025-12-31"
initial_capital = 500000.0
transaction_cost = 0.00
leverage = 0

portfolio_test1, strat_test1, stock_performances_test1 = run_multi_stock_backtest_unified(
    tickers, start, end,
    interval="1d",
    initial_capital=initial_capital,
    strategy_class=MACD_BB_ATR_Strategy,
    transaction_cost=transaction_cost,
    params=best_params,
    leverage = leverage,
    allocations = allocations, # delete this one if you don't use stocks and allocation our model suggested
    verbose=False,
    # show_each_stock=True
)
```

Step 3: Visualisation Section

Finally, use the visualisation dashboard to compare the strategy against SPY. The dashboard includes equity curves, monthly return heatmaps, rolling return/volatility, and drawdown plots. These charts provide a clear and intuitive assessment of how the strategy performs during the chosen test period.