Inter IIT Bootcamp

QUANT PS

TMinus4

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Background & Problem Description

- Problem Statement aims to test our proficiency in developing intraday strategies using only **OHLCV** data for a chosen subset of **NIFTY 100** companies.

- With an added constraint due to data availability issues of minimum data time frame of 15 minutes, we need to develop momentum tapping strategies to maximize returns while maintaining controlled risk levels.

Approaching the Problem

- Stock Selection
- Signal Generating Strategy

Three-fold Approach

We undertake three separate distinct methods to research.

01

Statistical Approach with Indicators

Using momentum based composite indicators on trend retenting stocks

02

Hypothesis Lookout

Taking advantage of patterns and correlation among diffrent time-zones

03

Machine Learning based Approach

High frequency trading with follwoing candle prediction using past momentum

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Stock Selection

With our aim to use momentum based strategies, we needed some way to quantify trend retention property of stocks

Kalman Filter

SImply used to smooth out stock returns before feeding the data into further models

$$x_{t|t} = x_{t|t-1} + K_t.\,(PredictionError)$$

Auto Regression

Finding correlation of current price to the past several candles. Higher correlation indicates more momentum carries forward.

$$r_t = \phi_1 r_{t-1} + \phi_2 r_{t-2} + \phi_3 r_{t-3} + c + \varepsilon_t$$

Ornstein-Uhlenbeck Process

Measuring mean reverting tendency of stock returns by categorizing into an OU Process.

$$dX_t = \theta(\mu - X_t)dt + \sigma dW_t$$

$$t_{\frac{1}{2}} = \frac{ln2}{\theta}$$

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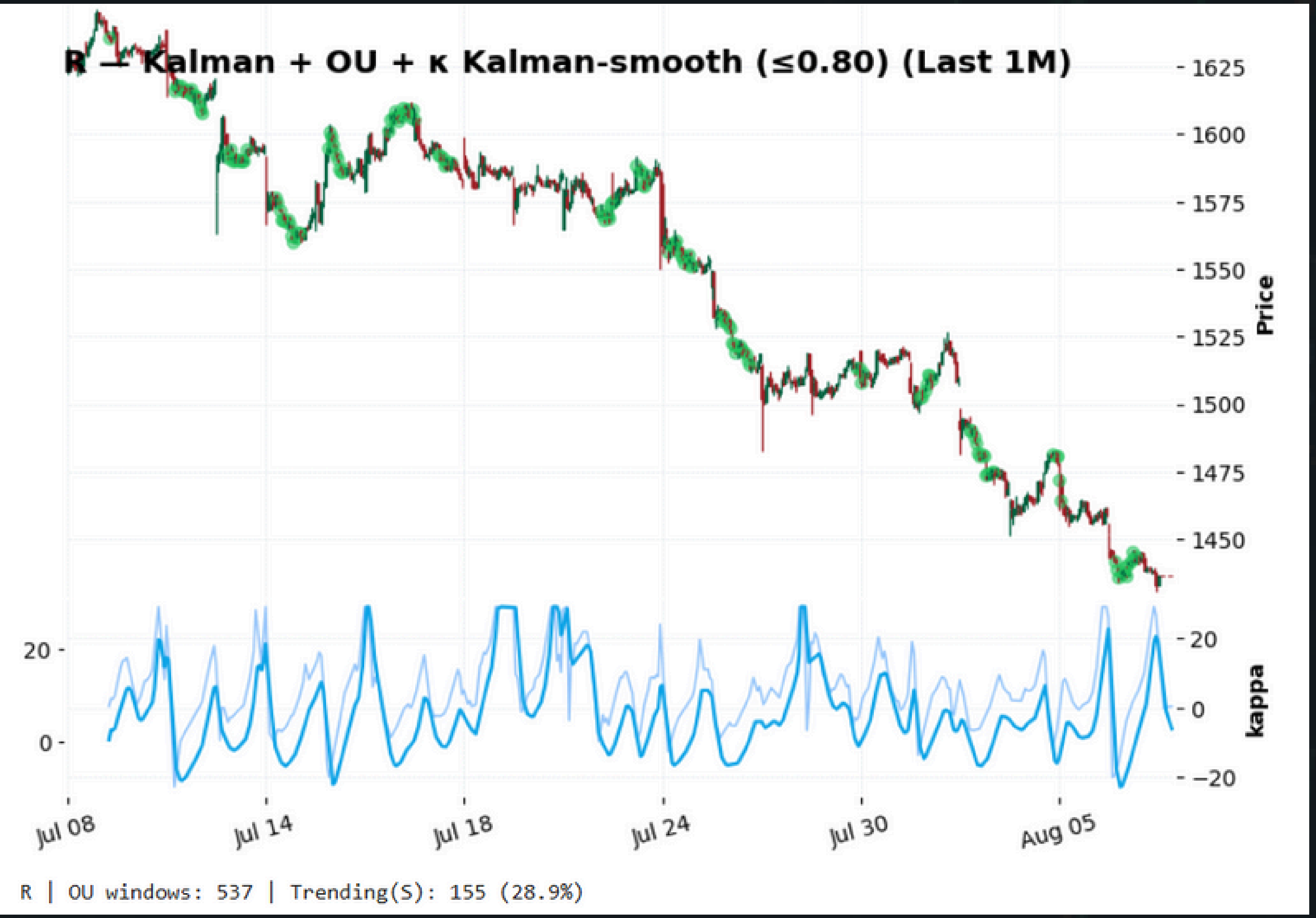
Tested Methods

Application of the forementioned methods on some stocks



Kalman Filter + OU Process

We applied OU mean reverting tendency measurement of kalman filtered stock returns..

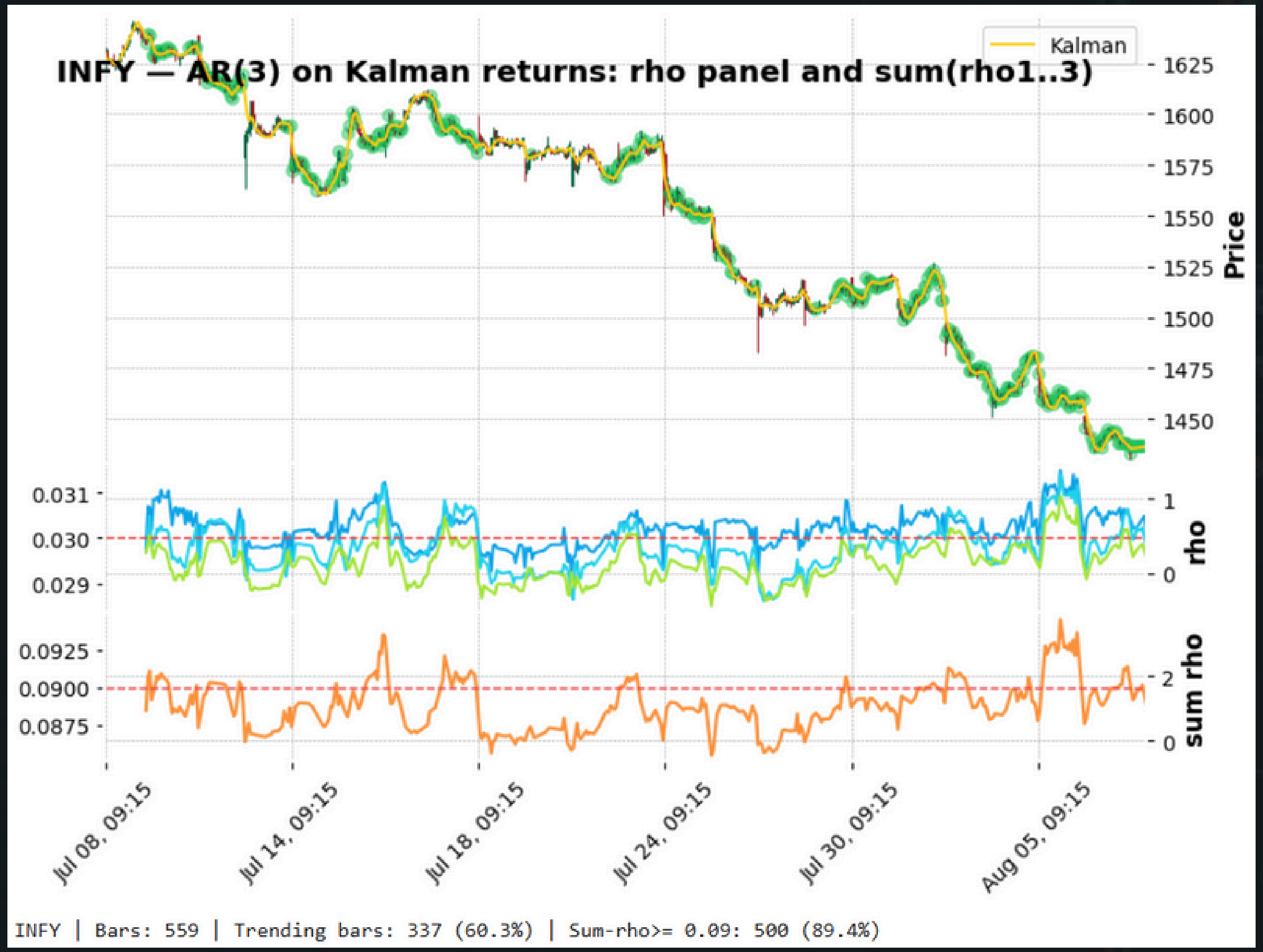
$$dX_t = \theta(\mu - X_t)dt + \sigma dW_t$$

$$t_{\frac{1}{2}} = \frac{ln2}{\theta}$$

if half time **is less than 0.8**, we consider that region that region to be trending.

Tested Methods

Application of the forementioned methods on some stocks



Kalman Filter + Auto Regression

We applied order 3 autocorrelation measurement of kalman filtered stock returns.

$$r_t = \phi_1 r_{t-1} + \phi_2 r_{t-2} + \phi_3 r_{t-3} + c + \varepsilon_t$$

We put two constraints,

$$\rho_1, \rho_2, \rho_3 > 0.03$$

$$\psi = \phi_1 + \phi_2 + \phi_3 > 0.25$$

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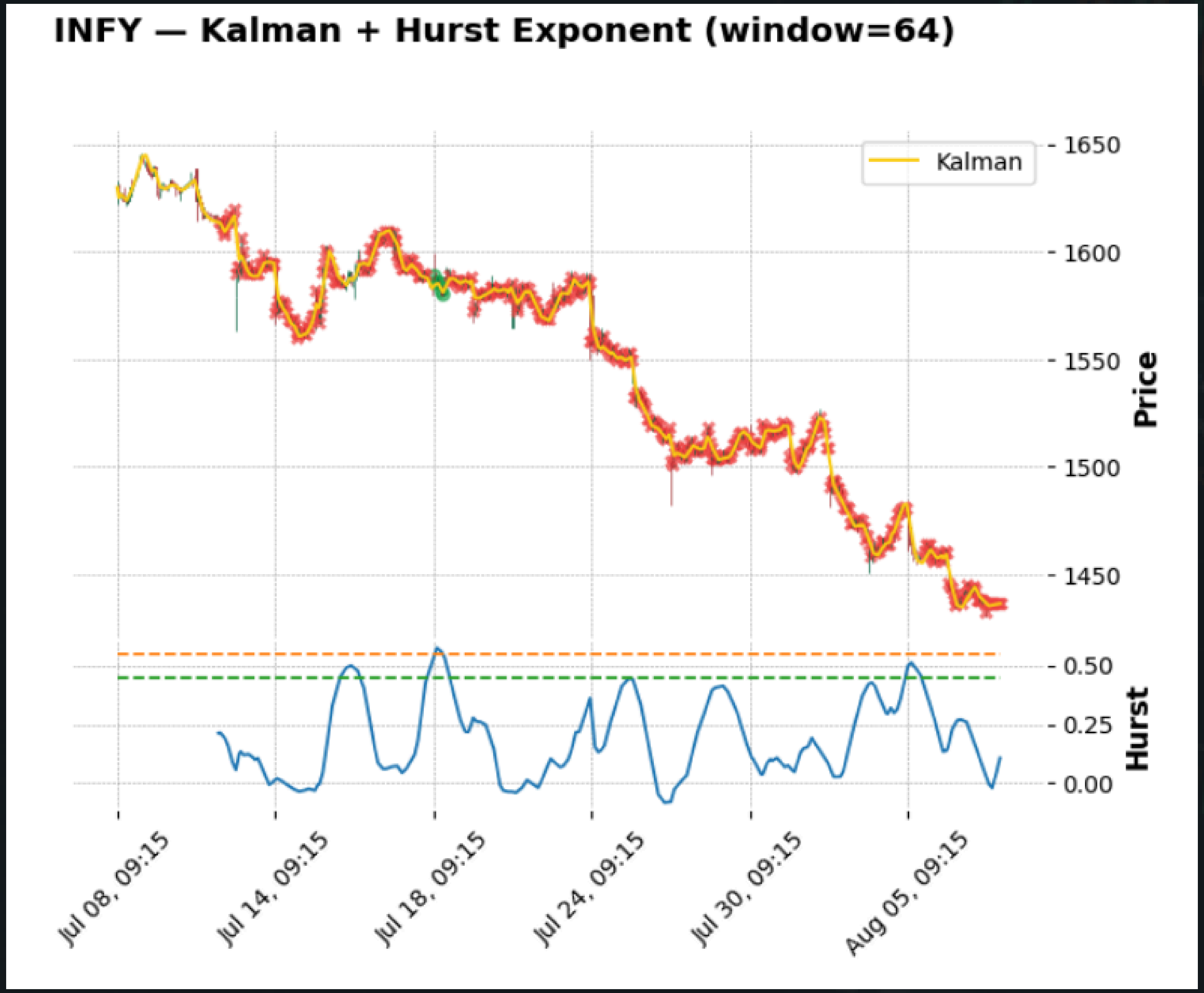
Tested Insufficient Methods

Application of the forementioned methods on some stocks



Kalman Filter + Hurst Exponent

We compute the hurst exponent using the variogram exponent method using a log-linear fit.

if it is greater than 0.5, the region is marked as trending.

However, this clearly breaks down because of high frequency noise in intra day data.

We further went to try more strategies involving GARCH and Sharon's Entropy but they were also insufficient

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Signal Generation

Being able to separate trending regions, we need to utilise their momentum trends in the best possible ways

Phi-Smoother MA Ribbon

Utilising the Phi-Smoother Filter over 32 seperate time periods accounting for both short term and long term momentum and Super Trend Indicator.

Composite Indicator

We utilize a group of 5 indicators and utilise them together after training over the past period.
MA20/MA50, RSI, MACD, BB, OBV

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PhiSmoother MA Ribbon

Utilising the Phi-Smoother Filter over 32 seperate time periods

$$\phi = \frac{1+\sqrt{5}}{2} \approx 1.618$$
$$a1 = e^{-1.414\pi/L}$$
$$b1 = 2a1\cos(\sqrt{5}\pi/L)$$
$$c2 = b1$$
$$c3 = -a1^2$$
$$c1 = 1 - c2 - c3$$

$$\text{PhiSmooth}[t] = c1 \cdot \frac{(Price[t] + Price[t-1])}{2} + c2 \cdot \text{PhiSmooth}[t-1] + c3 \cdot \text{PhiSmooth}[t-2]$$

Where:

- L = smoothing length (period)
- $Price[t]$ = input price at time t (usually close)
- $a1, b1, c1, c2, c3$ are filter coefficients

Signal Generation

- Long if, Price above most Phi Smoother bands → strong bullish consensus + SuperTrend below price
- Short if, Price below most Phi Smoother bands → strong bearish consensus + SuperTrend above price
- Exit if, Opposite signal appears
- All open trades are closed by day-end (intraday rule).

Risk Management

The ATR-based trailing stop adds dynamic risk control.

- When volatility expands, the stop loosens (avoiding premature exits).
- When volatility contracts, the stop tightens (locking in profit).

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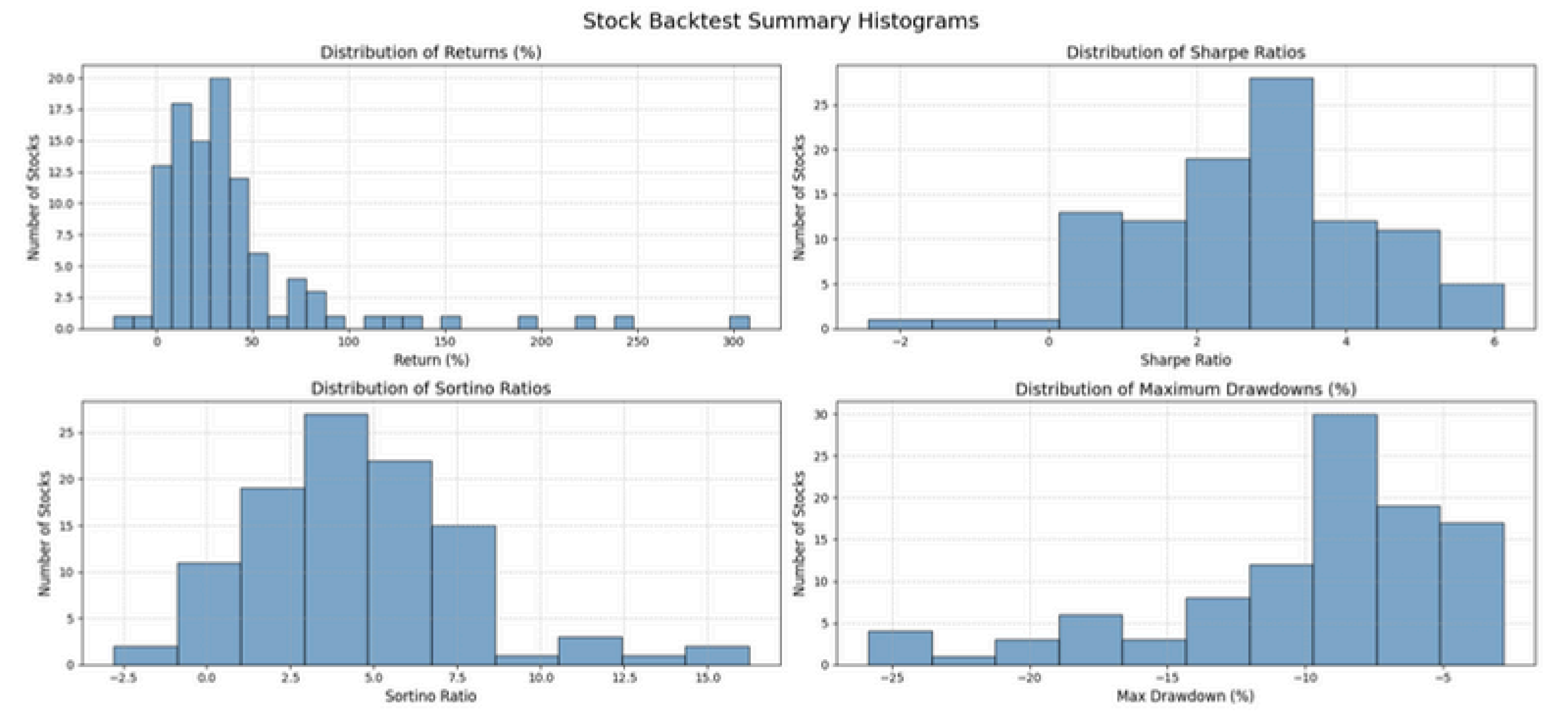

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Composite Indicator

Stock	Total Return	Sharpe Ratio	Max Drawdown
JIOFIN	47.88	1.32	15.65
NESTLEIND	39.91	0.30	23.70
NTPC	95.50	0.54	18.75
POWERGRID	74.28	0.51	17.11
HDFCBANK	73.87	0.48	21.22
SBILIFE	30.70	0.29	23.34
BAJAJHFL	-3.45	-0.96	4.60
SWIGGY	-0.23	0.079	21.56

Signal Generation

- Using small range of weights { 0, 1, 2, 3, 4 }. we run through all 3125 possible combinations for each indicator.
- Using back testing to find the best weight combination, we form the composite indicator.
- Signals are generated by using the value of the composite indicator:
  - $>$ 2 : Buy
  - $<$ -2 : Sell
  - Otherwise : Hold

Approach 2:

Hypothesis Lookout

Hypothesis Statement

Stocks that lose or gain the most in the morning tend to earn higher and positive returns in the second half of the trading day—especially during the last half-hour—compared to other stocks, forming a U-shaped pattern in cross-sectional intraday returns.

Possible Reasoning

- Closing-time concentrates large, price-insensitive benchmarked flows and auction demand, creating systematic upward pressure in the last half-hour.
- An early high flags strong demand/information, placing the stock among morning “winners” that historically receive the biggest late-day boost.
- Auction microstructure reduces adverse selection and aggregates liquidity, allowing buy imbalances to lift already-strong names efficiently into new highs.

Hypothesis Testing

Using Tests

t-statistics

	c	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30
15:30	3.46	2.24	1.92	1.77	0.78	2.44	1.12	-1.32	-0.10	-0.01	0.89	1.47
15:00	2.00	-2.04	-1.13	-2.70	-0.87	-0.32	-2.05	-2.05	0.33	-0.58	0.91	
14:30	2.58	-0.04	-0.92	1.39	0.97	0.64	0.67	0.69	2.48	0.81		
14:00	-0.87	-2.03	-0.76	-0.72	-0.49	-0.71	-0.33	-0.28	0.83			
13:30	0.11	-0.11	0.29	-1.39	-2.12	-1.31	-0.72	-1.00				
13:00	1.76	1.55	0.09	0.36	0.21	-1.67	-0.78					
12:30	2.47	0.68	0.22	0.69	-1.02	-0.69						
12:00	0.97	0.86	1.16	1.32	1.35							
11:30	0.10	0.75	-1.32	1.82								
11:00	-0.96	1.02	-1.76									
10:30	-0.10	-2.08										

Using T-Statistics Test

- This is a t-statistic heatmap for intraday return predictability across time-of-day intervals, showing how returns in an earlier interval predict returns in a later interval.
- Rows are “future” intervals (e.g., 15:30, 15:00, …), columns are “past” intervals and each cell is the t-stat from regressing a later-interval return on an earlier-interval return, with green indicating positive and orange indicating negative predictability.

- Positive t-stats in the top rows show last-hour (especially 15:30) returns tend to continue earlier intraday moves.
- Midday intervals exhibit weaker and some negative t-stats, implying less reliable predictability then; informative signals cluster in morning extremes and translate most clearly into end-of-day moves.

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Final Approach

ML Based Approach simply capitalizing through HFT

Simple Game

- Trading every 15 mins
- Top 7 stocks to go long and short
- Low profits but high frequency of trades
- Probability calculated through Random Forest using momentum
- Random Forest chosen as it surpasses ARIMA in prediction models

Random Forest comprises of 3 signals:

1. Intraday returns: $ir_{t,m}^{(s)} := \frac{cp_{t-m}^{(s)}}{op_{t-m}^{(s)}} - 1,$
2. Returns with respect to last closing price: $cr_{t,m}^{(s)} := \frac{cp_{t-1}^{(s)}}{cp_{t-1-m}^{(s)}} - 1,$
3. Returns with respect to opening price: $or_{t,m}^{(s)} := \frac{op_{t}^{(s)}}{cp_{t-m}^{(s)}} - 1,$

where m ∈ {1, 2, 3, ..., 20} ∪ {40, 60, 80, ..., 240}, obtaining 93 features.
1 through 20 capture short term momentum and further longer interval data capture long term momentum.

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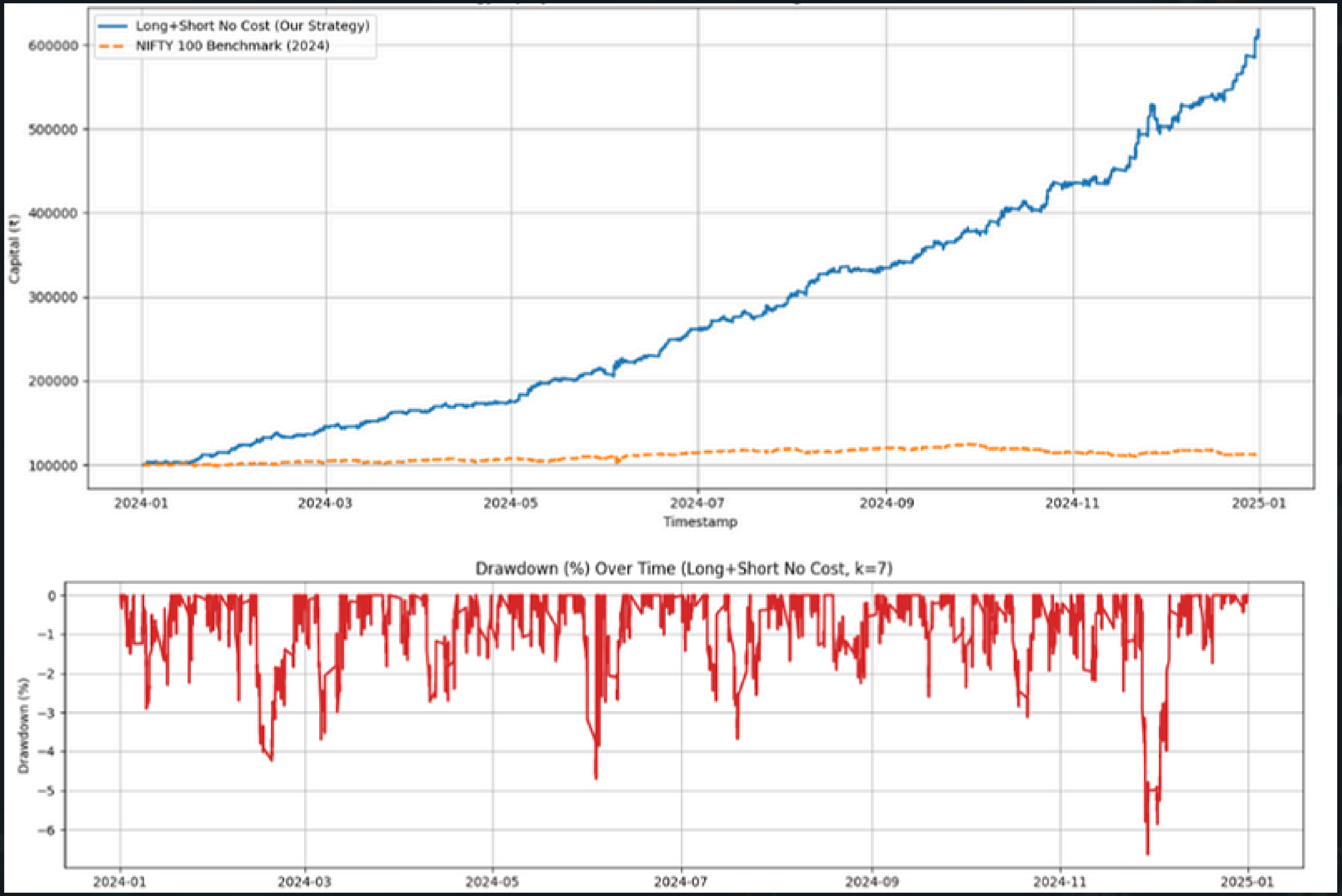
Results & Key Metrics

Key Metrics

Net Returns: 517.90%
Benchmark Returns: 11.89%
Max. Drawdown: 6.64%
Sharpe Ratio: 9.188
Sortino Ratio: 13.179
No. of Trades: 86352
Winning Trades: 56.47%
Avg. Win: 0.173%
Avg. Loss: -0.156%



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Strategy across conditions

Cost = 0.01 %	Net Returns	Max. Drawdown	Sharpe	Sortino	Winning Rate
Long+Short (No cost)	517.90	6.64	9.188	13.179	56.47
Long Only (No Cost)	328.93	9.59	7.337	9.531	55.06
Long+Short (With Cost)	80.00	7.83	3.037	4.419	51.31
Long Only (With Cost)	131.51	13.26	4.275	5.623	52.32

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Risk Management

K = No. of stocks	Net Returns	Max. Drawdown	Sharpe	Sortino	Winning Rate
K = 2	914.23	21.10	6.163	7.834	55.01
K = 3	798.69	15.46	7.050	9.253	54.77
K = 4	637	11.74	7.525	10.032	55.74
K = 5	590.52	9.28	8.142	11.121	56.26
K = 6	532.79	7.93	8.573	11.971	56.13
K = 7	517.90	6.64	9.188	13.179	56.47
K = 10	390.17	7.38	9.53	13.763	56.47

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Appendix

Research Papers

ML Based Strategy

Composite Indicator

Correlation Hypothesis

Shanon Entropy Strategy

Uhlenbeck-Ornstein Process

Phi Smoother Moving Average Ribbon

Notebooks

ML Based Strategy

ML Based Strategy(2024-25)

Strategy Tester Stock Selection

Phi Smoother Strategy

Shanon Entropy Strategy

Composite Indicator

Thank You!