Exploration of Exponentially Weighted Moving Averages in Cryptocurrency

Harrison Xu

1. Introduction

The rapid growth of cryptocurrency markets over the past decade has attracted significant interest from quantitative traders seeking to exploit inefficiencies and volatility for profit. Unlike traditional financial markets, cryptocurrencies operate 24/7, are relatively less regulated, and often exhibit unique microstructure characteristics. These features make them a compelling testbed for quantitative trading strategies.

This project investigates and evaluates two quantitative trading strategies applied to cryptocurrency securities, primarily revolving around the use of exponentially weighted moving averages (EMAs). The goal is to explore which approaches are most effective in this highly dynamic and volatile market. Each method is tested using historical price data, and then performance is compared using standard financial metrics including Sharpe ratio and cumulative return.

2. Methodology

2.1 Generating cryptocurrency data

Cryptocurrency data was obtained using the Binance API. Any available close prices and volume data was extracted starting from January 1st, 2019. To determine the tradeable universe, cryptocurrencies were ranked by average notional volume over the past 30 days. The top ten were selected, excluding:

- USDCUSDT: This is a stablecoin that has very minimal price fluctuations, meaning it is not useful for alpha generation.
- XRPUSDT: Data was missing from 2020 to 2024, making it unsuitable for consistent analysis.

This yields the final tradeable universe to be the following eight cryptocurrencies:

- Bitcoin (BTCUSDT)
- Ethereum (ETHUSDT)
- Solana (SOLUSDT)
- Dogecoin (DOGEUSDT)

- Binance Coin (BNBUSDT)
- Cardano (ADAUSDT)
- FLOKI Token (FLOKIUSDT)
- Sui (SUIUSDT)

Both hourly and daily close prices and volumes were collected. The dataset was split into training (70%, Jan 2019—Oct 2023) and test (30%, Nov 2023—Jul 2025) subset. The training set was used for strategy development and parameter optimization, while the test set was reserved for final evaluation.

2.2 Strategies and Implementations

Exponentially Weighted Moving Average (EMA) Momentum Strategy: This cross-sectional momentum strategy uses EMAs of returns of signals. At each time step, assets are ranked on their EMA values. A long-short portfolio is constructed by taking long positions in the top quantile and short positions in the bottom quantile and then normalizing to ensure unit leverage.

The key parameters in this strategy:

- **Lookback periods**: Time window for EMA calculation.
- **Signal lag**: Delay between signal generation and trade execution.
- **Entry quantiles**: Thresholds for long/short portfolio construction.

Moving Average Convergence Divergence (MACD) Strategy: This strategy computes a MACD indicator, which is the difference between fast and slow EMAs. The fast EMA must have a smaller lookback window than the slow EMA. A signal line is derived from the MACD by using another EMA on the MACD indicator. Assets are longed when the MACD indicator is greater than the signal line and are shorted when the opposite is true. Positions are normalized for unit leverage across the cross-sectional portfolio.

The key parameters in this strategy:

- **Fast lookback window**: Time window for fast EMA calculation.
- **Slow lookback window**: Time window for slow EMA calculation.
- **Signal lookback window**: Time window for the signal line calculation.

Strategy Evaluation: Each strategy was optimized via grid search over the relevant parameter space on the training set, using the Sharpe ratio as the primary evaluation metric. The top-performing configuration was then evaluated on the test set.

To assess correlation with the broader market, a passive buy-and-hold benchmark was created, consisting of equal-weighted positions in the eight selected cryptocurrencies in the tradeable universe. Alpha was computed as the component of returns uncorrelated with this benchmark.

3. Results

3.1 General Insights

Cryptocurrency trading often incurs higher transaction costs than traditional equities. For this study, a realistic transaction cost of 20 basis points (0.20%) was applied. Strategies that rebalanced frequently—like those using hourly data—performed poorly due to the accumulation transaction costs. As a result, most hourly-based strategies exhibited negative Sharpe ratios.

By contrast, using daily data significantly improved Sharpe ratios and return stability. Thus, all the results presented below use daily data.

3.2 EMA Momentum Strategy Results

After performing an exhaustive grid search over the key parameters in the EMA momentum strategy, we found the optimal configuration was a lookback window of around 35 days with no lag and 50% entry quantile. This configuration produced a training set Sharpe ratio of 1.467, shown in *Figure 1*, and a test set Sharpe ratio of 1.507, shown in *Figure 2*. Combining the training and test sets to form a full set, the Sharpe ratio computed was 1.502.

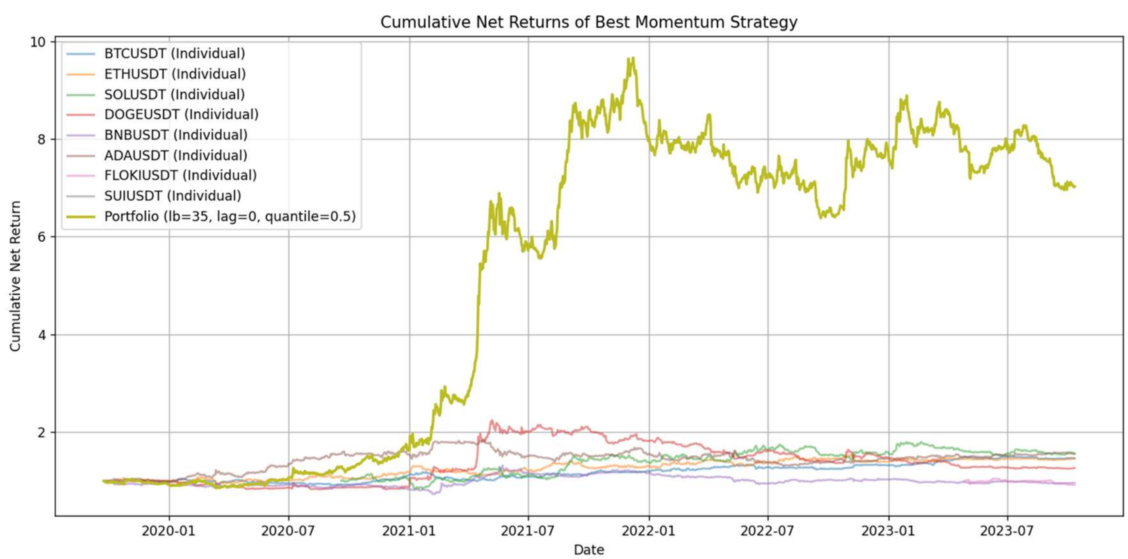

Figure 1. A plot of the net returns of the EMA momentum strategy with the highest Sharpe value on the training set. Includes the net returns of each individual asset in the strategy.

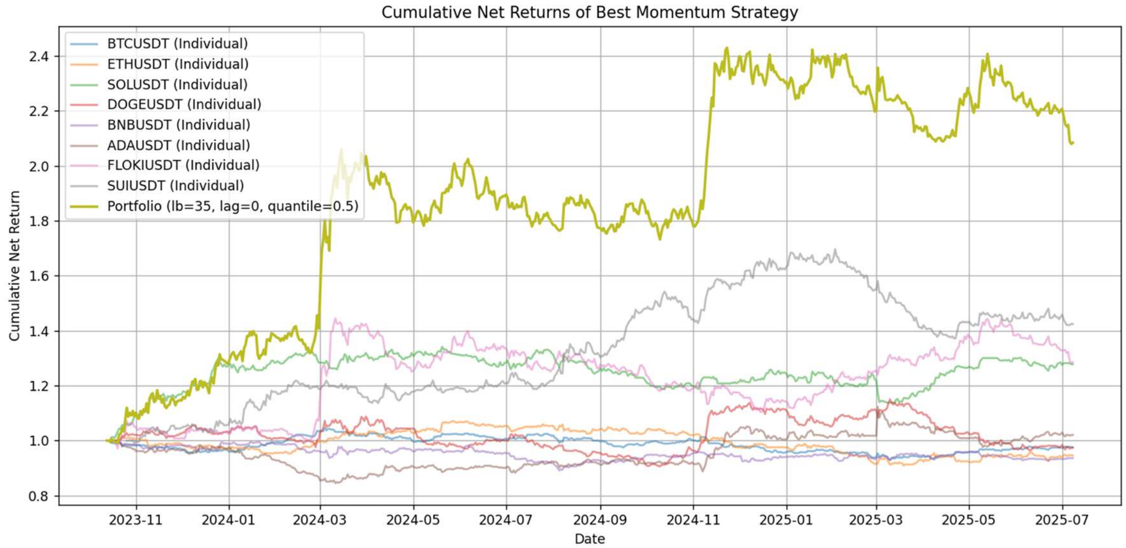

Figure 2. A plot of the net returns of the optimized EMA momentum strategy on the test set. Includes the net returns of each individual asset in the strategy.

A notable finding was that volume-based weighting reduced strategy performance. Although volume-based weighting was initially hypothesized to reduce exposure to risk and illiquid assets, in practice it often led to overexposure to trending, high-volume assets prone to sudden reversals. These spikes were followed by drawdowns, suggesting that volume may act as a lagging indicator in cryptocurrency markets.

The correlation between this strategy and the buy-and-hold benchmark was 0.475. Using the full dataset (the training and test set combined), the Sharpe value of this strategy after subtracting beta went from 1.502 to 0.959, shown below in *Figure 3*.

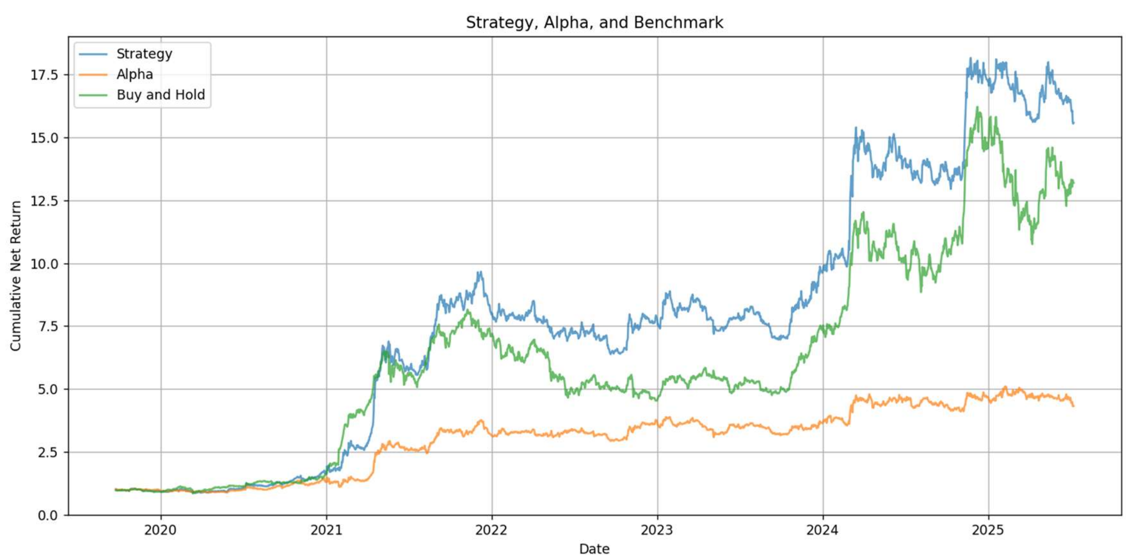

Figure 3. Plot of the cumulative net returns of the optimal EMA momentum strategy, the buy-and-hold benchmark, and the resulting alpha distilled from the strategy.

3.3 MACD Strategy Results

The grid search yielded the most optimal configuration as a fast EMA lookback window of 30 days, a slow EMA lookback window of 160 days, and signal line lookback window of 15 days. This optimal configuration generated a training Sharpe value of 1.515, shown in *Figure 4*, and a test Sharpe value of 1.405, shown in *Figure 5*. The Sharpe value of this strategy when evaluating on the entire dataset is 1.500.

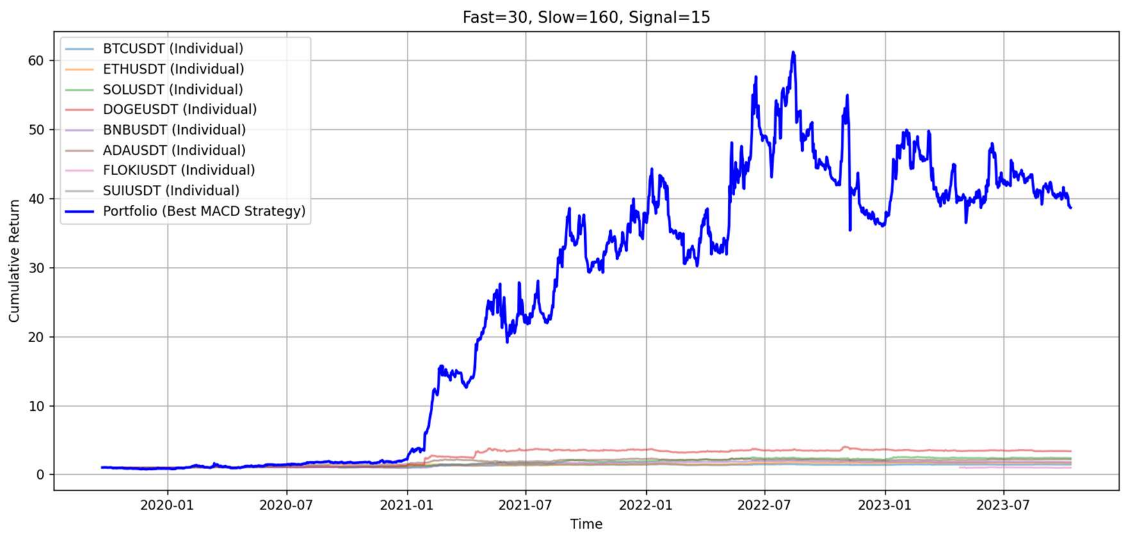

Figure 4. A plot of the net returns of the MACD strategy with the highest Sharpe value from the training set. Includes the net returns of each individual asset in the strategy.

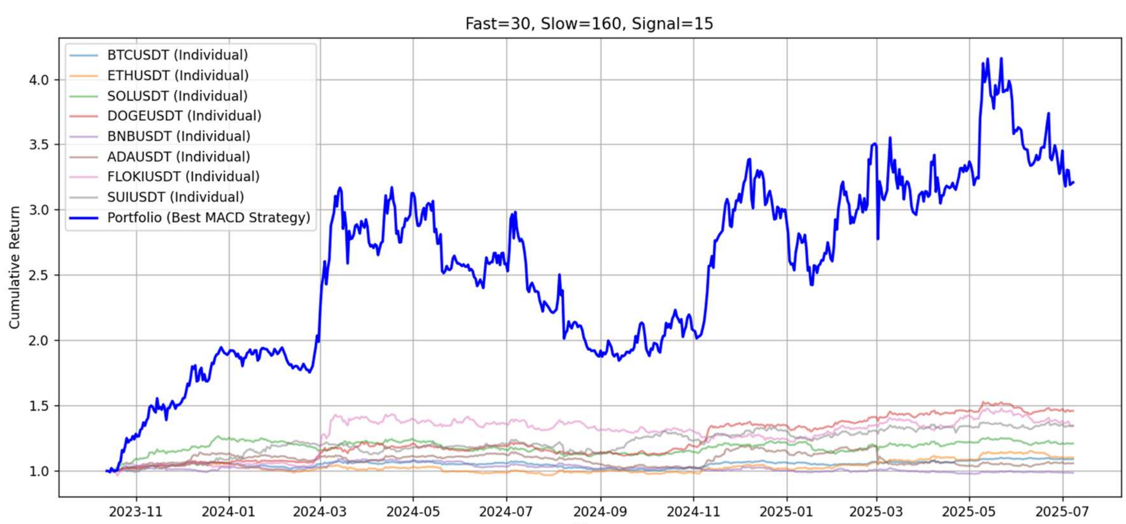

Figure 5. A plot of the net returns of the optimized MACD strategy on the test set. Includes the net returns of each individual asset in the strategy.

The correlation between this strategy and the buy-and-hold benchmark is 0.118. After decorrelating, the Sharpe value went from 1.500 to 1.346 (when evaluated on the full dataset). The net returns of this strategy, the benchmark, and the resulting are shown in *Figure 6*.

Figure 6. Plot of the cumulative net returns of the optimal MACD strategy, the buy-and-hold benchmark, and the resulting alpha distilled from the strategy.

4. Discussion

This study shows that simple EMA-based momentum strategies can perform well in the cryptocurrency market, even under realistic transaction cost assumptions. Both the EMA and MACD strategies delivered Sharpe ratios above 1.4 on out-of-sample data, indicating robustness.

The MACD strategy demonstrated stronger alpha (Sharpe 1.346 vs. 0.959) and lower market correlation (0.118 vs. 0.475) compared to the EMA strategy, suggesting it is more diversifying and may complement other strategies in a portfolio.

A key insight is the ineffectiveness of volume-based weighting in this market. While volume is commonly used in traditional markets as a proxy for liquidity and risk, in crypto it often reflects speculative spikes. Incorporating volume into signal generation can lead to chasing hype cycles and overfitting transient trends.

Ultimately, the findings suggest that well-structured EMA-based strategies can offer statistically significant returns and alpha in cryptocurrency markets, even when accounting for transaction costs.

5. Conclusion

This project explored two quantitative trading strategies—an EMA momentum strategy and a MACD strategy—applied to a select universe of high-volume cryptocurrencies. After conducting an extensive grid search over key hyperparameters and evaluating performance using historical price data, both strategies demonstrated strong performance on test data, with out-of-sample Sharpe ratios above 1.4. These results highlight the potential of relatively simple technical indicators to extract alpha in cryptocurrency markets, even when accounting for realistic transaction costs.

When compared to a buy-and-hold benchmark, the MACD strategy had low correlation and therefore could be useful for diversification purposes. The EMA momentum strategy, on the other hand, had moderate correlation and had a much lower alpha Sharpe ratio compared to the MACD strategy.

Overall, this study affirms the viability of rule-based, cross-sectional trading strategies in cryptocurrency markets, while also shedding light on some of the unique challenges posed by their high volatility, trend-driven dynamics, and transaction costs. Future work may consider combining multiple signals and introducing regime detection.