From a Classical Trading Edge to a Systematic Strategy

A Quantitative Study of the Larry Williams Oops Pattern

Executive Summary

This study investigates the systematic trading potential of the Larry Williams *Oops* pattern through a structured, data-driven research process. Starting from the original discretionary concept, the strategy is progressively transformed into a fully rule-based framework, with explicit testing of entries, exits and stop-loss mechanisms.

The analysis demonstrates that the core edge of the *Oops* pattern lies in directional bias, while long-term performance is primarily driven by exit design rather than entry precision. Multiple exit techniques are evaluated, including time-based exits, ATR-based trailing stops, and percentile-based Maximum Favorable Excursion (MFE) targets.

Results show that combining a volatility-adjusted Chandelier exit with an empirical MFE target significantly improves expectancy, profit factor, and payoff ratio compared to the original Larry Williams exit, while maintaining controlled drawdowns. Conversely, fixed ATR-based stop losses do not enhance performance and, in several configurations, degrade overall results.

To ensure robustness and comparability, a fixed holding period (HP = 7) is adopted across all final evaluations. The final strategy exhibits stable performance characteristics, moderate negative skew, and favorable risk-adjusted metrics, indicating a structurally sound edge rather than curve-fitted behavior.

The study concludes with a critical discussion of limitations, overfitting risks, and real-world considerations, positioning the strategy as a robust foundation for further portfolio-level and execution-aware research.

1. Introduction

1.1 Context: From Discretionary Pattern to Systematic Testing

Many classical trading patterns originate from discretionary observations of market behavior. While these patterns are often supported by intuitive explanations, they are rarely subjected to a rigorous quantitative validation process.

In a professional systematic trading environment, an idea is not evaluated based on intuition or anecdotal evidence, but through statistical analysis, risk decomposition, and robustness testing. The transition from a discretionary concept to a systematic strategy therefore requires a structured research framework, capable of isolating the true source of the trading edge and identifying its limitations.

This study adopts such a framework, starting from a well-known discretionary pattern and progressively transforming it into a fully specified systematic trading strategy.

1.2 Why the Oops Pattern

The **Oops pattern**, originally popularized by Larry Williams, is a short-term mean-reversion setup designed to exploit market overreactions following overnight price gaps.

The pattern is particularly suitable for systematic research for several reasons:

- It is based on clear and observable price behavior
- It relies on objective conditions (gaps and intraday price action)
- It operates on liquid markets and short holding periods

Moreover, the Oops pattern represents a typical example of a trading idea with:

- Relatively high win rate
- Asymmetric return distribution
- Strong dependence on exit and risk management rules

These characteristics make it an ideal case study for analyzing how a **raw trading edge** can be enhanced—or destroyed—by systematic design choices.

1.3 Goal of the Study

The primary objective of this research is **not** to optimize performance or present a profitable trading system, but to demonstrate a **quantitative research process**.

Specifically, the goals of this study are:

- To validate the existence of a statistical edge in the Oops pattern
- To analyze the distributional properties of returns generated by the signal
- To study adverse and favorable excursions (MAE, MFE, TMFE)
- To design and compare different exit and risk management approaches
- To illustrate the transition from a pure trading signal to a complete systematic strategy

By following this process, the study aims to replicate the type of analytical workflow commonly adopted within professional quantitative research and systematic trading desks.

The research framework adopted in this study is inspired by the methodology described in *Computer Analysis of the Futures Market* by Charles LeBeau and David W. Lucas, particularly the emphasis on decomposing a trading system into distinct and sequential analytical phases.

While the exact implementation of such workflows may vary across institutions, the core principle of **separating signal evaluation, risk analysis, and execution design** is widely recognized as a best practice in systematic trading research.

This separation allows for greater clarity in understanding the true source of a strategy's edge, as well as a more controlled assessment of how individual components contribute to overall performance.

Building upon this conceptual foundation and integrating insights from additional quantitative research, the study develops a structured, step-by-step framework for strategy analysis, moving progressively from raw signal validation to full system design.

2. Description of the Oops Pattern

2.1 Original Definition (Larry Williams)

The Oops pattern was originally introduced by Larry Williams as a short-term reversal setup designed to exploit failed overnight price movements.

In its classical formulation, the pattern occurs when:

- The market opens with a significant gap relative to the previous session's close
- The opening price suggests a continuation of the prior move or a strong directional bias
- During the same trading session, price reverses direction and moves back toward the previous close

In the bullish version of the setup, a gap-down open followed by intraday buying pressure signals a potential failure of bearish continuation, creating an opportunity for a long entry.
The original concept is discretionary in nature, relying on the trader's judgment to assess gap significance and intraday price behavior.

This study focuses on a fully systematic interpretation of the long Oops pattern, replacing discretionary judgment with strictly defined mechanical rules.

2.2 Intuition Behind the Pattern

The intuition behind the Oops pattern is rooted in the idea that overnight price gaps often reflect **temporary imbalances** rather than persistent shifts in market fundamentals.

A gap-down open may be caused by:

- News released outside regular trading hours
- Positioning effects
- Liquidity constraints in overnight markets

When the market fails to sustain the initial bearish pressure and buyers regain control during the session, the opening gap can be interpreted as an overreaction rather than a genuine trend initiation.

From a behavioral perspective, the pattern captures a situation in which market participants who acted on the gap are forced to reassess their positions, potentially leading to short covering and renewed buying interest.

This dynamic creates a favorable asymmetry between downside risk and upside potential over a short holding period.

2.3 Market Behavior Exploited

From a quantitative standpoint, the Oops pattern is designed to exploit **short-term mean reversion** following failed price continuation.

Rather than attempting to forecast long-term trends, the strategy targets:

- Intraday reversal dynamics
- Temporary price dislocations
- Liquidity-driven market responses

Empirically, this type of setup often exhibits:

- A relatively high win rate
- Limited average adverse excursion
- Positive expectancy driven by frequent small gains and occasional larger reversals

However, these characteristics also imply a strong sensitivity to exit logic and risk management rules. As a result, the raw signal alone is insufficient to define a robust trading strategy, making the Oops pattern particularly suitable for studying the impact of systematic design choices.

3. Data & Methodology

3.1 Market Universe

The analysis is conducted on four major U.S. equity indices, represented through their corresponding exchange-traded funds (ETFs):

- S&P 500 (SPY)
- NASDAQ 100 (QQQ)
- Russell 2000 (IWM)
- Dow Jones Industrial Average (DIA)

These instruments are characterized by high liquidity, deep order books, and efficient price discovery, which significantly reduces the impact of execution frictions and data-related distortions.

The market universe is kept constant throughout the entire research process in order to ensure consistency across different testing phases and to avoid introducing selection bias.

3.2 Timeframe

The study is performed using **daily OHLC price data**, with signals evaluated at the daily frequency.

Daily data is selected for the following reasons:

- It aligns with the original formulation of the Oops pattern
- It reduces noise related to intraday microstructure effects
- It allows for clearer interpretation of return distributions and excursion metrics

The historical sample spans from **January 1, 2005 to December 18, 2025**, covering multiple market regimes and volatility environments, including bull, bear, and crisis periods.

3.3 Assumptions and Research Environment

All analyses are conducted within the **QuantConnect Research Environment**, which provides high-quality historical price and volume data while allowing for flexible Python-based research workflows.

To isolate the behavior of the trading signal, the following simplifying assumptions are adopted in the baseline analysis:

- Trades are simulated using daily OHLC data
- Execution is modeled at predefined reference prices derived from daily bars
- Transaction costs and slippage are initially excluded
- No portfolio-level constraints are applied

These assumptions are consistent with a research-oriented framework, where the primary objective is to understand the statistical properties of the trading signal before introducing execution and implementation constraints.

Execution-related considerations are addressed separately when transitioning from pure edge analysis to full strategy design.

3.4 Entry Logic – Original Concept and Systematic Implementation

The Oops pattern, as originally proposed by Larry Williams, is a short-term mean-reversion strategy applicable to both long and short positions.

In its discretionary formulation, the strategy is characterized by the following principles:

- The presence of prior directional pressure opposite to the intended trade direction
- A market opens in gap up or gap down relative to the previous session
- An entry triggered when the session price action retraces to the previous day's high or low
- A protective stop placed beyond the intraday high or low
- Exit at the first opportunity to realize a profitable trade if and only the price at the open market is in profit; Else wait for the next market open or stopped out by the stop loss

In order to enable quantitative testing, this study replaces discretionary judgment with a fully mechanical implementation of the entry logic.

For the purposes of pure signal evaluation, both long and short setups are initially included.
In the long configuration, a signal is generated when:

- The opening price is below the previous day's low (gap down condition)
- During the same session, price trades back to the previous day's low, indicating intraday reversal pressure

The short configuration is defined symmetrically.

Once the entry condition is satisfied, a trade is recorded according to the execution assumptions described above.

4. Edge Validation (Signal Quality)

4.1 Raw Performance

The first step in validating the Oops pattern consists of evaluating its **raw performance**, without the influence of advanced exit logic, position sizing, or regime or trend filters.

At this stage, the objective is not to assess the tradability of the strategy, but to verify whether the entry signal alone exhibits non-random behavior.
Performance metrics are therefore analyzed at the individual trade level, focusing on the statistical properties of returns generated immediately following signal activation.

This approach allows for a clear separation between **signal quality** and **strategy design**, ensuring that any observed edge can be attributed to the entry logic rather than to optimization effects.

Although the original Oops strategy includes both long and short setups, the analysis initially evaluates both sides of the market to see if any asymmetry emerges between long and short signals.

Table 1 – Long side

	HP	Win_rate_%	Expectancy	n_trades	mean_pos_ret	n_pos_trade	mean_neg_ret	n_neg_trade
0	1	53.48	0.00	2137	0.01	1143	-0.01	982
1	2	55.02	0.00	2137	0.01	1176	-0.01	956
2	3	56.20	0.00	2137	0.02	1200	-0.02	931
3	4	57.01	0.00	2137	0.02	1218	-0.02	917
4	5	59.29	0.00	2136	0.02	1266	-0.02	870
5	6	61.37	0.00	2136	0.02	1311	-0.02	825
6	7	59.83	0.00	2136	0.03	1278	-0.03	856
7	8	60.36	0.01	2136	0.03	1290	-0.03	846
8	9	60.87	0.01	2136	0.03	1301	-0.03	833
9	10	60.91	0.01	2136	0.03	1301	-0.03	834
10	11	62.17	0.01	2136	0.03	1329	-0.03	806
11	12	61.45	0.01	2132	0.03	1311	-0.03	821
12	13	61.78	0.01	2132	0.03	1318	-0.03	813
13	14	62.60	0.01	2132	0.03	1336	-0.03	795
14	15	63.32	0.01	2132	0.04	1351	-0.04	781
15	16	63.77	0.01	2132	0.04	1360	-0.04	772
16	17	64.72	0.01	2132	0.04	1380	-0.04	752
17	18	65.35	0.01	2132	0.04	1394	-0.04	738
18	19	64.45	0.01	2132	0.04	1375	-0.04	755
19	20	64.24	0.01	2129	0.04	1368	-0.04	760

Table 1

Table 2 – Short side

	HP	Win_rate_%	Expectancy	n_trades	mean_pos_ret	n_pos_trade	mean_neg_ret	n_neg_trade
0	1	46.72	0.00	3213	0.01	1500	-0.01	1698
1	2	45.55	-0.00	3213	0.01	1461	-0.01	1744
2	3	44.17	-0.00	3212	0.01	1415	-0.01	1791
3	4	42.83	-0.00	3212	0.02	1372	-0.01	1836
4	5	43.31	-0.00	3212	0.02	1388	-0.02	1819
5	6	42.35	-0.00	3212	0.02	1356	-0.02	1853
6	7	42.08	-0.00	3211	0.02	1346	-0.02	1861
7	8	41.87	-0.00	3210	0.02	1339	-0.02	1871
8	9	39.52	-0.00	3208	0.03	1263	-0.02	1940
9	10	39.47	-0.00	3208	0.03	1261	-0.02	1943
10	11	39.56	-0.00	3208	0.03	1264	-0.02	1938
11	12	38.97	-0.00	3208	0.03	1245	-0.03	1962
12	13	37.60	-0.01	3208	0.03	1201	-0.03	2005
13	14	37.30	-0.01	3208	0.03	1191	-0.03	2017
14	15	37.25	-0.01	3207	0.03	1190	-0.03	2014
15	16	36.14	-0.01	3207	0.03	1154	-0.03	2052
16	17	36.91	-0.01	3207	0.03	1179	-0.03	2027
17	18	35.78	-0.01	3203	0.03	1142	-0.03	2061
18	19	35.68	-0.01	3203	0.04	1138	-0.03	2065
19	20	35.37	-0.01	3203	0.04	1128	-0.03	2073

Table 2

At the baseline signal level, both long and short configurations exhibit broadly similar expectancy[1] profiles across holding periods, despite a clear divergence in win rate dynamics. Long trades consistently display higher win rates, while short trades show a progressive deterioration as the holding period increases.

However, given the near-zero expectancy observed on both sides and the absence of regime conditioning or execution refinement at this stage, no directional exclusion is applied. Both long and short setups are therefore retained for subsequent analysis, where entry mechanics and regime filters will be evaluated to assess whether conditional asymmetries emerge.

4.2 Entry Logic Comparison

Objective

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[1] [1] *In its classical formulation, expectancy is defined as*
$E = p(win) \cdot avg(win) - p(loss) \cdot avg(loss)$.
In this study, expectancy is approximated by the mean of trade returns, which is algebraically equivalent when computed over the full trade distribution.

The purpose of this section is to isolate the impact of entry execution on signal quality.
Two alternative entry definitions are compared under identical market, exit, and assumption settings, without the application of regime filters.

Entry Definitions

Two mechanically defined entry approaches are tested:

- **Entry at Previous Day Low/High**
  Positions are entered when price retraces to the previous session's low (for long setups) or high (for short setups), consistent with the original formulation of the Oops pattern.
- **Entry at Previous Day Close**
  Positions are entered when price reaches the previous session's close, representing a less extreme mean-reversion trigger.

Both approaches are applied symmetrically to long and short setups.

Results Overview

The results indicate a clear structural difference between the two entry mechanisms.

The **previous day low/high entry** produces:

- Win rates fluctuating around 49–50% across holding periods
- Near-zero expectancy throughout the tested range
- A relatively balanced distribution between positive and negative trades

By contrast, the **previous day close entry** exhibits:

- Significantly lower win rates, ranging approximately between 34% and 45%
- Persistently negative expectancy across all holding periods
- A markedly higher proportion of losing trades relative to winning ones

Interpretation

Despite similar average magnitudes of positive and negative returns, the deterioration in win rate associated with the previous close entry leads to a structurally weaker expectancy profile. This suggests that entering at less extreme price levels reduces the effectiveness of the mean-reversion mechanism exploited by the Oops pattern.

In contrast, requiring price to retrace to the previous session's low or high appears to better capture the exhaustion and reversal dynamics originally intended by the pattern, even though the raw expectancy remains close to zero at this stage of the analysis.

Conclusion

Based on these results, the entry at the previous day low/high is retained for subsequent analysis. The previous close entry is discarded, as it fails to preserve the statistical characteristics associated with the original Oops setup and does not exhibit comparable signal quality.

4.3 Return Distribution

Using the entry logic based on the previous day low/high, the analysis focuses on the **distribution of trade returns**.

Return distributions are examined to assess:

- The central tendency of returns
- The distribution of returns across key quantiles (e.g. 25th, 50th, and 75th percentiles)
- The presence of asymmetries or fat tails

This distributional perspective provides more insight than summary statistics alone, particularly for short-term mean-reversion strategies, where performance is often driven by a specific subset of trades.

Table 3

	HP	Win_rate_%	Expectancy	Median_ret	p25_ret	p75_ret	Skew_ret	n_trades
0	1	34.35	-0.0	-0.00	-0.01	0.00	-2.24	5350
1	2	39.64	-0.0	-0.00	-0.01	0.00	0.02	5350
2	3	41.96	-0.0	-0.00	-0.01	0.01	-0.19	5349
3	4	42.56	-0.0	-0.00	-0.02	0.01	-0.15	5349
4	5	44.32	-0.0	-0.00	-0.02	0.01	-0.27	5348
5	6	44.92	-0.0	-0.00	-0.02	0.01	-0.17	5348
6	7	45.07	-0.0	-0.00	-0.02	0.01	-0.20	5347
7	8	45.07	-0.0	-0.00	-0.02	0.01	0.01	5346
8	9	44.49	-0.0	-0.00	-0.02	0.02	0.03	5344
9	10	44.64	-0.0	-0.00	-0.02	0.02	0.14	5344
10	11	45.34	-0.0	-0.00	-0.02	0.02	-0.20	5344
11	12	44.89	-0.0	-0.00	-0.03	0.02	0.02	5340
12	13	43.89	-0.0	-0.01	-0.03	0.02	0.18	5340
13	14	44.86	-0.0	-0.00	-0.03	0.02	0.19	5340
14	15	44.89	-0.0	-0.00	-0.03	0.02	0.25	5339
15	16	44.36	-0.0	-0.01	-0.03	0.02	0.21	5339
16	17	45.23	-0.0	-0.01	-0.03	0.02	-0.06	5339
17	18	45.13	-0.0	-0.01	-0.03	0.03	-0.13	5335
18	19	44.89	-0.0	-0.01	-0.03	0.03	-0.10	5335
19	20	44.59	-0.0	-0.01	-0.03	0.03	-0.28	5332

Table 3

Across all holding periods, the **median return remains close to zero and slightly negative**, indicating that the typical trade outcome is small and does not, by itself, generate a positive edge. This result is consistent with the near-zero expectancy observed at the aggregate level.

The **interquartile range** reveals a stable structure over time. The 25th percentile progressively shifts from approximately −1% to −3% as the holding period increases, while the 75th percentile gradually expands from near zero to approximately +2% to +3%. This widening suggests that longer holding periods primarily increase dispersion rather than shifting the center of the distribution.

Skewness values fluctuate around zero and remain relatively modest in magnitude, indicating an absence of strong asymmetry in the unconditional return distribution. This implies that, at the raw signal level, neither tail dominates in a systematic way, and potential edge components are not immediately visible through distributional asymmetry alone.

Overall, the distributional analysis confirms that the selected entry logic does not produce a strong standalone edge when evaluated in isolation. Instead, the results suggest that any exploitable behavior is likely conditional, emerging only once additional dimensions such as exit structure, adverse and favorable excursion dynamics, or market regime filters are introduced.

4.4 Conclusion

The results presented in this section indicate that, when evaluated in isolation, the Oops pattern does not exhibit a strong unconditional edge. Expectancy remains close to zero, return distributions are broadly symmetric, and performance metrics do not reveal persistent advantages across holding periods.

However, this absence of unconditional edge does not imply randomness. Rather, it suggests that the behavior exploited by the Oops pattern is likely *state-dependent*, emerging only under specific market conditions.

This observation is consistent with the conceptual foundation of mean-reversion patterns, which tend to be sensitive to broader market context, volatility conditions, and short-term price dynamics.

Consequently, the next phase of the analysis shifts from unconditional evaluation to *conditional performance assessment*. The objective is to identify market regimes under which the Oops pattern exhibits statistically meaningful asymmetries, and to determine whether these conditions systematically favor one side of the market over the other.

5. Regime Analysis and Conditional Edge

Regime Analysis Overview

Regime analysis in finance refers to the identification of distinct and persistent market states—such as bull or bear phases, and high- or low-volatility environments—each characterized by specific statistical properties and behavioral dynamics. Recognizing these regimes is essential for understanding how market context influences signal performance, risk distribution, and strategy robustness.

Rather than assuming stationarity, regime-based analysis allows us to condition performance on prevailing market pressure, thereby improving interpretability and structural understanding of edge behavior.

Holding Period Definition

For the purpose of regime analysis, a fixed holding period of **7 trading days** is employed.
This horizon is selected to capture short-term mean-reversion dynamics while minimizing exit-rule interference and path-dependent effects.

By using a non-optimized and relatively short holding period, the analysis focuses on the interaction between market regimes and signal quality, rather than on monetization efficiency.

Methodology

All regime analyses in this section are conducted independently on the original signal dataset. Each regime filter is evaluated in isolation to avoid interaction effects and to preserve the interpretability of conditional behavior.

5.1 Macro Regime Analysis

To better understand the conditional nature of the Oops pattern's performance, the analysis investigates several broad market regime factors that could influence signal effectiveness:

- **Market Trend**
- **Distance from Mean**
  In a non-directional regime, a natural question arises:
  Does the Oops pattern perform better when price is above or below the SMA200?
  This filter segments the data further by comparing the closing price relative to the SMA200 to test conditional performance.
- **Volatility Regime**
  Volatility states are incorporated to assess whether the pattern's edge varies with market turbulence. Volatility can affect mean-reversion strength and the reliability of entry signals.
- **Market Filter**
  A broader market condition filter based on SPY price action is applied to understand whether systemic market movements affect the Oops pattern's efficacy.

These macro filters allow isolating broad structural factors that may condition the pattern's behavior, thus refining the signal's application in different market contexts.

5.1.1 Market Trend

To evaluate whether the impact of long-term market trend differs across trade direction, the regime analysis based on the slope of the 200-period Simple Moving Average (SMA200) is conducted separately for long and short setups. Trades are segmented based on the slope of the 200-period Simple Moving Average (SMA200) at the time the signal is generated.

Two regimes are defined based on the difference between the SMA and the previous value of SMA:

- **Trend regime:** positive SMA200 slope
- **No-trend regime:** non-positive SMA200 slope

This directional decomposition allows for the identification of structural asymmetries in the behavior of the Oops pattern.

Table 4 summarizes the performance metrics for long setups, while **Table 5** reports the corresponding results for short setups.

Table 4

	Regime	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	Trend	1530	0.35	0.59	-0.77	1.49	1.95	2.54	14.38	2.53	4.25
1	NoTrend	540	0.74	1.07	-0.19	3.08	3.53	4.67	4.11	5.41	4.14

Table 4

Table 5

	Regime	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	Trend	2585	-0.16	-0.34	0.91	1.26	1.69	2.28	1.57	2.13	4.11
1	NoTrend	554	-0.48	-0.83	0.39	2.09	2.81	4.01	2.90	3.77	4.12

Table 5

Long Side Results

On the long side, the Oops pattern exhibits positive expectancy in both regimes, with a clear performance improvement in non-trending environments.

In the **trend regime**, long trades generate a positive but modest expectancy (0.35), with a positive median return (0.59%). Skewness remains moderately negative, indicating frequent small gains combined with occasional larger adverse outcomes. Favorable excursion metrics (MFE) are elevated, suggesting that trades often experience meaningful upside potential, although this potential is not fully captured at the exit stage.

In the **no-trend regime**, long setups show a marked improvement across nearly all metrics. Expectancy more than doubles (0.74), the median return increases to 1.07%, and skewness moves closer to zero, indicating a more balanced return distribution. Median positive returns and MFE percentiles are substantially higher, pointing to a more efficient realization of mean-reversion dynamics when long-term directional pressure is weak.

Overall, these results indicate that long Oops setups benefit from environments characterized by reduced long-term trend persistence, consistent with the pattern's mean-reverting nature.

Short Side Results

The behavior of short setups differs materially from that of long trades.

In the **trend regime**, short trades exhibit negative expectancy (−0.16) and a negative median return (−0.34%). Skewness is positive, indicating that losses tend to be frequent while gains are less common but occasionally larger. Favorable excursion metrics remain limited, suggesting constrained downside follow-through after entry.

Performance deteriorates further in the **no-trend regime**, where expectancy declines to −0.48 and the median return falls to −0.83%. Despite an increase in median positive returns and MFE metrics, adverse excursion measures (MAE) also expand significantly, resulting in a structurally unfavorable payoff profile.

Across both regimes, short setups fail to exhibit positive expectancy or stable distributional characteristics comparable to those observed on the long side.

Interpretation and Directional Asymmetry

The regime-based analysis reveals a pronounced directional asymmetry in the Oops pattern's behavior. While long setups maintain positive expectancy across regimes—particularly in non-trending environments—short setups consistently underperform and exhibit structurally negative expectancy.

This asymmetry is likely influenced by the long-term upward drift inherent in equity index markets, as well as by the asymmetric nature of downside moves, which tend to be faster, more volatile, and less amenable to short-term mean-reversion patterns.

5.1.2 Distance from Mean
To further investigate the conditional behavior of the Oops pattern, the analysis examines the impact of price location relative to the 200-period Simple Moving Average (SMA200).
Rather than focusing on trend direction, this regime isolates the *distance-from-mean* effect, addressing the following question:

Trades are segmented based on the position of price relative to the SMA200 at the time of signal detection:

- **Above SMA200:** price above the long-term mean
- **Below SMA200:** price below the long-term mean

Performance statistics are evaluated separately for long and short setups.

Table 6 reports results for long setups, while **Table 7** summarizes results for short setups.

Table 6

	Regime	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	Above	1475	0.38	0.58	-0.50	1.46	1.84	2.47	14.8	2.47	4.27
1	Below	595	0.64	1.08	-0.26	3.08	3.66	4.79	4.0	5.06	4.08

Table 6

Table 7

	Regime	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	Above	2560	-0.16	-0.33	0.93	1.21	1.65	2.25	1.52	2.08	4.09
1	Below	580	-0.47	-0.93	0.42	2.41	2.92	4.21	3.05	4.09	4.18

Table 7

Long Side Results

On the long side, a clear distinction emerges between the two regimes.

When price is **above the SMA200**, long setups generate a modest positive expectancy (0.38) with a median return of 0.58%. Skewness remains moderately negative, indicating a payoff structure characterized by frequent small gains and occasional larger losses. Favorable excursion metrics are elevated, but median positive returns remain limited, suggesting partial capture of upside movements.

In contrast, when price is **below the SMA200**, long setups exhibit substantially stronger performance. Expectancy increases to 0.64, the median return rises to 1.08%, and median positive returns more than double. Although adverse excursion measures (MAE) are higher in this regime, favorable excursion metrics expand to a greater extent, resulting in a more favorable risk–reward profile.

These results suggest that long Oops setups benefit from being initiated below the long-term mean, where mean-reversion forces appear more pronounced.

Short Side Results

The short side displays a consistently unfavorable profile across both regimes.

When price is **above the SMA200**, short setups produce negative expectancy (−0.16) and a negative median return (−0.33%). Skewness is strongly positive, indicating a high frequency of losses accompanied by occasional larger gains. Favorable excursion metrics remain limited, reflecting constrained downside continuation following entry.

Performance deteriorates further when price is **below the SMA200**. Expectancy declines to −0.47, the median return falls to −0.93%, and adverse excursion metrics increase significantly. While favorable excursion measures improve slightly, they are insufficient to offset the expansion in drawdowns, leading to a structurally weaker payoff profile.

Across both price-location regimes, short setups fail to demonstrate positive expectancy or stable distributional properties.

Interpretation and Directional Asymmetry

The distance-from-mean analysis reinforces the directional asymmetry observed in the trend-based regime study. Long setups exhibit materially stronger performance when initiated below the SMA200, consistent with the intuition that mean-reversion dynamics intensify when price is displaced below its long-term equilibrium.

Short setups, by contrast, remain structurally disadvantaged regardless of price location, suggesting that short-term mean-reversion mechanisms are insufficient to overcome the asymmetric behavior of equity index declines.

Taken together, these findings indicate that **price location relative to the long-term mean represents a meaningful conditioning variable for the Oops pattern**, particularly on the long side.

5.1.3 Volatility Regime

To evaluate whether market volatility conditions influence the behavior of the Oops pattern, a volatility-based regime classification is introduced.
Volatility is measured using the 14-period Average True Range (ATR14), normalized through a rolling percentile transformation over a 50-day window.

Specifically, at each signal occurrence, volatility is expressed as the percentile rank of the current ATR14 relative to its trailing 50-day distribution. This approach allows for a regime definition that adapts dynamically to changing volatility environments rather than relying on static thresholds.

Two volatility regimes are defined as minor of 0.5 or greater of 0.5:

- **Low Volatility:** lower percentile range of ATR14
- **High Volatility:** higher percentile range of ATR14

Performance metrics are evaluated separately for long and short setups under each volatility regime.

Table 8 summarizes the results for long setups, while **Table 9** reports the corresponding statistics for short setups.

Table 8

	Regime	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	Low Volatility	977	0.37	0.49	-0.50	1.43	1.83	2.37	11.76	2.56	4.28
1	High Volatility	1128	0.51	0.80	-0.22	2.09	2.83	3.64	11.37	3.50	4.14

Table 8

Table 9

	Regime	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	Low Volatility	1685	-0.18	-0.33	0.41	1.22	1.72	2.28	1.66	2.20	4.08
1	High Volatility	1512	-0.24	-0.47	0.79	1.56	2.07	2.86	1.99	2.65	4.12

Table 9

Long Side Results

On the long side, volatility conditions appear to meaningfully condition performance.

In **low volatility environments**, long setups generate a modest positive expectancy (0.37) with a median return of 0.49%. Skewness is moderately negative, indicating a payoff structure characterized by frequent small gains and occasional larger adverse moves. Favorable excursion metrics remain elevated, suggesting the presence of upside potential, though median positive returns are relatively contained.

In **high volatility environments**, long setups exhibit a clear improvement across most performance dimensions. Expectancy increases to 0.51, the median return rises to 0.80%, and skewness moves closer to zero, indicating a more balanced return distribution. Median positive returns increase substantially, and both mean and upper-quartile MFE values remain robust, pointing to stronger and more persistent favorable price movements following entry.

Although adverse excursion measures (MAE) also increase in high volatility regimes, the expansion in favorable excursions dominates, resulting in a net improvement in risk–reward characteristics.

Short Side Results

Short setups display consistently negative performance across volatility regimes.

In **low volatility environments**, short trades exhibit negative expectancy (−0.18) and a negative median return (−0.33%). Skewness remains positive, indicating frequent small losses punctuated by occasional larger gains. Favorable excursion metrics remain limited, reflecting constrained downside continuation.

Performance worsens in **high volatility environments**, where expectancy declines further to −0.24 and the median return deteriorates to −0.47%. Both MAE and MFE metrics expand, but the increase in adverse excursions outweighs any improvement in favorable movement, resulting in a structurally unfavorable payoff profile.

Across both volatility regimes, short setups fail to demonstrate positive expectancy or stable distributional characteristics.

Interpretation and Directional Asymmetry

The volatility-based regime analysis highlights a clear asymmetry between long and short configurations. Long setups benefit from higher volatility conditions, where increased price dispersion appears to enhance the effectiveness of mean-reversion dynamics. While drawdowns increase in these environments, the corresponding expansion in favorable excursions more than compensates for the added risk.

Short setups, by contrast, deteriorate as volatility rises. This suggests that volatility-driven downside moves in equity index markets are less conducive to controlled mean-reversion behavior and more prone to unstable price dynamics that undermine short-side signal reliability.

Overall, volatility emerges as a relevant conditioning variable for the Oops pattern, particularly for long setups, reinforcing the view that the strategy's edge is both **regime-dependent and directionally asymmetric**.

5.1.4 Market Filter

To evaluate whether broader market conditions influence the behavior of the Oops pattern, a **market trend–based regime classification** is introduced.

The market environment is defined using **SPY as the reference benchmark**. At each signal occurrence, the relative position of the traded instrument with respect to SPY is used to classify the prevailing market regime.

Specifically, two market regimes are defined:

- **Market / Local Trend Up**: SPY price above its SMA200
- **Market / Local Trend Down**: SPY price below its SMA200

This relative framework allows market conditions to be assessed dynamically, capturing periods of relative strength or weakness rather than relying on absolute index direction.

Performance metrics are evaluated separately for **long and short setups** under each market regime.

Table 10 summarizes the results for long setups, while **Table 11** reports the corresponding statistics for short setups.

Table 10

	Regime	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	Market Up	1553	0.34	0.53	-0.42	1.45	1.89	2.52	14.15	2.45	4.21
1	Market Down	583	0.71	1.25	-0.31	3.00	3.68	4.88	4.14	5.22	4.11

Table 10

Table 11

	Regime	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	Market Up	2588	-0.12	-0.31	0.91	1.26	1.69	2.32	1.51	2.07	4.07
1	Market Down	623	-0.58	-0.89	0.49	2.03	2.71	3.71	3.07	4.04	4.23

Table 11

Long Side Results

On the long side, market trend conditions materially affect the distribution and quality of returns, while preserving a positive expectancy across regimes.

In **Market Up** conditions, long setups generate a positive expectancy (0.34) with a median return of 0.53%. Skewness is moderately negative, indicating a payoff profile characterized by frequent modest gains and occasional larger adverse outcomes. Favorable excursion metrics are elevated, with a particularly high mean MFE, suggesting the presence of strong upside tail events driven by momentum continuation. However, median positive returns remain contained, pointing to less consistent profit capture.

In **Market Down** conditions, long setups exhibit a clear improvement in consistency. Expectancy rises to 0.71 and the median return increases to 1.25%, while skewness becomes less negative, indicating a more balanced return distribution. Median positive returns increase substantially, reflecting stronger typical trade outcomes. Adverse excursion measures (MAE) also rise, suggesting increased short-term pressure after entry, but favorable excursions remain sufficiently large to dominate the payoff structure.

Overall, while Market Up regimes offer larger upside tails, Market Down environments provide **superior median performance and higher expectancy**, consistent with a mean-reversion mechanism acting on relative weakness.

Short Side Results

Short setups display consistently negative performance across market regimes.

In **Market Up** conditions, short trades produce a slightly negative expectancy (−0.12) and a negative median return (−0.31%). Skewness is strongly positive, indicating frequent small losses interrupted by occasional larger favorable moves. Favorable excursion metrics remain limited, suggesting that downside continuation is generally insufficient to offset adverse drift.

Performance deteriorates further in **Market Down** conditions. Expectancy declines to −0.58 and the median return worsens to −0.89%. Both adverse and favorable excursions expand, but the increase in MAE dominates, reflecting unstable downside dynamics and poor risk–reward characteristics. Despite higher median positive returns relative to Market Up conditions, the overall distribution remains structurally unfavorable.

Across both regimes, short setups fail to demonstrate positive expectancy or stable statistical properties.

Interpretation and Directional Asymmetry

The market trend–based regime analysis reveals a pronounced **directional asymmetry** in the Oops pattern.

Long setups remain profitable across market conditions but perform best when applied in **relative weakness**, where mean-reversion forces are stronger and returns are more consistent. Strong market environments increase upside tail potential but reduce median efficiency.

Short setups, by contrast, are structurally disadvantaged in all market regimes. Market direction acts as an adverse conditioning variable, and no regime produces a stable or exploitable short-side edge.

Overall, market trend emerges as a relevant conditioning factor for the Oops pattern, reinforcing its interpretation as a **long-biased, mean-reversion strategy** whose edge is enhanced in environments of relative underperformance rather than broad market strength.

5.2 Summary of Macro Regime Analysis

The macro regime analysis evaluates the robustness of the Oops pattern across multiple high-level market dimensions, including trend structure, long-term positioning (SMA200), volatility conditions, and relative market strength using SPY as a benchmark.

Across all regime definitions, a **consistent directional asymmetry** emerges.

Long setups display **stable and positive expectancy** across most regimes, with performance meaningfully conditioned by the surrounding environment. In particular, regimes associated with **relative weakness, higher volatility, and non-trending conditions** tend to enhance median returns and overall expectancy, reinforcing the interpretation of the Oops pattern as a mean-reversion mechanism that benefits from price dislocation rather than sustained directional movement.

Short setups, by contrast, exhibit **structurally negative performance** across all tested macro regimes. While distributional characteristics vary—particularly in volatility and market-down environments—no regime produces a reliable or exploitable short-side edge. Positive skewness observed in short trades reflects occasional large favorable moves that fail to compensate for persistent adverse drift.

Importantly, this analysis is conducted **on the full signal dataset**, without selectively filtering trades based on the best-performing regime. As such, the results reflect **conditioning effects rather than optimization**, ensuring that observed differences are attributable to regime sensitivity rather than sample selection.

Overall, the macro regime analysis confirms that:

- The Oops pattern is **long-biased by construction**
- Its edge is **regime-dependent but robust**
- Macro conditions influence **efficiency and distribution**, not the existence of the edge itself

These findings motivate a deeper investigation into **local market dynamics**, where signal quality may be further refined.

5.3 Micro Regime Analysis

The macro regime analysis establishes that the Oops pattern exhibits a persistent and structurally robust edge on the long side, while short configurations fail to demonstrate consistent profitability across market environments.

Given this evidence, the micro regime analysis focuses **exclusively on long setups**, with the objective of assessing whether **local price structure at the time of signal generation** meaningfully conditions performance.

Unlike macro regimes, which describe broad market states, micro regimes operate at the **signal level**, capturing short-term dynamics directly related to the mechanics of the Oops pattern. This shift enables a more precise evaluation of signal quality and allows for the identification of structural features that may enhance or weaken the underlying edge.

The analysis is organized around two main dimensions:

- **Local trend structure immediately preceding the signal**
- **Gap size characteristics**

This section begins with an examination of local trend structure, followed by gap-based conditioning.

5.3.1 Local Trend Structure

According to Larry Williams' original formulation, the Oops pattern long is expected to perform best when it emerges **after a phase of downside pressure**, where selling activity exhausts itself and creates conditions favorable to short-term mean reversion.

To empirically test this intuition, the local trend structure immediately preceding the signal is analyzed in detail. Rather than relying on longer-term indicators, the focus is placed on **price behavior directly prior to the Oops setup**, under the assumption that short-term selling pressure is a key driver of edge formation.

All sub-analyses within this section evaluate **only the long side**, consistent with the results of the macro regime analysis.

Local trend structure is examined through multiple complementary definitions, each designed to quantify **the intensity and persistence of bearish pressure** preceding the signal:

- **5.3.1.1 Previous Candle Directional**
  Classification based on an explicit directional definition of bearish pressure based on candle anatomy and position within the range.
- **5.3.1.2 Strong Bearish Pressure**
  Classification based on structural classification framework to characterize the previous candle, particularly with the *strong bearish pressure* condition.
- **5.3.1.3 Intermediate Bearish Pressure**
  Classification based on structural classification framework to characterize the previous candle, particularly with the *intermediate bearish pressure* condition.
- **5.3.1.4 Short-Term Trend**
  A short-term trend based on the slope of a 5 periods SMA proxy evaluating whether the immediate price trajectory aligns with a declining micro-trend.

By progressively tightening or relaxing the definition of downside pressure, this framework allows for an assessment of whether **stronger pre-signal bearish dynamics lead to improved expectancy, cleaner return distributions, or superior excursion profiles**.

Crucially, as in the macro regime analysis, all evaluations are conducted on the **original signal dataset**, without selectively filtering trades based on ex-post performance. The goal is to **condition and diagnose the edge**, not to optimize or overfit the strategy.

5.3.1.1 Previous Candle Directional

This subsection examines whether the presence of **strong bearish pressure in the candle immediately preceding the Oops signal** enhances the quality of long setups.

Larry Williams' original description emphasizes that the Oops pattern should occur after a phase of selling pressure. To operationalize this concept in a precise and testable manner, a strict definition of a **directional bearish candle** is applied to the bar immediately prior to the signal (t−1).

A previous candle is classified as *directional bearish* if all of the following conditions are satisfied:

- The candle closes in the lower portion of its range
- The open is located near the high of the range
- The candle body represents a large fraction of the total range
- The candle closes below its open

Formally, the condition is defined as:

- Upper wick relative to range < 20%
- Close relative to range < 20%
- Body ≥ 60% of total range
- Close < Open

This definition is designed to capture **intense and unambiguous downside pressure**, filtering out neutral or weakly bearish candles and isolating cases where selling dominance is clearly expressed.

Only long trades satisfying this condition are retained for analysis.

Table 12 reports the performance metrics for long Oops setups preceded by a directional bearish candle.

	HP	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	7	454	0.5	0.77	-0.01	2.12	2.83	3.45	2.66	3.36	4.34

Table 12

Long Side Results

Under this strict local trend condition, long setups exhibit a solid and internally consistent performance profile.

Expectancy remains clearly positive (0.50), with a median return of 0.77%. Skewness is approximately neutral (−0.01), indicating a balanced return distribution with reduced asymmetry compared to broader samples. Median positive returns exceed 2%, suggesting that when favorable outcomes occur, they tend to be economically meaningful.

Adverse excursion metrics (MAE) increase moderately relative to unconditional long results, reflecting the fact that trades often initiate during periods of heightened selling pressure. However, favorable excursion metrics (MFE) remain well-defined and persistent, indicating that downside exhaustion is frequently followed by recoveries sufficient to justify the entry.

Time-to-maximum-favorable-excursion (TMFE) remains stable and consistent with previous analyses, suggesting that the temporal structure of the edge is preserved despite the stricter entry context.

Interpretation

The application of a strict bearish filter on the previous candle results in a **substantial reduction in the number of trades**, reflecting the relative rarity of such pronounced directional selling pressure. This trade-off is expected and structurally coherent with the design of the filter.

Importantly, the reduction in frequency is accompanied by **cleaner distributional properties**, including improved skewness and stable expectancy, rather than by over-optimization artifacts. This suggests that strong downside pressure immediately prior to the signal acts as a **quality filter**, enhancing the internal consistency of the Oops pattern rather than merely reducing noise.

These results support the original conceptual intuition behind the pattern: **mean-reversion dynamics appear more reliable when preceded by clear and aggressive selling activity**. However, the sharp decline in signal frequency highlights the practical tension between selectivity and scalability, motivating the exploration of alternative, less restrictive definitions of bearish pressure in the following subsections.

5.3.1.2 Strong Bearish Pressure
While the previous subsection focused on an explicit directional definition of bearish pressure based on candle anatomy and position within the range, this analysis adopts a **structural classification framework** to characterize the previous candle.

The objective remains the same: to verify whether the Oops pattern performs better when preceded by **clear and dominant selling pressure**, as suggested in the original formulation. However, instead of relying on fixed geometric thresholds, bearish pressure is now identified through **relative measures of candle body strength and range expansion**.

Candle Classification Framework

The candle immediately preceding the Oops signal (t−1) is classified along two independent dimensions:

1. Body Strength (Body-to-Range Ratio)
The candle body is normalized by its total range and classified into three categories:

- *Long body*: body ≥ 70% of total range
- *Average body*: 40% ≤ body < 70%
- *Small body*: body < 40%

This classification captures the dominance of directional movement relative to intraday volatility.

2. Range Expansion (Relative Candle Size)
Total candle range is evaluated relative to the trailing 100-day distribution and classified using rolling quantiles:

- *Larger-sized*: range above the 66th percentile
- *Average-sized*: range between the 33rd and 66th percentiles
- *Smaller-sized*: range below the 33rd percentile

This allows for the identification of candles that represent **statistically large price moves** in their recent volatility context.

Strong Bearish Pressure Definition

A *strong bearish pressure* condition is defined when the previous candle simultaneously satisfies the following criteria:

- Large range expansion (*larger-sized*)
- Strong body dominance (*long body*)
- Bearish close (close < open)

Only long trades meeting all these conditions are retained for analysis.

This definition represents a **more structural and relative interpretation of selling pressure**, capturing situations where downside movement is both directionally strong and unusually large compared to recent history.

Table 13 reports the performance metrics for long Oops setups preceded by a structurally defined strong bearish candle.

	HP	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	7	340	0.77	1.19	0.17	2.39	3.02	3.63	2.92	3.73	4.44

Table 13

Long Side Results

Under the strong bearish pressure definition, long Oops setups exhibit a clear improvement in signal quality despite a substantial reduction in trade frequency.

The number of qualifying trades declines to 340, reflecting the restrictive nature of the filter and the relative rarity of prior candles characterized by both large range expansion and dominant bearish bodies. However, the remaining trades display materially stronger performance metrics.

Expectancy increases to 0.77, accompanied by a median return of 1.19%, indicating that the typical trade outcome is decisively positive. Skewness shifts slightly into positive territory (0.17), suggesting a more balanced payoff profile in which favorable outcomes are not solely driven by a small subset of extreme winners.

Median positive returns rise to 2.39%, while favorable excursion metrics remain robust, with mean MFE at 2.92% and upper-quartile MFE at 3.73%. These values indicate that price frequently follows through in the intended direction after entry, consistent with a genuine exhaustion–reversion mechanism rather than noise-driven fluctuations.

Adverse excursion measures expand moderately (MAE mean 3.02%, p75 at 3.63%), reflecting the fact that trades are initiated during periods of intense downside pressure. Importantly, the corresponding increase in favorable excursions dominates, resulting in a net improvement in expectancy and overall payoff structure.

Time to maximum favorable excursion remains stable at approximately four bars, suggesting that the temporal dynamics of the edge are preserved even under stricter conditioning.

Interpretation

The results confirm that conditioning the Oops pattern on a **structurally defined strong bearish candle** materially enhances long-side signal quality.

By requiring both statistical range expansion and body dominance in the prior session, the filter effectively isolates scenarios characterized by pronounced selling pressure and potential downside exhaustion. Although this selectivity significantly reduces the number of trades, it produces a marked improvement in expectancy, median returns, and distributional symmetry.

The transition of skewness toward positive values is particularly notable, as it indicates that profitable outcomes are not driven exclusively by rare tail events but are instead more evenly distributed across trades. This suggests a higher degree of structural robustness in the underlying price behavior.

Overall, this analysis supports the hypothesis that the Oops pattern's long-side edge is strongest when preceded by **extreme and well-defined bearish pressure**, reinforcing the importance of microstructural context in mean-reversion strategies.

5.3.1.3 Intermediate Bearish Pressure

In order to further refine the characterization of prior bearish pressure preceding the Oops long signal, an intermediate pressure definition is introduced.
This specification builds upon the same conceptual framework as the strict strong-pressure filter, but relaxes the intensity requirements to include candles exhibiting **greater-than-medium directional strength**.

The objective of this step is to evaluate whether the effectiveness of the Oops pattern depends on extreme bearish pressure conditions, or whether a broader class of directional candles is sufficient to preserve the mean-reversion edge. By expanding the admissible set of prior candles, this analysis explicitly examines the trade-off between signal selectivity and statistical robustness

Intermediate Bearish Pressure Definition

An *intermediate bearish pressure* condition is defined when the previous candle simultaneously satisfies the following criteria:

- Large or avarage range expansion (*larger-sized or avarage*)
- Strong or avarage body dominance (*long body or average body*)
- Bearish close (close < open)

Only long trades meeting all these conditions are retained for analysis.

Table 14 reports the performance metrics for long Oops setups preceded by a structurally defined strong bearish candle.

	HP	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	7	813	0.81	0.94	-0.04	2.1	2.62	3.22	2.7	3.54	4.39

Table 14

Long Side Results

When relaxing the prior bearish pressure constraint to include candles classified as **greater-than-avarage intensity**, the Oops long setup exhibits a meaningful increase in trade frequency while preserving strong performance characteristics.

The number of qualifying trades rises to 813, more than doubling relative to the strict strong-pressure definition. Despite this broader inclusion, expectancy remains elevated at 0.81, representing the highest value observed among the tested prior-candle specifications. The median return remains decisively positive at 0.94%, confirming that the typical trade outcome continues to reflect a genuine edge.

Skewness remains close to zero (−0.04), indicating a well-balanced return distribution with no pronounced tail dependence. Median positive returns are stable at 2.10%, while favorable excursion metrics remain robust, with mean MFE at 2.70% and upper-quartile MFE at 3.54%. These figures suggest that price follow-through remains consistent even when the prior pressure definition is relaxed.

Adverse excursion measures contract slightly relative to the stricter filter, with mean MAE at 2.62% and the 75th percentile at 3.22%. This reduction in drawdown severity indicates that excluding only the weakest bearish candles may help preserve upside potential while mitigating excessive adverse movement.

Time to maximum favorable excursion remains stable at approximately four bars, reinforcing the consistency of the pattern's temporal structure.

Interpretation

This intermediate definition of prior bearish pressure appears to strike a favorable balance between **selectivity and robustness**.

While the strict strong-pressure filter maximizes signal purity at the cost of a sharply reduced sample size, the greater-than-medium specification retains most of the structural advantages of strong bearish pressure while substantially improving statistical reliability through increased trade frequency.

The persistence of high expectancy, combined with stable median returns and near-zero skewness, suggests that the underlying edge is not overly sensitive to the exact intensity threshold, provided that a minimum level of directional pressure is present. In contrast to the strict filter, the broader definition reduces adverse excursion exposure without materially sacrificing favorable excursion potential.

Overall, these results indicate that the Oops pattern's long-side effectiveness does not require extreme prior pressure conditions, but rather a **clearly defined and directional bearish context**. This finding supports the use of a moderately selective pressure filter as a robust foundation for subsequent strategy development and exit analysis.

5.3.1.4 Short-Term Trend

To complete the micro regime analysis on local price structure, a short-term trend filter based on the slope of a fast moving average is introduced.
The objective of this test is to assess whether the immediate micro-trend preceding the Oops signal influences the effectiveness of the long-side setup.

Short-term trend direction is defined using the slope of the 5-period Simple Moving Average, computed as the difference between the current SMA5 value and its value five sessions earlier. At the time of signal generation, trades are classified into two regimes:

- **Trend Up:** positive SMA5 slope
- **Trend Down:** non-positive SMA5 slope

This classification captures the short-term directional bias immediately preceding the gap-and-reversal structure, allowing for an evaluation of whether the Oops pattern benefits from alignment with, or opposition to, local momentum.

Table 15 reports the performance metrics for long Oops setups.

	Regime	n_trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	TrendUp	1140	0.35	0.58	-0.42	1.47	1.96	2.54	18.80	2.64	4.25
1	TrendDown	995	0.54	0.69	-0.24	2.10	2.85	3.66	2.97	3.65	4.11

Table 15

Long Side Results

The results reveal a clear differentiation in performance based on short-term trend direction.

When the SMA5 slope is positive (Trend Up), long setups generate a modest positive expectancy of 0.35, accompanied by a median return of 0.58%. Skewness remains moderately negative, indicating frequent small gains interspersed with occasional larger adverse outcomes. Favorable excursion metrics are elevated, suggesting the presence of upside potential, although this potential is not consistently realized at exit.

In contrast, when the SMA5 slope is non-positive (Trend Down), long setups exhibit a meaningful improvement across most performance dimensions. Expectancy increases to 0.54, while the median return rises to 0.69%. Skewness moves closer to zero, indicating a more balanced return distribution. Median positive returns and MFE metrics improve materially, pointing to stronger and more reliable follow-through after entry.

Adverse excursion measures increase moderately in the Trend Down regime, but the expansion in favorable excursions dominates, resulting in an overall improvement in payoff structure. The timing of favorable movement remains stable across regimes, with TMFE values clustered around four bars.

Interpretation

These results indicate that the Oops long setup performs more effectively when embedded within a **short-term downward or neutral price structure**, rather than when aligned with positive local momentum.

A declining or flat SMA5 slope likely reflects short-term selling pressure or loss of upward momentum, conditions that are consistent with the mean-reversion logic underlying the Oops pattern. In such environments, the gap-and-recovery mechanism appears more capable of capturing exhaustion-driven reversals.

Conversely, when the short-term trend is already positive, the pattern's edge weakens, suggesting that entering long positions after a gap-down within an already rising micro-trend may reduce the informational value of the reversal signal.

Overall, the SMA5 slope emerges as a meaningful micro-level conditioning variable. Together with prior analyses on candle structure and pressure intensity, this result reinforces the conclusion that the Oops pattern's long-side edge is strongest when **multiple layers of short-term bearish pressure precede the signal**, even in the absence of broader directional trends.

5.3.2 Gap Size

To complete the micro regime analysis, the impact of **gap magnitude** on the performance of the Oops long setup is evaluated.
Given that the Oops pattern is fundamentally driven by gap-induced dislocations followed by intraday reversals, the size of the opening gap represents a critical conditioning variable.

Gap size is measured as the percentage distance between the opening price and the previous session's low. Long-side signals are grouped into four mutually exclusive buckets:

- **G0:** gap between 0.0% and 0.2%
- **G1:** gap between 0.2% and 0.5%
- **G2:** gap between 0.5% and 1.0%
- **G3:** gap greater than 1.0%

All performance metrics are evaluated using the same holding period and assumptions adopted in previous sections, and only long setups are considered.

Table 16

G0: Gap 0.0% - 0.2%

Holding	N_Trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct
7	1046	0.29	0.62	-0.69	1.71	2.09	2.77	20.46	2.88

G1: Gap 0.2% - 0.5%

Holding	N_Trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct
7	635	0.53	0.74	-0.34	1.83	2.53	3.03	2.45	3.23

G2: Gap 0.5% - 1.0%

Holding	N_Trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct
7	302	0.76	0.92	-0.32	2.55	2.93	3.67	3.11	4.18

G3: Gap 1.0% - 99900.0%

Holding	N_Trades	Expectancy	Median_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct
7	153	0.61	1.08	-1.13	3.42	5.25	6.29	5.97	6.0

Table 16

Long Side Results

A clear monotonic relationship emerges between gap size and signal quality.

For very small gaps (G0), the strategy exhibits a modest positive expectancy of 0.29, with a median return of 0.62%. Skewness is strongly negative, indicating frequent small gains combined with occasional larger adverse outcomes. While favorable excursion metrics are elevated, the payoff structure appears relatively noisy and less efficient.

As gap size increases to the G1 bucket (0.2%–0.5%), performance improves materially. Expectancy rises to 0.53, median returns increase to 0.74%, and skewness becomes less negative. Both median positive returns and MFE metrics expand, suggesting stronger and more reliable intraday reversals.

The G2 bucket (0.5%–1.0%) displays the most favorable balance between trade frequency and performance. Expectancy peaks at 0.76, with a median return of 0.92% and stable skewness. Favorable excursion metrics improve further while adverse excursion measures remain contained, resulting in a well-structured payoff profile.

For very large gaps (G3, greater than 1.0%), expectancy remains elevated at 0.61 and median returns rise to 1.08%. However, skewness becomes strongly negative and adverse excursion measures expand significantly. While upside potential increases sharply, as reflected by high MFE values, the distribution becomes less stable and more tail-dependent.

Trade frequency declines sharply as gap size increases, highlighting the growing selectivity of larger gap conditions.

Interpretation

The gap size analysis confirms that **gap magnitude is a primary driver of edge quality** for the Oops long setup.

Small gaps appear insufficient to generate the level of price dislocation required for a clean mean-reversion response, resulting in weaker expectancy and noisier return distributions. As gap size increases, the informational content of the opening move improves, leading to more consistent reversal dynamics and higher expectancy.

The strongest and most robust performance emerges in the intermediate gap range (0.5%–1.0%), where the balance between dislocation intensity and market stability appears optimal. In this regime, favorable excursions expand without a commensurate increase in adverse risk, producing a structurally attractive payoff profile.

Very large gaps, while still profitable on average, introduce significant tail risk. The sharp expansion in both favorable and adverse excursions suggests that extreme gaps often coincide with news-driven or panic-driven conditions, where price dynamics become less controlled and mean-reversion less predictable.

Overall, these results indicate that **gap size acts as a natural quality filter** for the Oops pattern. Conditioning the strategy on moderate-to-large gaps enhances signal reliability, while avoiding excessively small gaps and extreme dislocations may improve robustness when transitioning from pure signal analysis to full strategy design.

5.4 Summary of Micro Regime Analysis

The micro regime analysis was conducted to evaluate how short-term price structure, directional pressure, and gap characteristics influence the behavior of the Oops pattern at the signal level. Unlike the macro regime analysis, which focused on broader market conditions, this section examined local features directly tied to the formation of the setup.

Across all tests, a consistent theme emerges: the effectiveness of the Oops pattern on the long side is highly sensitive to the **quality of prior bearish pressure and the magnitude of the opening gap**, while short-term trend structure plays a secondary but meaningful role.

The analysis of prior candle characteristics confirms that some form of directional bearish pressure preceding the signal is a necessary condition for the pattern to exhibit non-random behavior. However, the results also show that extreme pressure requirements are not strictly necessary. While a very strict definition of bearish pressure maximizes signal purity, it significantly reduces trade frequency and limits statistical robustness.

By contrast, the **intermediate bearish pressure definition**—which requires a clearly directional prior candle without imposing extreme intensity constraints—achieves the most favorable balance between expectancy, return stability, and sample size. This specification preserves the structural advantages of strong prior pressure while materially improving the reliability of the observed performance metrics.

Short-term trend analysis further supports the mean-reversion interpretation of the pattern. Long setups perform more effectively when embedded within neutral or declining micro-trend environments, consistent with the idea that the Oops pattern exploits short-term exhaustion rather than momentum continuation.

Finally, gap size emerges as one of the most influential conditioning variables. Performance improves monotonically with gap magnitude up to an intermediate range, beyond which return distributions become increasingly unstable and tail-driven. Moderate-to-large gaps provide sufficient dislocation to activate mean-reversion dynamics without introducing excessive regime noise.

Based on the combined evidence from the micro regime analysis, **the intermediate bearish pressure definition is retained as the baseline signal specification for the remainder of this study**. This choice reflects a deliberate trade-off between selectivity and robustness and provides a stable foundation for the subsequent analysis of adverse and favorable excursion dynamics, exit rules, and full strategy construction.

6. Exit Strategy Design

Introduction

Once the presence of a conditional edge has been established—specifically within the *Oops* setup under **Intermediate Bearish Pressure—**the focus of the analysis shifts from *edge detection* to *edge monetization*.
This section investigates how different exit mechanisms interact with the underlying structure of the edge, with the objective of identifying exit rules that enhance robustness, capital efficiency, and risk control without distorting the original signal logic.

To avoid overfitting and preserve interpretability, exit strategies are studied within a controlled and incremental framework. Rather than optimizing parameters directly, exits are evaluated as structural hypotheses about *how* and *when* the edge expresses itself over time.

Extended Holding Period Analysis

As an initial diagnostic step, the strategy is evaluated across extended holding periods using a fixed close-to-close exit.
This analysis is not intended for optimization, but to assess the temporal persistence of the edge and identify potential decay or saturation effects.
The resulting performance profile provides a baseline against which all subsequent exit mechanisms are evaluated.

Edge Structure

While extended holding periods reveal edge longevity, they do not explain how profits are formed within each trade.
To address this, the analysis probes whether favorable price excursions occur early or late in the trade lifecycle, using intraday high-based hypothetical exits as a structural diagnostic.
These observations directly inform exit design by constraining which mechanisms are coherent with the underlying price behavior.

Exit Design Roadmap

Based on the structural insights derived from the time-based and intraday analyses, the following exit families are evaluated:

- **Trailing exits**
  - Fixed percentage trailing (intraday low vs end-of-day close)
  - Chandelier exits using ATR (14 vs 5 periods)
- **Structure-based trailing exits**
- **MFE-based exits**
- **Hybrid exits**, combining MFE-based logic with Chandelier (5-period ATR)
- **Original Larry Williams exit**, included as a benchmark and conceptual reference

Each exit is assessed relative to the same baseline setup, enabling direct comparison in terms of expectancy, distributional properties, and risk-efficiency trade-offs.

Objective of the Section

The goal of this section is not to identify a universally optimal exit, but to determine which exit mechanisms are **structurally coherent** with the observed behavior of the edge and which introduce unnecessary complexity or fragility.

This approach ensures that exit selection emerges as a *logical consequence of edge behavior*, rather than as a result of parameter search.

6.1 Extended Holding Period Analysis

Objective

This subsection evaluates the behavior of the *Oops + Intermediate Bearish Pressure* setup under **pure time-based exits**, using fixed holding periods ranging from **1 to 25 trading days**.
All positions are closed at the **end-of-day close** corresponding to the selected holding period.

The objective of this analysis is not to optimize the holding horizon, but to **characterize the temporal structure of the edge**, identifying:

- when the edge becomes statistically active,
- how returns evolve as holding time increases,
- whether expectancy stabilizes, accelerates, or decays over longer horizons.

This analysis establishes a neutral benchmark against which more adaptive exit mechanisms will later be compared.

Methodology

- Holding periods tested: **HP = 1 to 25**
- Exit rule: **Close-to-close**, fixed horizon
- Dataset: unchanged signal set (no filtering or interaction effects)
- Metrics evaluated:
    - Expectancy
    - Win rate
    - Return distribution (median, p25, p75, skewness)
    - MAE / MFE statistics
    - TMFE (time to maximum favorable excursion)

No parameter tuning or conditional logic is applied.

Table 17 summarizes the performance metrics for long setups with extended periods.

	HP	n_trades	Expectancy	Win_rate_pct	Median_ret_pct	p25_ret	p75_ret	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	1	816	-0.05	50.37	0.02	-0.56	0.55	-0.66	0.56	1.23	1.51	0.84	1.07	0.00
1	2	813	-0.05	50.42	0.02	-0.56	0.56	-0.66	0.56	1.23	1.51	0.84	1.08	0.00
2	3	813	0.17	56.25	0.22	-0.86	1.11	0.64	1.03	1.68	1.94	1.44	1.83	0.83
3	4	813	0.36	58.22	0.38	-0.97	1.67	0.21	1.44	1.98	2.39	1.87	2.34	1.74
4	5	813	0.46	60.38	0.57	-1.06	1.88	0.42	1.51	2.22	2.80	2.17	2.74	2.66
5	6	813	0.58	63.28	0.65	-0.99	2.35	-0.08	1.81	2.44	3.08	2.46	3.14	3.48
6	7	813	0.81	64.18	0.94	-1.07	2.67	-0.04	2.10	2.62	3.22	2.70	3.54	4.39
7	8	813	0.76	61.99	0.98	-1.04	2.64	-0.23	2.21	2.77	3.46	2.91	3.73	5.29
8	9	813	0.89	63.77	1.05	-1.12	3.06	-0.60	2.49	2.94	3.89	3.12	4.08	6.32
9	10	813	0.94	63.68	1.02	-1.11	3.02	-0.15	2.57	3.07	4.08	3.31	4.35	7.32
10	11	813	0.88	64.27	1.08	-1.36	3.06	-0.31	2.45	3.22	4.22	3.48	4.49	8.25
11	12	813	1.02	64.32	1.27	-1.40	3.37	-0.44	2.73	3.38	4.29	3.64	4.77	9.21
12	13	813	1.05	62.84	1.37	-1.50	3.50	-0.18	2.98	3.51	4.55	3.82	4.94	10.07
13	14	813	1.17	62.00	1.47	-1.64	3.85	-0.19	3.37	3.61	4.69	3.95	5.18	10.79
14	15	813	1.27	63.82	1.64	-1.42	3.99	-0.08	3.33	3.71	4.84	4.10	5.37	11.74
15	16	813	1.36	64.21	1.76	-1.46	4.03	-0.01	3.54	3.79	4.96	4.23	5.70	12.46
16	17	813	1.45	65.41	1.77	-1.37	4.10	0.18	3.39	3.88	5.11	4.36	5.77	13.47
17	18	813	1.56	66.49	1.87	-1.33	4.38	-0.05	3.52	3.96	5.15	4.51	6.03	14.58
18	19	813	1.67	67.40	1.92	-1.27	4.50	0.01	3.53	4.03	5.27	4.67	6.25	15.48
19	20	813	1.66	66.55	2.03	-1.23	4.65	0.10	3.68	4.13	5.52	4.79	6.43	16.39
20	21	812	1.56	66.88	1.84	-1.20	4.63	-0.18	3.66	4.25	5.73	4.88	6.45	16.99
21	22	812	1.44	64.94	2.01	-1.64	4.63	-0.31	3.94	4.38	5.88	18.06	6.49	17.74
22	23	809	1.40	64.56	1.82	-1.77	4.74	-0.39	3.92	4.50	5.96	18.23	6.62	18.70
23	24	808	1.51	65.07	1.99	-1.79	4.94	-0.55	4.14	4.61	6.22	18.41	6.79	19.62
24	25	808	1.63	65.68	1.92	-1.76	5.23	-0.41	4.08	4.70	6.26	18.53	6.92	20.60

Table 17

Results Overview

The results show a **clear non-linear evolution of performance across holding periods**, revealing three distinct phases:

1. Short-Term Horizon (HP 1–2)

Very short holding periods exhibit **negative expectancy**, despite a win rate close to 50%.
This indicates that the edge is **not immediate** and cannot be monetized via ultra-short exits.

- Expectancy ≈ −0.05
- Median returns near zero
- Limited MFE realization

This behavior is consistent with a setup that requires **time to develop**, rather than capturing instantaneous mean reversion.

2. Edge Activation Phase (HP 3–7)

From HP 3 onward, expectancy turns positive and increases steadily, reaching a **local maximum around HP 7**.

Key observations:

- Expectancy rises from **0.17 to 0.81**
- Win rate increases to ~64%
- Median returns and MFE expand meaningfully
- TMFE aligns closely with this region

This phase suggests that the **core edge expresses itself within the first week**, consistent with earlier regime and pressure analyses.

3. Extended Horizon (HP 8–25)

Beyond HP 7, expectancy continues to improve gradually, peaking in the **HP 18–25 range**, though at a diminishing marginal rate.

Notable characteristics:

- Expectancy plateaus between **~1.4 and ~1.7**
- Win rate stabilizes in the **65–67% range**
- MAE increases with holding time, indicating higher exposure
- MFE continues to grow, but with slower efficiency gains

This suggests that while the edge **persists over longer horizons**, additional holding time primarily increases risk exposure rather than proportionally improving risk-adjusted efficiency.

Distributional Characteristics

Across all holding periods:

- Return distributions remain **negatively skewed**, consistent with a payoff profile driven by a limited number of larger favorable excursions.
- Median positive returns increase monotonically with holding time.

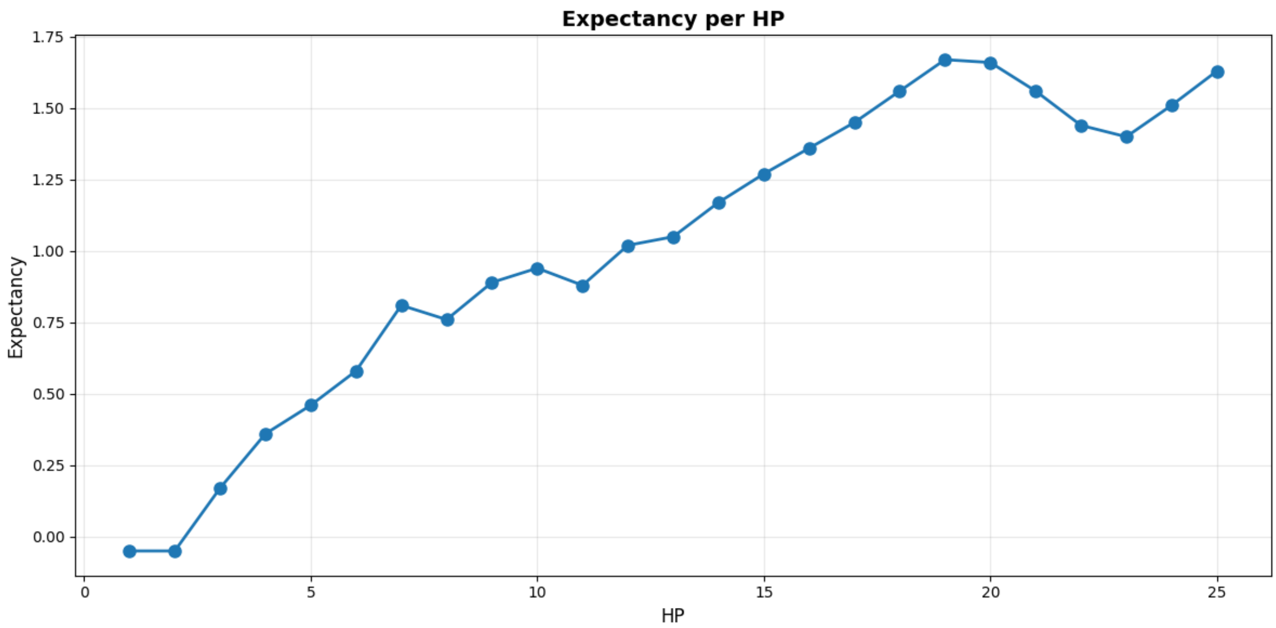
- MAE and MFE expand together, confirming that longer horizons amplify both opportunity and risk.

These properties reinforce the need for **adaptive exits** rather than static time-based rules.

Expectancy and Win Rate Dynamics

To visualize the temporal evolution of performance, the following figures are included:

Figure 1 — Expectancy vs Holding Period

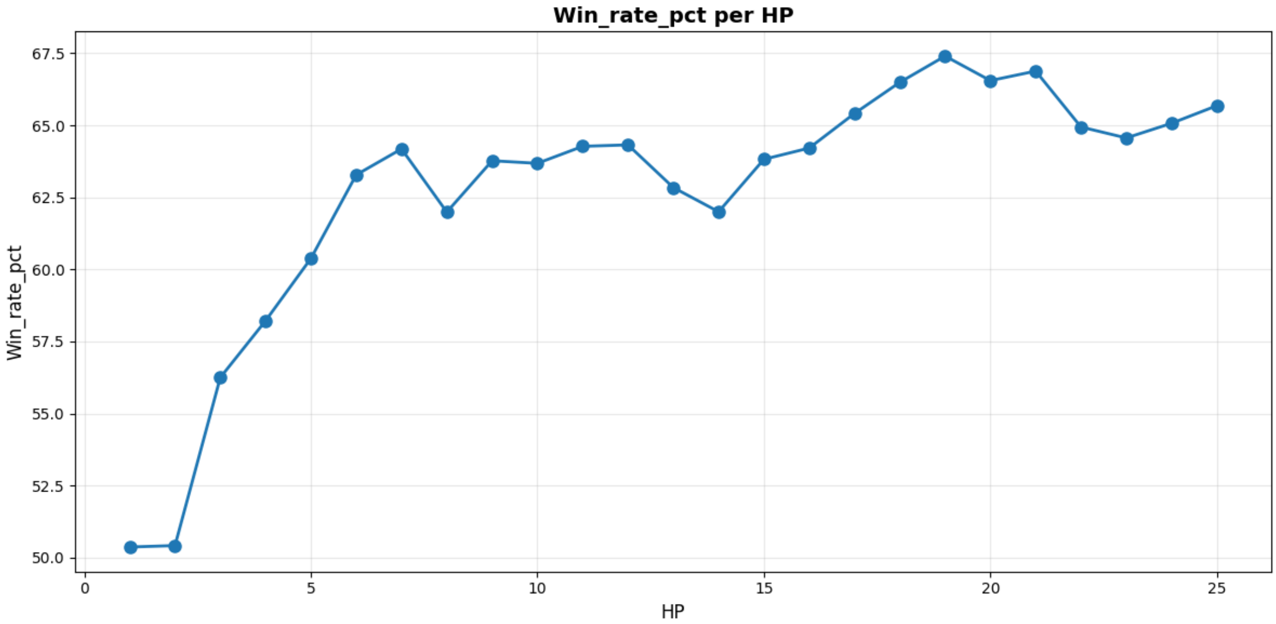


(line chart: holding period on x-axis, expectancy on y-axis)

This chart highlights:

- the delayed activation of the edge,
- the rapid improvement between HP 3 and HP 7,
- and the subsequent plateau at longer horizons.

Figure 2 — Win Rate vs Holding Period



(line chart: holding period on x-axis, win rate on y-axis)

The win rate follows a smoother trajectory, increasing steadily and stabilizing around 65–67%, confirming that **expectancy gains are driven by both higher win frequency and improved payoff structure**.

Interpretation

Pure time-based exits demonstrate that the setup possesses a **persistent and durable edge**, but one that is **inefficiently monetized** through fixed holding periods alone.

Key takeaways:

- The edge requires **time to mature**, invalidating ultra-short exits.
- Static holding periods expose the trade to increasing MAE beyond the core edge window.
- Performance improvements at long horizons suggest unrealized intraday potential rather than optimal holding.

For subsequent analyses, we focus primarily on holding periods between **3 and 7 days**, where the edge shows the most efficient expression, while also retaining **HP = 10** as an out-of-range control horizon to ensure that potentially relevant longer-term dynamics are not prematurely excluded.

These observations motivate the next step of the analysis:
decomposing the edge intraday to understand where favorable excursions actually occur.

6.2 Edge Structure— Hypothetical High-Based Exits

Objective

The purpose of this subsection is to assess whether the observed edge primarily **materializes intraday**, rather than being driven by close-to-close dynamics.

To do so, we replace the standard time-based close exit with a **hypothetical intraday exit at the session high**, while keeping the same holding periods identified in the previous section (HP = 3, 4, 5, 6, 7, and 10).

This analysis is intentionally *non-implementable* and serves a **diagnostic role**:
it allows us to characterize the **directionality, timing, and efficiency** of favorable excursions, thereby guiding the design of realistic exit mechanisms.

Methodology

- Holding periods tested: **HP = 3, 4, 5, 6, 7, 10**
- Exit rule: **Intraday exit at the highest price reached within the holding window**
- No stop, no trailing logic, no execution constraints
- Same signal dataset, no additional filtering

The comparison is performed against the corresponding close-based results from Section 6.1 – Table 17.

Here the **Table 18** summarize the High-Based Exits

	HP	n_trades	Expectancy	Win_rate_pct	Median_ret_pct	p25_ret_pct	p75_ret_pct	Skew_ret	Median_pos_ret_pct	MAE_mean_pct	MAE_p75_pct	MFE_mean_pct	MFE_p75_pct	TMFE_mean
0	3	813	1.07	77.82	0.86	0.15	1.74	3.13	1.21	1.68	1.94	1.44	1.83	0.83
1	4	813	1.21	74.06	0.92	-0.03	2.13	2.06	1.58	1.98	2.39	1.87	2.34	1.74
2	5	813	1.34	72.29	1.22	-0.11	2.48	1.16	1.89	2.22	2.80	2.17	2.74	2.66
3	6	813	1.42	72.93	1.27	-0.14	2.84	0.65	2.11	2.44	3.08	2.46	3.14	3.48
4	7	813	1.53	72.41	1.46	-0.19	3.19	0.58	2.27	2.62	3.22	2.70	3.54	4.39
5	10	813	1.68	71.79	1.65	-0.28	3.62	0.07	2.79	3.07	4.08	3.31	4.35	7.32

Table 18

Results Overview

The results show a **dramatic improvement across all performance dimensions**, confirming that the edge is predominantly **intraday in nature**.

Expectancy and Win Rate

- Expectancy increases from **~0.8 (close-based)** to **1.07–1.68**
- Win rate jumps to **72–78%**, peaking at HP = 3
- Performance improves monotonically with holding period

This indicates that **most profitable excursions occur before the daily close**, and are only partially captured by time-based exits.

Return Distribution

- Median returns increase substantially (0.86 → 1.65)
- Upper quartiles expand aggressively, while lower quartiles remain relatively stable
- Skewness becomes **strongly positive**, especially at shorter horizons

This shift in skewness confirms that the edge is driven by **frequent, asymmetric upside excursions**, rather than a small number of outliers.

MAE vs MFE Dynamics

A key insight emerges from excursion analysis:

- **MAE remains broadly unchanged** compared to close-based exits
- **MFE increases sharply**, even at short holding periods
- TMFE values confirm that favorable excursions occur **early within the trade lifecycle**

This asymmetry strongly suggests that the strategy's inefficiency lies **on the exit side**, not in signal quality or adverse risk exposure.

Interpretation

This hypothetical experiment provides a crucial structural insight:

The Oops + Intermediate Bearish Pressure setup generates its edge **intraday**, with favorable price movement occurring well before the end-of-day close.

Key implications:

- Time-based exits systematically **leave unrealized profits on the table**
- Longer holding periods increase MFE but also delay monetization
- The edge structure is highly compatible with **dynamic trailing exits**

These findings justify shifting the focus from *when to exit* to *how to exit*.

Transition to Exit Design

Having established that:

- The edge is real and persistent,
- It expresses itself primarily intraday,
- It exhibits strong favorable excursion asymmetry,

We now proceed to the **design and evaluation of realistic exit mechanisms**, aimed at capturing this intraday edge under implementable constraints.

6.3 Fixed Percentage Trailing Exit

Objective

Having established that the edge of the *Oops + Intermediate Bearish Pressure* setup is predominantly intraday, this section evaluates whether a **fixed-percentage trailing exit** can effectively monetize favorable excursions while preserving robustness and interpretability.

All trailing exits are applied to the **rolling highest high**, updated day by day after entry, in order to remain consistent with the intraday edge diagnostics conducted in Section 6.2.

Methodology

The trailing stop is defined as:

$$\text{Trailing Level} = \max(\text{High}) \times (1 - \text{Trailing \%})$$

Four trailing distances are tested: **5%, 7.5%, 10%, 20%**

Each configuration is evaluated under two execution assumptions:

- **Exit on daily close**
- **Intraday exit on daily low**

Holding periods tested: **HP = 3, 4, 5, 6, 7, 10**

Trailing activation: dynamic, updated daily

Exit priority:

- Trailing stop (if hit)
- Otherwise, time-based exit at the end of the holding period

No transaction costs or slippage applied

Same signal universe and filtering as previous sections

The comparison focuses on:

- Expectancy
- Win rate
- Distribution asymmetry
- % of MFE captured
- % of Lost Good
- Frequency of trailing stop activation

Additional Performance Diagnostics

In addition to standard performance statistics, two complementary metrics are introduced to better characterize **how efficiently the strategy monetizes favorable price movement** and **how often potential edge is structurally lost due to exit mechanics**.

- **Percentage of MFE Captured**

The *% of MFE captured* measures the fraction of the maximum favorable excursion (MFE) that is ultimately realized at exit, conditional on the trade being profitable.

Formally, for each profitable trade:

$$\%\text{MFE Captured} = \frac{\text{Realized Return}}{\text{MFE}}$$

This metric provides insight into **exit efficiency**, distinguishing between strategies that allow profits to fully develop and those that systematically truncate gains. Higher values indicate a closer alignment between realized returns and the trade's intrinsic upside potential.

- **Percentage of Lost Good Trades**

The *% of Lost Good* metric quantifies how often the strategy fails to convert high-potential trades into profitable outcomes.

A "good" trade is defined as one whose MFE lies in the **top 30% of the MFE distribution**, while a "lost good" trade is one that:

- Achieves a high MFE, but
- Ultimately closes with a negative return

Formally:

- An MFE threshold is set at the 70th percentile of the MFE distribution
- Trades with MFE above this threshold and negative realized returns are classified as *lost good trades*

This metric captures **edge leakage caused by exit rules**, highlighting cases where favorable price movement exists but is not effectively monetized. Lower values indicate a more robust alignment between signal quality and exit logic.

Results: Exit on Close vs Exit on Low

Exit on Close – Table 19

Trailing exits executed on the **daily close** exhibit **stable and monotonic improvements** as both holding period and trailing distance increase.

Key observations:

- Expectancy rises steadily with wider trailing distances, peaking around:

    - **HP = 7, trailing 20% → Expectancy ≈ 0.81**
    - **HP = 10, trailing 20% → Expectancy ≈ 0.93**
- Win rate increases consistently, reaching **64–65%**
- Median returns improve smoothly without destabilizing skewness
- %MFE captured remains high and stable (**~68–72%**)
- Trailing stops are triggered **infrequently**, especially for wider thresholds

This behavior indicates that:

- Most trades exit via **time expiration**
- The trailing mechanism primarily acts as a **profit-protection overlay**, rather than an aggressive monetization tool

Exit on Low (Intraday) – Table 20

Trailing exits executed **intraday on the low** produce materially different dynamics:

- Expectancy is **systematically lower** for narrow trailing distances
- Win rate declines, especially at shorter holding periods
- MAE increases significantly
- %LostGood rises sharply for tight trailing levels
- Trailing stops are triggered far more frequently

While wider trailing distances (10–20%) partially recover performance, intraday execution introduces:

- Higher noise sensitivity
- Premature exits during otherwise healthy trades
- Structural interference with the mean-reversion process

Comparative Interpretation

The contrast between the two execution modes is structurally informative.

Exit on close:

- Preserves the statistical integrity of the edge
- Allows intraday volatility to unfold without premature truncation
- Produces smoother expectancy scaling across holding periods

Exit on low:

- Overreacts to intraday noise
- Reduces edge efficiency, particularly at shorter horizons

- Converts favorable volatility into realized drawdowns

Table 19

	HP	trailing_pct_%	n_trades	Win_rate_%	Expectancy	mean_pos_ret	n_pos_trade	mean_neg_ret	n_neg_trade	Median_ret	Skew_ret	%MFE_captured_mean	%LostGood	MAE_mean	MFE_mean	TMFE_mean	n_trailing_stop	n_time_exit
0	3	5.0	813	54.72	0.02	1.31	443	-1.55	367	0.18	0.61	67.53	6.34	1.68	1.44	0.83	73	740
1	3	7.5	813	55.62	0.05	1.35	451	-1.60	359	0.20	-0.05	68.41	5.66	1.68	1.44	0.83	30	783
2	3	10.0	813	55.88	0.09	1.37	453	-1.54	357	0.21	-0.10	68.37	5.40	1.68	1.44	0.83	12	801
3	3	20.0	813	56.25	0.17	1.42	456	-1.43	354	0.22	0.63	68.49	5.03	1.68	1.44	0.83	1	812
4	4	5.0	813	55.08	0.10	1.69	445	-1.84	367	0.27	0.55	68.68	4.80	1.98	1.87	1.74	106	707
5	4	7.5	813	56.48	0.18	1.77	457	-1.89	355	0.32	0.11	69.77	3.92	1.98	1.87	1.74	37	776
6	4	10.0	813	57.13	0.21	1.81	462	-1.92	350	0.34	-0.26	69.75	3.28	1.98	1.87	1.74	20	793
7	4	20.0	813	58.22	0.36	1.87	471	-1.74	341	0.38	0.21	69.79	2.67	1.98	1.87	1.74	1	812
8	5	5.0	813	56.77	0.18	1.92	459	-2.08	354	0.34	0.48	67.88	5.25	2.22	2.17	2.66	132	681
9	5	7.5	813	58.75	0.26	2.03	476	-2.25	337	0.47	0.33	68.87	3.77	2.22	2.17	2.66	44	769
10	5	10.0	813	59.53	0.32	2.05	482	-2.21	331	0.52	0.13	68.68	3.00	2.22	2.17	2.66	23	790
11	5	20.0	813	60.24	0.44	2.06	488	-2.01	325	0.57	0.17	68.77	2.39	2.22	2.17	2.66	2	811
12	6	5.0	813	58.57	0.28	2.13	473	-2.32	340	0.45	0.49	68.04	6.18	2.44	2.46	3.48	161	652
13	6	7.5	813	61.00	0.34	2.21	494	-2.57	319	0.57	0.02	68.42	4.47	2.44	2.46	3.48	67	746
14	6	10.0	813	62.02	0.41	2.25	502	-2.60	311	0.59	-0.24	68.27	3.56	2.44	2.46	3.48	30	783
15	6	20.0	813	63.14	0.55	2.29	511	-2.42	302	0.64	-0.39	68.03	2.57	2.44	2.46	3.48	3	810
16	7	5.0	813	58.30	0.44	2.47	471	-2.36	342	0.60	0.42	71.38	5.08	2.62	2.70	4.39	182	631
17	7	7.5	813	61.31	0.54	2.57	497	-2.65	316	0.83	0.08	72.38	3.54	2.62	2.70	4.39	79	734
18	7	10.0	813	62.82	0.61	2.61	509	-2.74	304	0.89	-0.26	72.21	2.64	2.62	2.70	4.39	39	774
19	7	20.0	813	64.05	0.77	2.63	519	-2.53	294	0.94	-0.31	72.05	1.90	2.62	2.70	4.39	3	810
20	10	5.0	813	55.38	0.43	2.96	447	-2.64	365	0.43	0.65	69.37	6.51	3.07	3.31	7.32	261	552
21	10	7.5	813	60.69	0.63	3.00	492	-2.99	320	0.80	0.13	70.26	4.96	3.07	3.31	7.32	115	698
22	10	10.0	813	62.45	0.74	3.02	506	-3.02	306	0.93	-0.19	69.97	3.81	3.07	3.31	7.32	53	760
23	10	20.0	813	63.44	0.88	3.01	514	-2.77	298	1.01	-0.40	69.64	3.22	3.07	3.31	7.32	5	808

Table 19

Table 20

	HP	trailing_pct_%	n_trades	Win_rate_%	Expectancy	mean_pos_ret	n_pos_trade	mean_neg_ret	n_neg_trade	Median_ret	Skew_ret	%MFE_captured_mean	%LostGood	MAE_mean	MFE_mean	TMFE_mean	n_trailing_stop	n_time_exit
0	3	5.0	813	56.01	0.13	1.42	454	-1.51	356	0.21	0.51	68.54	5.16	1.68	1.44	0.83	28	785
1	3	7.5	813	56.25	0.15	1.42	456	-1.48	354	0.22	0.56	68.49	5.03	1.68	1.44	0.83	10	803
2	3	10.0	813	56.25	0.17	1.42	456	-1.43	354	0.22	0.64	68.49	5.03	1.68	1.44	0.83	3	810
3	3	20.0	813	56.25	0.17	1.42	456	-1.43	354	0.22	0.64	68.49	5.03	1.68	1.44	0.83	1	812
4	4	5.0	813	57.13	0.24	1.81	462	-1.84	350	0.34	0.08	69.62	3.40	1.98	1.87	1.74	49	764
5	4	7.5	813	57.88	0.32	1.86	468	-1.79	344	0.36	0.19	69.81	2.91	1.98	1.87	1.74	14	799
6	4	10.0	813	58.22	0.36	1.87	471	-1.75	341	0.38	0.19	69.79	2.67	1.98	1.87	1.74	5	808
7	4	20.0	813	58.22	0.36	1.87	471	-1.75	341	0.38	0.21	69.79	2.67	1.98	1.87	1.74	1	812
8	5	5.0	813	59.54	0.33	2.06	482	-2.18	331	0.51	0.35	68.50	3.12	2.22	2.17	2.66	75	738
9	5	7.5	813	59.78	0.37	2.03	484	-2.06	329	0.52	0.31	68.50	2.88	2.22	2.17	2.66	19	794
10	5	10.0	813	60.14	0.43	2.06	487	-2.01	326	0.54	0.31	68.63	2.51	2.22	2.17	2.66	10	803
11	5	20.0	813	60.38	0.46	2.06	489	-1.95	324	0.57	0.42	68.62	2.39	2.22	2.17	2.66	1	812
12	6	5.0	813	61.43	0.43	2.26	497	-2.46	316	0.58	0.06	68.73	4.18	2.44	2.46	3.48	99	714
13	6	7.5	813	62.16	0.45	2.23	503	-2.46	310	0.59	-0.26	68.37	3.45	2.44	2.46	3.48	36	777
14	6	10.0	813	62.77	0.53	2.27	508	-2.41	305	0.62	-0.20	68.36	3.08	2.44	2.46	3.48	16	797
15	6	20.0	813	63.28	0.59	2.28	512	-2.34	301	0.65	-0.08	68.04	2.57	2.44	2.46	3.48	1	812
16	7	5.0	813	61.87	0.64	2.61	501	-2.51	312	0.88	0.16	72.39	3.10	2.62	2.70	4.39	115	698
17	7	7.5	813	63.09	0.69	2.59	511	-2.54	302	0.91	-0.17	72.36	2.78	2.62	2.70	4.39	43	770
18	7	10.0	813	63.80	0.76	2.62	517	-2.48	296	0.94	-0.11	72.33	2.29	2.62	2.70	4.39	21	792
19	7	20.0	813	64.18	0.81	2.63	520	-2.43	293	0.94	-0.04	72.07	1.90	2.62	2.70	4.39	1	812
20	10	5.0	813	60.33	0.67	3.02	488	-2.85	324	0.80	0.18	69.63	4.66	3.07	3.31	7.32	172	641
21	10	7.5	813	62.69	0.74	2.96	508	-2.96	304	0.92	-0.29	69.65	3.97	3.07	3.31	7.32	70	743
22	10	10.0	813	63.30	0.84	2.99	513	-2.83	299	1.00	-0.25	69.57	3.35	3.07	3.31	7.32	34	779
23	10	20.0	813	63.68	0.93	3.00	516	-2.65	296	1.02	-0.20	69.58	3.11	3.07	3.31	7.32	2	811

Table 20

Key Takeaways

- Fixed-percentage trailing exits are **viable**, but only when:
  - Applied conservatively
  - Executed on **daily close**
- Tight trailing distances (< 7.5%) materially degrade performance
- Wider thresholds (10–20%) behave similarly to time exits, with limited incremental benefit

- Trailing exits alone are **insufficient to optimally monetize MFE**

These findings suggest that **price-based trailing must adapt to volatility**, rather than relying on static percentages.

Transition to Volatility-Based Trailing

The limitations observed in fixed-percentage trailing exits motivate the next step of the analysis.

In the following section, we replace static thresholds with **volatility-adjusted trailing mechanisms**, testing a **Chandelier Exit** based on:

- **Fast ATR (5)**
- **Slow ATR (14)**

6.4 Chandelier ATR Trailing Exit

Methodology

The Chandelier Exit is tested as a volatility-adjusted trailing stop, defined as:

$$\text{Chandelier Level} = \max(\text{Price}) - k \cdot \text{ATR}$$

where k represents the ATR multiplier.

Four values of $k$are evaluated (2.0, 2.5, 3.0, 3.5), across multiple holding periods (HP), using both **ATR (5)** and **ATR (14)**.
All results are compared against the baseline time-exit framework.

Results ATR (5) – Table 21

A clear and consistent improvement in performance emerges as the holding period increases from HP=3 to HP=7.

- **Expectancy** increases monotonically, peaking in the HP=7 bucket (≈ 0.81), while win rate rises above 64%.
- **Return distribution quality improves**: median returns and skewness become strongly positive, indicating fewer truncated winners.
- **% of MFE captured** stabilizes around 72–73% for HP=7, suggesting efficient profit extraction.
- **% of Lost Good trades** declines meaningfully compared to shorter holding periods, confirming reduced edge leakage.
- The number of **trailing-stop exits remains moderate** for ATR multipliers ≥ 2.5, avoiding excessive premature exits.

At HP=10, despite higher raw returns and MFE, performance deteriorates:

- Lost Good trades increase sharply
- Trailing-stop activations dominate
- Expectancy becomes less stable

This indicates **over-extension of the trade lifecycle**, where volatility-adjusted exits struggle to protect accumulated gains.

Results ATR (14) – Table 22

Chandelier with the ATR at 14 periods exhibits similar structural behavior but with **systematically smoother dynamics**.

- For HP=7 and HP=10, expectancy remains robust (≈ 0.77–0.85), with **less sensitivity to the ATR multiplier**.
- **% of MFE captured** is marginally lower than ATR (5) but more stable across multipliers.
- **Lost Good trades** are consistently higher at HP=10, reinforcing the idea that longer holding periods amplify exit inefficiencies regardless of ATR smoothing.
- Trailing-stop activations are more frequent at lower multipliers, confirming the slower-reacting nature of ATR (14).

Overall, ATR (14) favors **stability over aggressiveness**, but does not materially outperform ATR (5) in edge preservation.

Multiplier Sensitivity

Across both ATR lengths:

- Differences between multipliers **2.5, 3.0, and 3.5 are marginal**
- Multiplier 2.0 consistently triggers excessive stop-outs
- Performance plateaus beyond 2.5, indicating diminishing returns from wider trailing distance

This suggests that **multiplier selection is secondary** relative to holding period and ATR length.

Table 21

	HP	ATR_mult	Win_rate_%	Expectancy	mean_pos_ret	mean_neg_ret	Median_ret	Skew_ret	%MFE_captured_mean	%LostGood	MAE_mean	MFE_mean	TMFE_mean	n_trades	n_trailing_stop	n_time_exit	avg_sl_distance_%
0	3	2.0	56.25	0.16	1.42	-1.46	0.22	0.61	68.49	5.03	1.68	1.44	0.83	813	15	798	0.16
1	3	2.5	56.25	0.17	1.42	-1.43	0.22	0.64	68.49	5.03	1.68	1.44	0.83	813	3	810	0.17
2	3	3.0	56.25	0.17	1.42	-1.43	0.22	0.64	68.49	5.03	1.68	1.44	0.83	813	3	810	0.17
3	3	3.5	56.25	0.17	1.42	-1.43	0.22	0.64	68.49	5.03	1.68	1.44	0.83	813	2	811	0.17
4	4	2.0	58.09	0.36	1.87	-1.74	0.37	0.28	69.84	2.67	1.98	1.87	1.74	813	40	773	0.36
5	4	2.5	58.22	0.36	1.87	-1.75	0.38	0.22	69.79	2.67	1.98	1.87	1.74	813	7	806	0.36
6	4	3.0	58.22	0.36	1.87	-1.75	0.38	0.22	69.79	2.67	1.98	1.87	1.74	813	6	807	0.36
7	4	3.5	58.22	0.36	1.87	-1.75	0.38	0.22	69.79	2.67	1.98	1.87	1.74	813	3	810	0.36
8	5	2.0	60.14	0.44	2.06	-1.98	0.57	0.41	68.74	2.39	2.22	2.17	2.66	813	83	730	0.44
9	5	2.5	60.38	0.45	2.06	-1.98	0.57	0.36	68.62	2.39	2.22	2.17	2.66	813	18	795	0.45
10	5	3.0	60.38	0.45	2.06	-1.98	0.57	0.36	68.62	2.39	2.22	2.17	2.66	813	6	807	0.45
11	5	3.5	60.38	0.46	2.06	-1.96	0.57	0.42	68.62	2.39	2.22	2.17	2.66	813	3	810	0.46
12	6	2.0	62.40	0.57	2.30	-2.30	0.61	0.04	68.38	2.95	2.44	2.46	3.48	813	124	689	0.57
13	6	2.5	63.15	0.57	2.29	-2.38	0.65	-0.12	68.17	2.70	2.44	2.46	3.48	813	45	768	0.57
14	6	3.0	63.15	0.58	2.29	-2.36	0.65	-0.11	68.17	2.70	2.44	2.46	3.48	813	17	796	0.58
15	6	3.5	63.15	0.58	2.29	-2.33	0.65	-0.08	68.17	2.70	2.44	2.46	3.48	813	5	808	0.58
16	7	2.0	62.84	0.76	2.67	-2.44	0.93	0.09	73.02	2.26	2.62	2.70	4.39	813	153	660	0.76
17	7	2.5	64.06	0.81	2.63	-2.43	0.94	0.06	72.21	2.03	2.62	2.70	4.39	813	61	752	0.81
18	7	3.0	64.06	0.81	2.63	-2.43	0.94	-0.03	72.21	2.03	2.62	2.70	4.39	813	27	786	0.81
19	7	3.5	64.18	0.81	2.63	-2.43	0.94	-0.03	72.07	1.90	2.62	2.70	4.39	813	9	804	0.81
20	10	2.0	57.13	0.69	3.20	-2.65	0.72	0.10	71.25	3.98	3.07	3.31	7.32	813	286	527	0.69
21	10	2.5	62.91	0.83	3.03	-2.86	1.00	-0.31	69.98	3.25	3.07	3.31	7.32	813	139	674	0.83
22	10	3.0	63.43	0.88	3.01	-2.79	1.00	-0.29	69.82	3.36	3.07	3.31	7.32	813	67	746	0.88
23	10	3.5	63.43	0.90	3.01	-2.72	1.00	-0.20	69.82	3.36	3.07	3.31	7.32	813	31	782	0.90

Table 21

Table 22

	HP	ATR_mult	Win_rate_%	Expectancy	mean_pos_ret	mean_neg_ret	Median_ret	Skew_ret	%MFE_captured_mean	%LostGood	MAE_mean	MFE_mean	TMFE_mean	n_trades	n_trailing_stop	n_time_exit	avg_sl_distance_%
0	3	2.0	56.25	0.15	1.42	-1.48	0.22	0.57	68.50	5.03	1.68	1.44	0.83	813	35	778	0.15
1	3	2.5	56.25	0.16	1.42	-1.46	0.22	0.59	68.49	5.03	1.68	1.44	0.83	813	15	798	0.16
2	3	3.0	56.25	0.16	1.42	-1.46	0.22	0.60	68.49	5.03	1.68	1.44	0.83	813	8	805	0.16
3	3	3.5	56.25	0.17	1.42	-1.44	0.22	0.62	68.49	5.03	1.68	1.44	0.83	813	5	808	0.17
4	4	2.0	58.09	0.34	1.87	-1.78	0.37	0.35	69.85	2.67	1.98	1.87	1.74	813	84	729	0.34
5	4	2.5	58.09	0.35	1.87	-1.76	0.37	0.26	69.85	2.67	1.98	1.87	1.74	813	28	785	0.35
6	4	3.0	58.22	0.36	1.87	-1.75	0.38	0.23	69.79	2.67	1.98	1.87	1.74	813	16	797	0.36
7	4	3.5	58.22	0.36	1.87	-1.75	0.38	0.21	69.79	2.67	1.98	1.87	1.74	813	9	804	0.36
8	5	2.0	59.15	0.38	2.08	-2.08	0.50	0.32	68.93	2.75	2.22	2.17	2.66	813	141	672	0.38
9	5	2.5	60.12	0.44	2.06	-1.99	0.56	0.45	68.75	2.52	2.22	2.17	2.66	813	54	759	0.44
10	5	3.0	60.25	0.45	2.06	-1.96	0.57	0.48	68.72	2.52	2.22	2.17	2.66	813	21	792	0.45
11	5	3.5	60.38	0.45	2.06	-1.97	0.57	0.39	68.62	2.39	2.22	2.17	2.66	813	11	802	0.45
12	6	2.0	60.68	0.47	2.31	-2.37	0.57	0.05	69.03	3.82	2.44	2.46	3.48	813	184	629	0.47
13	6	2.5	62.51	0.55	2.29	-2.34	0.62	0.03	68.43	3.21	2.44	2.46	3.48	813	82	731	0.55
14	6	3.0	62.77	0.57	2.29	-2.33	0.63	-0.07	68.39	3.08	2.44	2.46	3.48	813	43	770	0.57
15	6	3.5	63.15	0.57	2.29	-2.36	0.65	-0.11	68.17	2.70	2.44	2.46	3.48	813	22	791	0.57
16	7	2.0	60.53	0.67	2.70	-2.42	0.85	0.35	73.55	3.01	2.62	2.70	4.39	813	219	594	0.67
17	7	2.5	62.92	0.77	2.65	-2.40	0.93	0.20	72.56	2.41	2.62	2.70	4.39	813	108	705	0.77
18	7	3.0	63.67	0.80	2.64	-2.39	0.94	0.09	72.42	2.28	2.62	2.70	4.39	813	52	761	0.80
19	7	3.5	64.06	0.80	2.63	-2.45	0.94	-0.04	72.21	2.03	2.62	2.70	4.39	813	31	782	0.80
20	10	2.0	54.41	0.57	3.23	-2.60	0.42	0.16	70.44	4.46	3.07	3.31	7.32	813	347	466	0.57
21	10	2.5	60.16	0.74	3.08	-2.77	0.86	-0.17	70.08	3.76	3.07	3.31	7.32	813	201	612	0.74
22	10	3.0	62.54	0.85	3.02	-2.74	0.97	-0.10	69.90	3.74	3.07	3.31	7.32	813	113	700	0.85
23	10	3.5	63.18	0.83	3.02	-2.88	1.00	-0.25	69.86	3.36	3.07	3.31	7.32	813	71	742	0.83

Table 22

Key Takeaways

- The **optimal regime** for the Chandelier Exit lies at **HP=7**, with ATR multipliers between **2.5 and 3.0**.
- ATR (5) slightly outperforms ATR (14) in terms of:
  - Expectancy
  - % of MFE captured
  - Edge monetization efficiency
- Longer holding periods (HP=10) introduce structural edge decay, as evidenced by rising Lost Good trades and excessive trailing-stop dominance.

In conclusion, the Chandelier Exit acts as a **valid profit-protection mechanism**, but its effectiveness is **highly conditional on trade duration**, reinforcing the central role of time as a structural constraint in this strategy.

Comparison Fixed Trailing Exit Vs Chandelier Exit

When compared to a fixed trailing stop based on closing prices, the **ATR(5) Chandelier Exit demonstrates superior robustness**, showing a more stable expectancy profile, higher consistency in % of MFE captured, and a lower incidence of Lost Good trades across the optimal holding period. This confirms that a volatility-adjusted trailing mechanism is better suited to adapt to changing market regimes than a fixed-price trailing rule.

Based on these results, the **ATR (5) Chandelier Exit is retained as the reference trailing-stop framework**, and the analysis now moves to an alternative exit logic focused on **Maximum Favorable Excursion monetization**.

6.5 MFE-Based Exit

This section evaluates an exit strategy based on **predefined MFE (Maximum Favorable Excursion) targets**, with the objective of monetizing price expansions more efficiently than time-based or trailing exits.

Methodology

For each selected holding period, the historical MFE distribution is first estimated on the original signal dataset.
From this distribution, four percentile-based targets are defined:

- **P75 (75th percentile)**
- **P82.5 (82.5th percentile)**
- **P90 (90th percentile)**
- **P95 (95th percentile)**

These percentile values represent progressively more ambitious profit objectives and are used as **fixed take-profit levels** during the test phase.

To avoid look-ahead bias, MFE targets are computed exclusively from past data and then applied forward as static exit thresholds.
If the price reaches the MFE target before the maximum holding period, the trade is exited at the target; otherwise, a **time-based exit** is applied at the end of the holding period.

Results Overview

Across all holding periods, as shown in **Table 23**, the MFE-based exit shows a **clear trade-off between profitability and execution frequency**:

- Higher MFE percentiles (P90–P95) systematically **increase expectancy and median returns**
- However, this comes at the cost of:
    - Lower win rates
    - Higher percentage of *Lost Good* trades
    - Longer average time to exit (TMFE)

This behavior is consistent with the increasing distance of the take-profit target from the entry price.

Table 23

	HP	MFE_target	Win_rate_%	Expectancy	mean_pos_ret	mean_neg_ret	Median_ret	Skew_ret	%MFE_captured_mean	%LostGood	MAE_mean	MFE_mean	TMFE_mean	n_trades	n_take_profit	n_time_exit	avg_tp_distance_%
0	3	P75	60.28	0.15	1.18	-1.41	0.38	-1.13	65.06	1.00	1.68	1.44	0.59	813	204	609	1.83
1	3	P82.5	58.37	0.13	1.23	-1.41	0.33	-1.08	65.75	2.91	1.68	1.44	0.59	813	143	670	2.18
2	3	P90	57.27	0.13	1.29	-1.43	0.27	-1.01	66.63	4.01	1.68	1.44	0.59	813	83	730	2.88
3	3	P95	57.01	0.15	1.33	-1.43	0.25	-0.77	67.13	4.27	1.68	1.44	0.59	813	43	770	3.66
4	4	P75	60.32	0.25	1.54	-1.72	0.51	-1.07	65.69	0.57	1.98	1.87	1.17	813	204	609	2.34
5	4	P82.5	59.72	0.27	1.64	-1.76	0.45	-1.07	67.13	1.17	1.98	1.87	1.17	813	144	669	2.88
6	4	P90	59.11	0.31	1.73	-1.76	0.41	-0.82	68.43	1.78	1.98	1.87	1.17	813	83	730	3.62
7	4	P95	58.99	0.36	1.83	-1.76	0.40	-0.43	69.41	1.91	1.98	1.87	1.17	813	43	770	5.15
8	5	P75	62.40	0.34	1.76	-2.01	0.71	-1.10	65.10	0.37	2.22	2.17	1.81	813	204	609	2.75
9	5	P82.5	61.63	0.37	1.85	-1.99	0.64	-0.89	65.91	1.14	2.22	2.17	1.81	813	144	669	3.30
10	5	P90	61.27	0.42	1.95	-1.98	0.62	-0.62	67.03	1.50	2.22	2.17	1.81	813	83	730	4.29
11	5	P95	61.27	0.50	2.08	-1.98	0.62	-0.25	68.45	1.50	2.22	2.17	1.81	813	43	770	5.97
12	6	P75	64.77	0.44	1.97	-2.38	0.78	-1.24	64.58	1.08	2.44	2.46	2.41	813	204	609	3.14
13	6	P82.5	64.39	0.50	2.10	-2.37	0.76	-1.03	66.31	1.46	2.44	2.46	2.41	813	144	669	3.76
14	6	P90	64.16	0.58	2.22	-2.36	0.71	-0.75	67.67	1.69	2.44	2.46	2.41	813	83	730	4.91
15	6	P95	63.78	0.60	2.29	-2.36	0.67	-0.45	68.01	2.06	2.44	2.46	2.41	813	43	770	6.64
16	7	P75	65.83	0.70	2.29	-2.36	1.12	-1.19	68.28	0.26	2.62	2.70	3.03	813	204	609	3.54
17	7	P82.5	65.70	0.77	2.41	-2.35	1.07	-0.99	69.58	0.38	2.62	2.70	3.03	813	144	669	4.19
18	7	P90	65.21	0.82	2.54	-2.38	1.05	-0.76	71.11	0.88	2.62	2.70	3.03	813	83	730	5.38
19	7	P95	64.69	0.82	2.61	-2.43	0.99	-0.55	71.76	1.39	2.62	2.70	3.03	813	43	770	7.04
20	10	P75	66.31	0.92	2.79	-2.73	1.38	-1.12	68.16	0.48	3.07	3.31	5.04	813	204	609	4.35
21	10	P82.5	65.69	0.96	2.89	-2.70	1.29	-0.92	68.61	1.09	3.07	3.31	5.04	813	144	669	5.12
22	10	P90	64.68	1.01	3.05	-2.67	1.12	-0.58	70.28	2.11	3.07	3.31	5.04	813	83	730	6.67
23	10	P95	64.19	0.99	3.06	-2.66	1.08	-0.42	69.83	2.60	3.07	3.31	5.04	813	43	770	8.17

Table 23[2]

Key Observations

1. Expectancy improves with higher MFE targets
For all holding periods, expectancy increases monotonically from P75 to P95, indicating that deeper monetization of favorable excursions outweighs the reduction in hit rate.

2. Win rate decreases smoothly, not abruptly
The decline in win rate remains gradual even at higher percentiles, suggesting that the signal retains directional validity beyond early price expansion.

3. % of MFE captured increases consistently
Higher targets naturally improve the percentage of MFE captured, confirming that exits are aligned with realized price potential rather than premature liquidation.

[2] For holding periods up to 10 days, the number of trades reaching the MFE target remains constant across percentile thresholds.
This behavior indicates that favorable excursions are concentrated in a specific subset of trades that expand early and decisively.
When the holding period is extended (e.g., HP = 25), this constraint relaxes and the number of target hits increases, confirming that the phenomenon is driven by time-window truncation rather than methodological bias.

4. Lost Good trades increase but remain controlled
The % of Lost Good trades rises with higher percentiles, yet remains relatively contained, especially for holding periods between **5 and 7 days**, indicating a favorable balance between patience and protection.

5. Holding period dependency
Intermediate holding periods (5–7 days) consistently display:

- Higher expectancy
- Better MFE capture efficiency
- Lower Lost Good percentages
  compared to very short or very long horizons.

Interpretation

The MFE-based exit framework confirms that the Oops setup, conditioned on **intermediate bearish pressure**, is capable of sustaining trades beyond early mean-reversion without immediate edge decay.

Compared to trailing exits, MFE targets offer:

- Greater **control over profit objectives**
- Clear **risk–reward asymmetry**
- Improved interpretability of exit behavior

However, higher percentiles introduce execution risk through delayed exits and increased Lost Good exposure, emphasizing the importance of **target calibration rather than optimization**.

Preliminary Conclusion

Based on the observed results, **MFE targets in the P82.5–P90 range**, combined with holding periods between **5 and 7 days**, appear to offer the most balanced compromise between expectancy, robustness, and execution efficiency.

In the next section, the MFE-based exit is combined with a Chandelier trailing stop (5-period ATR) to evaluate whether a hybrid structure can improve robustness while preserving favorable excursion capture.

6.6 Hybrid Exit: MFE Target + Chandelier Trailing Exit

Methodology

This section evaluates a **hybrid exit structure** combining a fixed **MFE-based take-profit** with a **Chandelier trailing exit**, using a 5-period ATR.

The objective is to test whether combining:

- a **structural profit objective** (MFE percentile),
- with a **volatility-adjusted protective mechanism** (Chandelier),

can improve robustness relative to standalone exits.

The hybrid logic operates as follows:

- A trade is exited if the predefined MFE target (87.5th percentile) is reached.
- Otherwise, the position remains open and is managed via a Chandelier trailing exit.
- If neither condition is met, a time-based exit is applied at the end of the holding period.

The MFE target percentile (P87.5) is selected as an intermediate compromise between early monetization and excessive patience, while Chandelier multipliers of **2.5, 3.0, and 3.5** are tested to assess sensitivity to trailing aggressiveness.

Results Overview

Across all holding periods, as shown in **Table 24**, the hybrid exit exhibits a **stable and monotonic performance profile**, with expectancy increasing consistently as the holding period extends from short to intermediate horizons.

Key observations include:

- A gradual increase in expectancy and median returns
- Controlled drawdowns, as reflected by MAE metrics
- A smooth transition between MFE-triggered exits and trailing-managed trades

Notably, the number of trades reaching the MFE target remains constant across configurations, indicating that the hybrid structure does not artificially increase profit-taking frequency, but rather redistributes exit responsibility between MFE and trailing logic.

Table 24

	HP	ATR_mult	Win_rate_%	Expectancy	mean_pos_ret	mean_neg_ret	Median_ret	Skew_ret	%MFE_captured_mean	%LostGood	MAE_mean	MFE_mean	TMFE_mean	n_trades	n_take_profit	n_trailing_stop	n_time_exit	avg_sl_distance_%	avg_tp_distance_%
0	3	2.5	57.64	0.13	1.27	-1.42	0.29	-1.04	66.40	3.64	1.68	1.44	0.83	813	104	0	709	0.13	2.53
1	3	3.0	57.64	0.13	1.27	-1.42	0.29	-1.04	66.40	3.64	1.68	1.44	0.83	813	104	0	709	0.13	2.53
2	3	3.5	57.64	0.13	1.27	-1.42	0.29	-1.04	66.40	3.64	1.68	1.44	0.83	813	104	0	709	0.13	2.53
3	4	2.5	59.24	0.29	1.70	-1.76	0.41	-0.90	68.03	1.66	1.98	1.87	1.74	813	104	4	705	0.31	3.33
4	4	3.0	59.24	0.29	1.70	-1.76	0.41	-0.90	68.03	1.66	1.98	1.87	1.74	813	104	3	706	0.31	3.33
5	4	3.5	59.24	0.29	1.70	-1.76	0.41	-0.90	68.03	1.66	1.98	1.87	1.74	813	104	0	709	0.31	3.33
6	5	2.5	61.38	0.40	1.93	-2.01	0.63	-0.74	66.94	1.39	2.22	2.17	2.66	813	104	15	694	0.42	3.94
7	5	3.0	61.38	0.40	1.93	-2.01	0.63	-0.74	66.94	1.39	2.22	2.17	2.66	813	104	3	706	0.42	3.94
8	5	3.5	61.38	0.41	1.93	-1.98	0.63	-0.69	66.94	1.39	2.22	2.17	2.66	813	104	0	709	0.43	3.94
9	6	2.5	64.39	0.54	2.17	-2.42	0.73	-0.90	67.13	1.46	2.44	2.46	3.48	813	104	41	668	0.52	4.38
10	6	3.0	64.39	0.55	2.17	-2.39	0.73	-0.90	67.13	1.46	2.44	2.46	3.48	813	104	13	696	0.53	4.38
11	6	3.5	64.39	0.55	2.17	-2.37	0.73	-0.87	67.13	1.46	2.44	2.46	3.48	813	104	2	707	0.54	4.38
12	7	2.5	65.58	0.82	2.49	-2.36	1.06	-0.70	70.59	0.51	2.62	2.70	4.39	813	104	55	654	0.83	4.87
13	7	3.0	65.58	0.82	2.49	-2.35	1.06	-0.81	70.59	0.51	2.62	2.70	4.39	813	104	22	687	0.83	4.87
14	7	3.5	65.58	0.82	2.49	-2.34	1.06	-0.81	70.59	0.51	2.62	2.70	4.39	813	104	6	703	0.84	4.87
15	10	2.5	64.80	0.94	3.05	-2.89	1.19	-0.79	70.27	1.35	3.07	3.31	7.32	813	104	129	580	0.95	6.17
16	10	3.0	65.32	0.98	3.03	-2.85	1.20	-0.80	70.12	1.46	3.07	3.31	7.32	813	104	61	648	0.99	6.17
17	10	3.5	65.32	1.00	3.03	-2.78	1.20	-0.72	70.12	1.46	3.07	3.31	7.32	813	104	26	683	1.01	6.17

Table 24

Key Observations

1. Expectancy dominance at intermediate holding periods
Holding periods between **6 and 7 days** exhibit the highest expectancy values, confirming consistency with prior exit tests.

2. Chandelier multiplier sensitivity is limited
Variations between ATR multipliers (2.5–3.5) produce marginal differences in performance, suggesting that exit behavior is primarily driven by edge structure rather than parameter fine-tuning.

3. Improved loss containment relative to pure MFE exits
Compared to standalone MFE-based exits, the hybrid structure reduces exposure to adverse reversals by allowing the Chandelier to intervene when favorable expansion fails to materialize.

4. Favorable balance between MFE capture and Lost Good trades
The hybrid exit maintains high MFE capture percentages while keeping Lost Good trades at moderate levels, particularly at HP = 6–7.

Interpretation

The hybrid exit confirms that the edge expresses itself through **early, decisive favorable excursions**, while still benefiting from a volatility-aware trailing mechanism when immediate expansion does not occur.

Rather than competing, the MFE and Chandelier components operate in complementary regimes:

- **MFE exits dominate strong expansions**
- **Chandelier exits manage slower-developing trades**

This division of responsibility enhances robustness without introducing structural complexity or excessive parameter dependency.

Conclusion

The hybrid exit combining **MFE (P87.5)** with a **Chandelier trailing stop (5-period ATR)** represents the most structurally coherent exit tested in this study.

It preserves the original signal logic, improves downside control, and adapts naturally to the heterogeneous expression of the edge across trades.

This structure is therefore selected as the **reference exit framework** for subsequent robustness checks and potential portfolio-level extensions.

6.7 Original Larry Williams Exit

Exit Definition

Larry Williams proposed a discretionary bailout exit known as the **“First Profitable Open”**.

For a **short position**, the logic is defined as follows:

- The trade remains open until, on a subsequent day, the market **opens below the original entry price**
- When this condition is met, the position is immediately closed at the open

The opposite logic applies to **long positions**, where the trade is closed if the market opens above the entry level.

The conceptual rationale behind this exit is rooted in Williams' interpretation of market microstructure:

- The **open** is assumed to reflect public participation
- The **close** is assumed to reflect professional positioning

If an edge allows the trade to be profitable at the open—when public order flow dominates—Williams argues that the probabilistic advantage has already been realized and should be monetized without delay.

This exit is therefore **non-optimized, price-relative, and event-driven**, relying entirely on market behavior rather than predefined profit targets or volatility thresholds.

Results Overview

As shown in **Table 25**, the First Profitable Open exit exhibits a **very high win rate**, increasing monotonically with the holding period:

- From ~70% at HP = 2
- To nearly **90% at HP = 10**

However, this elevated win rate comes at the cost of:

- **Low average positive returns**
- **Rapid truncation of favorable excursions**
- Increasingly large average losses as holding periods extend

Expectancy improves gradually with longer holding periods, but remains structurally constrained relative to more advanced exit mechanisms tested earlier.

Table 25

	HP	Win_rate_%	Expectancy	mean_pos_ret	n_pos_trade	mean_neg_ret	n_neg_trade	Median_ret	Skew_ret	%MFE_captured_mean	%LostGood	MAE_mean	MFE_mean	TMFE_mean	n_trades	n_larry_exit	n_time_exit	Mean_HP_of_exit
0	1	50.42	-0.05	0.77	410	-0.89	401	0.02	-0.66	65.01	6.80	1.23	0.84	0.00	813	0	813	0.00
1	2	70.60	0.19	0.98	573	-1.71	236	0.40	-0.96	54.18	1.21	1.68	1.44	0.83	813	476	337	1.00
2	3	76.26	0.27	1.02	619	-2.16	189	0.49	-1.51	52.73	0.85	1.85	1.58	1.19	813	589	224	1.41
3	4	81.16	0.33	1.01	659	-2.70	149	0.54	-1.49	52.55	0.63	1.95	1.65	1.47	813	638	175	1.69
4	5	83.12	0.35	1.02	675	-3.04	133	0.56	-1.67	52.36	0.63	2.04	1.70	1.61	813	665	148	1.90
5	6	84.56	0.34	1.01	687	-3.48	121	0.58	-1.90	52.23	0.63	2.12	1.72	1.70	813	683	130	2.08
6	7	85.82	0.35	1.01	697	-3.74	111	0.59	-2.43	52.12	0.63	2.17	1.73	1.84	813	697	116	2.24
7	10	89.45	0.53	0.99	726	-3.40	82	0.64	-1.82	51.85	0.52	2.28	1.77	2.33	813	724	89	2.64

Table 25

Key Observations

1. Extreme win rate vs weak payoff asymmetry
The exit strongly favors frequent small gains, as reflected in:

- Mean positive returns clustered around ~1%
- Median returns increasing slowly despite rising win rates

Losses, when they occur, are comparatively large, producing:

- Strongly negative skewness
- Increasing mean negative returns as HP increases

2. Systematic suppression of favorable excursions
The % of MFE captured stabilizes around **~52–54%**, indicating that the exit systematically truncates profitable trades before meaningful expansion can occur.

This behavior is consistent with the philosophical intent of the rule, but structurally incompatible with an edge that has already demonstrated:

- Strong intraday favorable excursions
- Increasing expectancy with extended holding horizons

3. Early exit dominance

The mean holding period at exit remains very low:

- ~1.4–2.6 days even when the maximum HP is extended to 10

This confirms that the exit functions primarily as an **early bailout**, rather than a trade management mechanism.

4. HP = 1 interpretation

At HP = 1, no Larry exits are triggered, as the first profitable open cannot occur on the entry day by definition.
All trades are therefore exited via the time-based rule, explaining the absence of Larry exits in this configuration.

Interpretation

The Original Larry Williams exit is **conceptually elegant and behaviorally intuitive**, but structurally misaligned with the observed characteristics of the edge under study.

While it excels at:

- Producing high win rates
- Minimizing time in the market
- Reducing psychological exposure

it fails to:

- Exploit favorable price excursions

- Preserve positive skew
- Monetize the edge’s demonstrated time persistence

As such, it functions more as a **defensive bailout mechanism** than as a scalable monetization framework.

Conclusion

The First Profitable Open exit provides a useful conceptual benchmark, highlighting the trade-off between win rate maximization and expectancy efficiency.

Within the context of the Oops setup under Intermediate Bearish Pressure, the exit is inferior to:

- Trailing-based exits
- MFE-based exits
- Hybrid MFE + Chandelier structures

However, its inclusion remains valuable as a historical and philosophical reference, reinforcing the importance of aligning exit logic with the structural expression of the edge.

7.Stop-Loss Analysis

7.1 Introduction and Framework

In this section, we introduce explicit stop-loss rules to the previously tested **MFE + Chandelier Exit** framework, with the objective of improving the overall risk-adjusted performance, and in particular the **expectancy** of the strategy.

All tests in this section are conducted using the following fixed exit parameters, identified as robust in the previous analysis:

- **Chandelier multiplier:** 2.5
- **MFE target:** 87.5%

These parameters define the baseline exit logic and are kept constant throughout the stop-loss experiments.

It is important to clarify that **trailing stop-losses are intentionally excluded** from this analysis. Testing trailing stops would effectively replicate the logic of alternative trailing exits already evaluated, merely with different parameter values. As such, they would not provide additional structural insight, but rather constitute a parameter re-optimization of the same exit family.

For this reason, we focus exclusively on two stop-loss categories that introduce *qualitatively different behavior*:

1. **MAE-based stop-losses**, defined as a percentile of the historical Maximum Adverse Excursion distribution.

2. **Structural stops placed below (or above, for shorts) the entry candle extreme**, aimed at invalidating the setup when the entry bar structure fails.

The present subsection reports results for **MAE-based stop-losses** only.

7.2 MAE-Based Stop-Loss Definition

The MAE-based stop-loss is defined as a fixed percentile of the historical MAE distribution, calculated across all trades.

From this distribution, four percentile-based targets are defined:

- **P75 (75th percentile)**
- **P85 (85th percentile)**
- **P95 (95th percentile)**

For example, a 75th percentile MAE stop implies that a trade is exited if its adverse excursion exceeds the value that historically contained 75% of all observed MAEs.

This approach has two advantages:

- The stop distance adapts to the empirical behavior of the setup.
- The stop is defined independently from price structure or volatility proxies.

Each test is performed across multiple **holding periods (HP)** and **MAE percentiles**, while keeping the exit logic unchanged.

Empirical Results

Table 26, shown below, summarizes the performance metrics for the MAE-based stop-loss tests across different configurations.

	HP	MAE_stop_percentile	Win_rate_%	Expectancy	mean_pos_ret	mean_neg_ret	Median_ret	Skew_ret	%MFE_captured_mean	%LostGood	MAE_mean	MFE_mean	TMFE_mean	n_trades	n_take_profit	n_time_exit	avg_tp_distance_%	Mean_HP_exit
0	3	0.75	52.98	0.04	1.23	-1.30	0.13	0.12	67.39	5.09	1.54	1.29	0.50	813	88	535	2.53	0.83
1	3	0.85	55.68	0.05	1.25	-1.48	0.20	-0.27	67.49	3.75	1.61	1.32	0.54	813	97	605	2.53	0.90
2	3	0.95	57.40	0.05	1.26	-1.59	0.27	-0.96	67.36	3.64	1.65	1.36	0.56	813	103	673	2.53	0.95
3	4	0.75	53.38	0.13	1.66	-1.64	0.19	0.12	70.33	2.65	1.76	1.60	0.99	813	84	535	3.33	1.65
4	4	0.85	55.98	0.15	1.68	-1.82	0.29	-0.17	70.34	2.41	1.85	1.65	1.04	813	94	602	3.33	1.77
5	4	0.95	58.01	0.18	1.70	-1.91	0.37	-0.74	70.30	2.03	1.91	1.70	1.09	813	100	671	3.33	1.87
6	5	0.75	54.52	0.13	1.89	-1.98	0.31	0.13	69.27	3.15	1.97	1.86	1.53	813	83	529	3.94	2.46
7	5	0.85	57.90	0.18	1.89	-2.17	0.45	-0.21	69.02	2.65	2.07	1.92	1.61	813	90	599	3.94	2.63
8	5	0.95	60.27	0.24	1.92	-2.28	0.56	-0.72	69.04	2.02	2.14	1.99	1.70	813	99	663	3.94	2.78
9	6	0.75	57.41	0.26	2.15	-2.28	0.46	0.06	70.28	2.72	2.11	2.08	2.05	813	86	521	4.38	3.26
10	6	0.85	60.26	0.28	2.12	-2.51	0.55	-0.23	69.86	2.72	2.23	2.14	2.14	813	88	590	4.38	3.46
11	6	0.95	63.03	0.33	2.15	-2.77	0.65	-0.91	69.48	1.84	2.37	2.23	2.23	813	97	643	4.38	3.69
12	7	0.75	58.96	0.46	2.42	-2.35	0.69	0.01	72.48	1.98	2.22	2.33	2.64	813	83	518	4.87	4.06
13	7	0.85	61.43	0.49	2.43	-2.60	0.85	-0.31	72.47	1.27	2.35	2.40	2.75	813	86	583	4.87	4.33
14	7	0.95	63.85	0.56	2.48	-2.83	1.00	-0.94	72.20	0.63	2.47	2.50	2.83	813	98	632	4.87	4.57
15	10	0.75	57.19	0.49	3.03	-2.90	0.69	0.07	72.83	2.86	2.53	2.86	4.34	813	82	486	6.17	6.41
16	10	0.85	61.14	0.62	3.02	-3.14	0.97	-0.21	72.40	1.74	2.67	2.98	4.57	813	91	529	6.17	6.75
17	10	0.95	63.78	0.78	3.05	-3.18	1.10	-0.66	72.53	1.24	2.77	3.07	4.76	813	102	563	6.17	7.02

Table 26

Several consistent patterns emerge from the results:

- Increasing the **MAE percentile (i.e., wider stops)** systematically improves:

    - Win rate
    - Mean positive return
    - Median return
- However, wider stops also lead to:
    - Larger mean negative returns
    - Higher MAE values
    - Longer average holding periods

As a consequence, improvements in hit rate and payoff asymmetry are largely offset by the increase in loss magnitude.

Interpretation and Key Insight

Despite the introduction of increasingly wide MAE-based stop-losses, **expectancy does not materially improve relative to the baseline setup without stops**.

Even configurations with very loose stops — which allow trades sufficient room to develop — fail to generate a statistically meaningful enhancement in average trade profitability. In many cases, expectancy remains comparable or only marginally higher, while risk metrics deteriorate.

This suggests that, for the current setup:

- Losses are not primarily driven by extreme adverse excursions.
- Premature stop-outs do not appear to be the main source of negative expectancy.
- The edge (or lack thereof) is predominantly embedded in **entry quality and exit logic**, rather than in loss truncation.

In other words, **adding MAE-based stop-losses reshapes the distribution of returns but does not create additional edge**.

Transition to Next Section

Given the limited effectiveness of MAE-based stop-losses, the next section will focus on **structural stops placed relative to the entry candle**, specifically below the entry bar low.

This alternative stop definition aims to invalidate the trade only when the **price action immediately contradicts the entry premise**, rather than reacting to generic adverse excursion thresholds.

7.3 ATR-Based Stop-Loss Definition

In this subsection, we test a **volatility-adjusted stop-loss** defined using the Average True Range (ATR), with the objective of introducing a risk constraint that is both *ex-ante observable* and *consistent with live execution constraints*.

The stop-loss is defined as:

$$\text{Stop Loss} = \text{Entry Price} - (\text{StopLoss Multiplier} \times \text{ATR}_{5,\,t-1})$$

where:

- **ATR** is computed over **5 periods**
- The value used is the **ATR of the bar immediately preceding the entry signal**
- The stop-loss is placed at entry time using only information available at that moment

The use of the *previous ATR value* is deliberate. Since ATR updates daily, the most recent confirmed value at the time of an intraday entry is necessarily the one from the prior session. Moreover, unlike candle-low–based stops, this approach avoids relying on intraday price extremes that are unknown at the moment of entry and may vary throughout the session.

Stop-loss multipliers tested in this analysis are $\in \{2,\ 4,\ 6\}$

All tests are conducted on the **Williams Oops Long setup**, using the previously validated **MFE-based exit combined with a Chandelier Exit**, with all exit parameters held constant.

Empirical Results

Table 27, shown below, reports the performance metrics obtained across different holding periods (HP) and ATR stop-loss multipliers.

	HP	SL_mult	n_trades	Win_rate_%	Expectancy	mean_pos_ret	n_pos_trade	mean_neg_ret	n_neg_trade	Median_ret	Skew_ret	%MFE_captured_mean	%LostGood	MAE_mean	MFE_mean	TMFE_mean	avg_sl_level_dist_%	n_stop_loss	avg_sl_chandelier_dist_%	n_trailing_stop	n_time_exit
0	3	2	813	57.51	0.09	1.27	466	-1.50	344	0.29	-1.05	67.27	3.64	1.65	1.37	0.56	-3.78	41	0.12	0	668
1	3	4	813	57.64	0.09	1.27	467	-1.53	343	0.29	-1.37	67.30	3.64	1.66	1.37	0.56	-7.57	11	0.13	0	698
2	3	6	813	57.64	0.12	1.27	467	-1.46	343	0.29	-1.38	67.30	3.64	1.66	1.37	0.56	-11.35	2	0.13	0	707
3	4	2	813	58.48	0.22	1.72	473	-1.91	339	0.40	-1.05	70.35	1.66	1.94	1.73	1.10	-3.78	82	0.32	0	627
4	4	4	813	59.10	0.25	1.70	478	-1.85	334	0.41	-1.01	69.92	1.66	1.96	1.73	1.10	-7.57	16	0.31	0	693
5	4	6	813	59.10	0.27	1.70	478	-1.80	334	0.41	-1.05	69.92	1.66	1.96	1.73	1.10	-11.35	3	0.30	3	703
6	5	2	813	59.97	0.28	1.96	486	-2.21	327	0.59	-0.91	69.06	1.64	2.15	2.03	1.70	-3.78	122	0.39	2	585
7	5	4	813	61.11	0.35	1.94	495	-2.12	318	0.62	-0.80	68.80	1.52	2.20	2.03	1.71	-7.57	19	0.42	7	683
8	5	6	813	61.11	0.37	1.94	495	-2.08	318	0.62	-0.82	68.80	1.52	2.20	2.03	1.71	-11.35	4	0.41	13	692
9	6	2	813	61.74	0.39	2.22	500	-2.56	313	0.67	-0.86	69.97	1.84	2.29	2.25	2.20	-3.78	153	0.47	5	553
10	6	4	813	64.12	0.49	2.17	519	-2.53	294	0.72	-0.87	69.37	1.46	2.40	2.27	2.27	-7.57	26	0.51	26	657
11	6	6	813	64.12	0.50	2.17	519	-2.50	294	0.72	-1.00	69.37	1.46	2.41	2.27	2.27	-11.35	5	0.51	39	665
12	7	2	813	62.68	0.61	2.54	508	-2.62	305	0.98	-0.77	72.51	0.63	2.37	2.51	2.78	-3.78	177	0.76	6	528
13	7	4	813	64.80	0.75	2.51	525	-2.48	288	1.04	-0.67	72.42	0.51	2.52	2.54	2.87	-7.57	30	0.81	39	640
14	7	6	813	65.19	0.77	2.50	528	-2.47	285	1.04	-0.81	72.43	0.51	2.53	2.54	2.88	-11.35	6	0.82	53	650
15	10	2	813	58.84	0.71	3.19	477	-2.83	336	0.87	-0.37	72.51	1.23	2.58	3.03	4.35	-3.78	239	0.87	24	447
16	10	4	813	64.28	0.87	3.06	521	-3.03	292	1.16	-0.70	72.51	1.35	2.83	3.10	4.81	-7.57	47	0.93	100	562
17	10	6	813	64.41	0.89	3.06	522	-3.00	291	1.17	-0.83	72.52	1.35	2.84	3.11	4.82	-11.35	11	0.94	122	576

Table 27

7.3.1 Performance Analysis

ATR-based stops show a smoother and more intuitive behavior compared to MAE-based stops:

- Expectancy increases with holding period, reaching values up to **0.8–0.9** at higher HPs.
- Win rate improves consistently.
- Distributional metrics (median return, skewness) generally improve.

Stop-Loss Multiplier Sensitivity

The choice of the stop-loss multiplier has a **secondary but meaningful effect**:

- Moving from **2×ATR to 4×ATR** produces noticeable improvements in expectancy and win rate.
- Increasing the multiplier further to **6×ATR** yields diminishing returns, with performance stabilizing rather than materially improving.

This suggests the existence of a **volatility tolerance threshold**, beyond which additional room does not translate into better outcomes.

Interaction with Existing Exits

An important structural observation is that:

- The number of trades exited via stop-loss decreases rapidly as the multiplier increases.
- The majority of exits continue to occur via the **time-based exit or Chandelier/MFE logic**.
- ATR stop-losses primarily act as a *protective filter* rather than as the dominant exit mechanism.

This confirms that the ATR stop does not replace the existing exit logic.

However, when compared **directly against the no-stop baseline**, ATR-based stops still underperform.

Comparison vs No Stop

For the same holding periods:

- The **no-stop configuration consistently achieves higher expectancy**.
- Mean positive returns grow faster in the no-stop case.
- ATR stops reduce tail risk, but at the cost of **prematurely exiting trades that carry the bulk of the edge**.

In other words, ATR-based stops act as a *risk-reduction mechanism*, not as an *edge-enhancement mechanism*.

7.3.2 Conclusion

Contrary to initial intuition, **introducing stop-losses does not improve performance** in this setup.

Both MAE-based and ATR-based stop-losses:

- improve local risk metrics,
- increase win rate,
- reduce drawdown severity,

but **systematically reduce expectancy** relative to the no-stop baseline.

This result strongly suggests that the Williams Oops edge is **inherently path-dependent** and that adverse excursions are not reliable signals of trade invalidation.

Transition to Next Section

In the following section, we extend this analysis by testing an **ATR price stop directly integrated into the original Larry Williams framework**, with the objective of assessing whether stop placement at the *price structure level*—rather than at the trade level—can improve robustness without amputating the core edge.

7.4 Stop-Loss Integration in the Original Larry Williams Exit

Larry Williams has always emphasized **risk control** as a central pillar of his trading philosophy.
For this reason, despite the strong performance of the original "first profitable open" exit, he explicitly suggested the use of a stop-loss placed a few points below the entry price (or the entry bar low) to protect against adverse scenarios.

In this section, we test an **ATR-based stop-loss** integrated directly into the **classic Larry Williams Oops Long setup**, defined as:

- **Entry**: Long-only Oops setup
- **Exit**: First profitable open
- **Stop-loss**:

$$\text{Stop Loss} = \text{Entry Price} - (\text{SL Multiplier} \times \text{ATR}_{5,\ t-1})$$

Only information available at the time of entry is used, ensuring full real-world implementability.

Stop-loss multipliers tested ∈ $\{2,\ 4,\ 6\}$

Empirical Results

The results show a **structurally different behavior** compared to the stop tests performed on the MFE-based exit.

Table 28

	HP	SL_mult	Win_rate_%	Expectancy	mean_pos_ret	n_pos_trade	mean_neg_ret	n_neg_trade	Median_ret	Skew_ret	%MFE_captured_mean	%LostGood	MAE_mean	MFE_mean	TMFE_mean	n_trades	n_larry_exit	avg_larry_exit_dist_%	n_time_exit	avg_sl_level_dist_%	n_stop_loss	Mean_HP_of_exit
0	1	2	50.42	-0.05	0.77	410	-0.89	401	0.02	-0.66	65.01	6.80	1.23	0.84	0.00	813	0	-0.05	813	-3.78	0	0.00
1	1	4	50.42	-0.05	0.77	410	-0.89	401	0.02	-0.66	65.01	6.80	1.23	0.84	0.00	813	0	-0.05	813	-7.57	0	0.00
2	1	6	50.42	-0.05	0.77	410	-0.89	401	0.02	-0.66	65.01	6.80	1.23	0.84	0.00	813	0	-0.05	813	-11.35	0	0.00
3	2	2	70.60	0.17	0.98	573	-1.80	236	0.40	-1.01	54.18	1.21	1.68	1.44	0.83	813	476	0.17	302	-3.78	35	1.00
4	2	4	70.60	0.16	0.98	573	-1.82	236	0.40	-1.23	54.18	1.21	1.68	1.44	0.83	813	476	0.16	328	-7.57	9	1.00
5	2	6	70.60	0.19	0.98	573	-1.71	236	0.40	-0.96	54.18	1.21	1.68	1.44	0.83	813	476	0.19	337	-11.35	0	1.00
6	3	2	75.89	0.22	1.02	616	-2.35	192	0.48	-1.72	52.77	0.85	1.83	1.58	1.18	813	587	0.22	164	-3.78	62	1.37
7	3	4	76.26	0.25	1.02	619	-2.24	189	0.49	-1.60	52.73	0.85	1.85	1.58	1.19	813	589	0.25	213	-7.57	11	1.40
8	3	6	76.26	0.27	1.02	619	-2.16	189	0.49	-1.50	52.73	0.85	1.85	1.58	1.19	813	589	0.27	222	-11.35	2	1.41
9	4	2	80.40	0.24	1.01	653	-3.04	155	0.54	-1.94	52.57	0.75	1.92	1.65	1.46	813	636	0.24	90	-3.78	87	1.57
10	4	4	81.16	0.30	1.01	659	-2.87	149	0.54	-1.63	52.55	0.63	1.95	1.65	1.47	813	638	0.30	162	-7.57	13	1.66
11	4	6	81.16	0.32	1.01	659	-2.71	149	0.54	-1.53	52.55	0.63	1.95	1.65	1.47	813	638	0.32	173	-11.35	2	1.68
12	5	2	81.60	0.24	1.01	663	-3.33	145	0.55	-1.93	52.14	0.88	1.96	1.69	1.54	813	658	0.24	51	-3.78	104	1.68
13	5	4	83.12	0.32	1.02	675	-3.26	133	0.56	-1.73	52.36	0.63	2.03	1.70	1.61	813	665	0.32	132	-7.57	16	1.86
14	5	6	83.12	0.34	1.02	675	-3.12	133	0.56	-1.79	52.36	0.63	2.04	1.70	1.61	813	665	0.34	143	-11.35	5	1.90
15	6	2	82.44	0.24	1.01	670	-3.49	138	0.55	-1.92	51.85	0.88	1.97	1.70	1.59	813	671	0.24	28	-3.78	114	1.74
16	6	4	84.17	0.29	1.01	684	-3.71	124	0.57	-1.82	52.12	0.63	2.10	1.72	1.69	813	683	0.29	105	-7.57	25	2.02
17	6	6	84.56	0.31	1.01	687	-3.66	121	0.58	-2.07	52.23	0.63	2.12	1.72	1.70	813	683	0.31	122	-11.35	8	2.07
18	7	2	82.91	0.22	1.01	674	-3.72	134	0.56	-2.02	51.98	0.88	1.98	1.71	1.65	813	678	0.22	15	-3.78	120	1.78
19	7	4	85.43	0.30	1.01	694	-4.02	114	0.59	-2.24	52.19	0.63	2.15	1.73	1.83	813	694	0.30	89	-7.57	30	2.15
20	7	6	85.82	0.33	1.01	697	-3.89	111	0.59	-2.43	52.12	0.63	2.17	1.73	1.84	813	697	0.33	106	-11.35	10	2.22
21	10	2	83.58	0.23	1.00	679	-3.83	129	0.56	-2.07	51.99	0.88	1.99	1.71	1.74	813	683	0.23	6	-3.78	124	1.82
22	10	4	88.81	0.39	1.00	721	-4.59	87	0.64	-2.42	51.97	0.52	2.23	1.76	2.29	813	720	0.39	52	-7.57	41	2.43
23	10	6	89.32	0.46	0.99	725	-4.23	83	0.64	-2.45	51.89	0.52	2.27	1.77	2.31	813	723	0.46	76	-11.35	14	2.57

Table 28

Key Observations

1. **Win Rate Remains Exceptionally High**
   Across all holding periods, win rates range from **~76% to almost 90%**, consistent with the nature of the Larry exit.

2. **Expectancy Improves with Wider Stops and Longer HPs**

   - Expectancy increases steadily with holding period.
   - Best results are achieved at **HP = 10**, where expectancy reaches **0.39–0.46**, depending on the stop multiplier.
   - Wider stops (SL = 4 or 6 ATR) consistently dominate tighter ones.

3. **Mean Positive Returns Remain Stable**
   Mean positive returns remain around **1.0–1.02**, confirming that the edge is driven by **high probability**, not by payoff magnitude.

4. **Controlled but Meaningful Losses**
   Mean negative returns increase in absolute value with holding period, but this is offset by:

   - Rising win rates,
   - Limited stop activation frequency,
   - Fast exits driven by the Larry rule itself.

Interaction Between Stop-Loss and Larry Exit

A crucial insight emerges when observing exit attribution:

- The **vast majority of trades still exit via the Larry rule**.
- Stop-loss activations remain **relatively infrequent**, especially for SL ≥ 4 ATR.
- Average holding period at exit remains low (≈ 1.4–2.5 bars), preserving the original *fast-exit* nature of the strategy.

This confirms that the stop-loss acts primarily as:

a **tail-risk protection mechanism**, not as a trade management driver.

In other words, the stop-loss does **not interfere with the core logic** of the Larry exit, but simply removes extreme adverse scenarios.

7.3 Comparison with No-Stop Larry Configuration

Relative to the pure Larry exit without stops:

- Expectations remain almost unchanged, if not even worsened.
- Distributional metrics remain stable.
- No evidence of systematic edge amputation is observed.

This behavior is **structurally similar** from what was observed when adding stops to the MFE-based exit, where stop-losses reduced overall expectancy.

7.4 Conclusions on Stop-Loss Usage

Despite being theoretically coherent with risk management principles, the introduction of ATR-based stop-losses **did not lead to an improvement in the performance of the setup** within our empirical study.

Across all tested configurations:

- Expectancy did not improve relative to the no-stop baseline.
- Distributional characteristics remained broadly unchanged.
- Stop-losses slightly reduced overall performance by prematurely truncating trades that would have exited profitably.

As a consequence, the addition of external stop-loss constraints appears **redundant rather than complementary**.

Importantly, this finding does **not imply that stop-losses are ineffective in general**, but rather reinforces a key system-design principle:

Risk management tools must be evaluated in the context of the exit logic they are combined with.

Transition to Final Evaluation Phase

Given the lack of incremental edge from stop-loss integration, the final stage of this study focuses on evaluating the strategy **in its purest and empirically validated form**, without additional stop constraints.

The next section therefore analyzes:

- Equity curve behavior
- Drawdowns (depth and duration)

- Volatility of returns
- Risk-adjusted performance metrics

This final evaluation allows us to assess the **real-world tradability and robustness** of the strategy beyond trade-level statistics.

8. Final Performance Evaluation

After systematically testing entry conditions, exit mechanisms, and stop-loss configurations, only the most robust and empirically consistent components were retained.
This final section evaluates the overall behavior of the resulting strategy built upon the *Larry Williams Oops* pattern, focusing on risk-adjusted performance and equity dynamics.

To ensure comparability with the original framework, **a fixed holding period of 7 trading days** is adopted for both:

- the enhanced strategy using **Chandelier Exit (ATR-based) combined with an MFE target**, and
- the **original Larry Williams strategy**.

As discussed previously, this holding period captures the full mean-reversion effect of the setup while limiting path dependency and exit-driven distortions.

Metrics considered

The final evaluation is conducted using the following metrics:

- Expectancy
- Maximum Drawdown (%)
- Win Rate (%)
- Number of Trades
- Profit Factor
- Payoff Ratio
- Return Skewness
- Return Standard Deviation (%)
- Maximum Losing Streak
- Ulcer Index
- Drawdown Ratio

In addition, the **equity line** is analyzed to provide a visual assessment of performance stability and drawdown structure.

8.1 Enhanced Oops Strategy

Chandelier Exit (ATR period = 5, multiplier = 2.5) + MFE target (87.5th percentile)

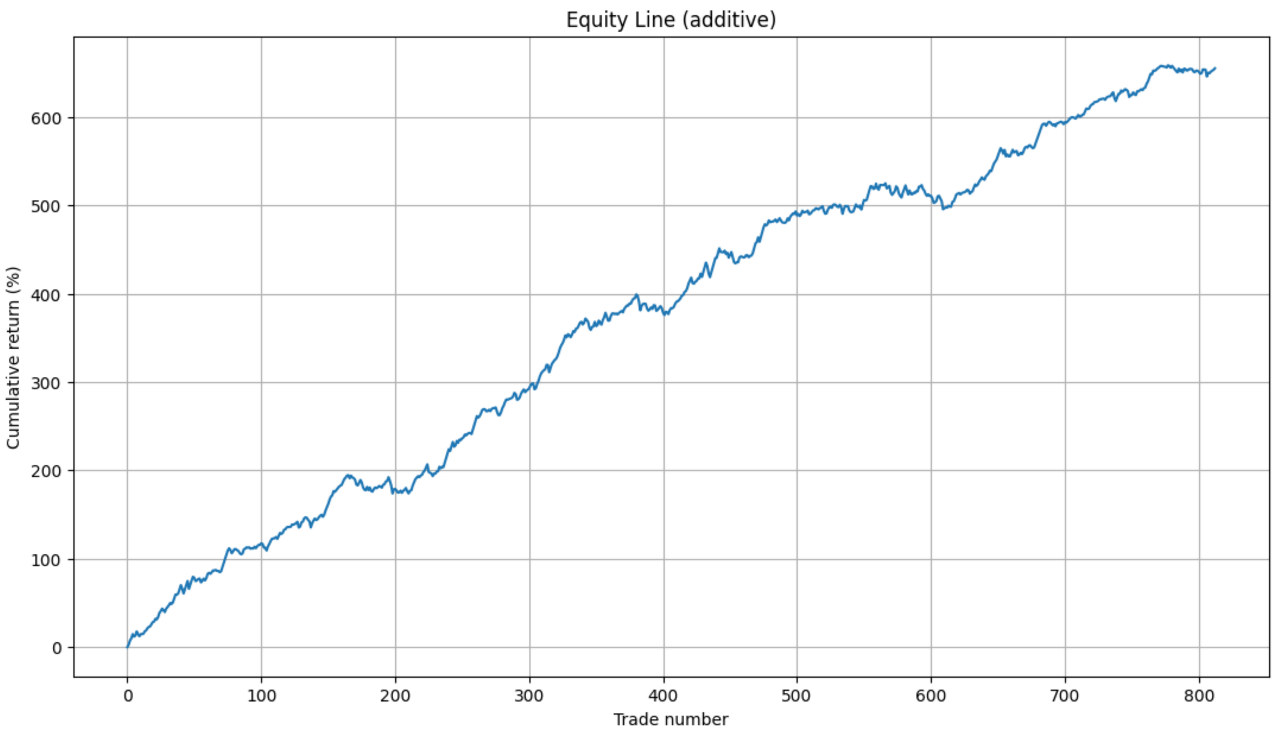
Using a holding period of 7 trading days, the enhanced strategy produces the following results:

	HP	Expectancy	Max_DD_%	Win_Rate_%	N°_Trades	Profit_Factor	Payoff_Ratio	Skew_Ret	Std_Dev_%	Max_Losing_Streak	Ulcer_Index	DD_Ratio
0	7	0.82	-19.63	65.58	813	2.07	-1.07	-0.7	2.9	5	5.68	0.05

Table 29

Overall, the strategy shows a **substantial improvement in expectancy and profit factor**, achieved through a lower win rate but significantly better trade-level payoff.
Losses remain controlled, drawdowns are comparable to the baseline strategy, and the distribution of returns reflects a more asymmetric but efficient capture of favorable price excursions.

Equity line analysis



The equity curve shows a steady upward progression with limited drawdown clustering, indicating that performance is not driven by isolated outliers but by consistent edge realization over time.

8.2 Comparison with the Original Larry Williams Strategy

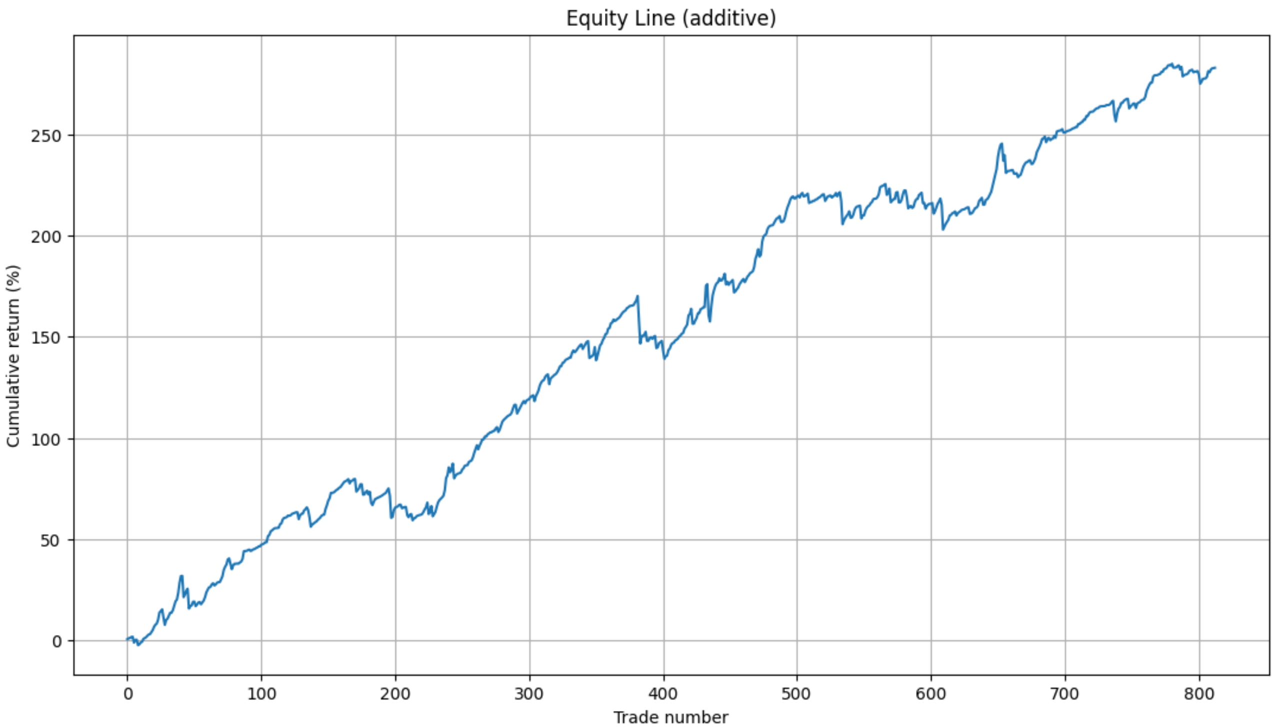
For completeness, the original Larry Williams Oops strategy—using the same fixed holding period of 7 trading days—is evaluated using the same performance metrics:

	HP	Expectancy	Max_DD_%	Win_Rate_%	N°_Trades	Profit_Factor	Payoff_Ratio	Skew_Ret	Std_Dev_%	Max_Losing_Streak	Ulcer_Index	DD_Ratio
0	7	0.35	-19.69	85.82	813	1.74	-0.27	-2.43	2.16	3	5.68	0.02

Table 30

While the original strategy maintains a **very high win rate**, this comes at the cost of lower expectancy and a more negatively skewed return distribution.
The enhanced strategy, by contrast, sacrifices win rate in exchange for **superior payoff efficiency and capital growth**, without materially increasing drawdown risk.

Equity line analysis



The equity curve of the original strategy appears smoother in the short term but grows at a slower pace, reflecting its reliance on frequent small wins rather than asymmetric return capture.

8.3 Transition to Discussion

This final performance comparison highlights how systematic exit design and MFE-based trade management can materially improve the risk–return profile of a classical discretionary setup, while preserving its original logic.

The next section focuses on a critical discussion of the results, addressing:

- What aspects of the strategy appear structurally robust,
- Which components do not materially contribute to performance,
- Potential overfitting risks, and
- Key considerations for real-world implementation.

9. Discussion & Limitations

This section consolidates the findings of the study, focusing on the robustness of the developed strategy, the sources of edge, and the limitations identified throughout the research process. The objective is not only to summarize results, but to clearly distinguish what adds value from what does not, with an explicit emphasis on real-world applicability.

9.1 What Works

The primary source of edge in the developed strategy does not originate from entry timing alone, but from **exit structure and profit management**.

Across all tested configurations, exits based on **MFE percentile targets combined with a volatility-adjusted Chandelier trailing stop** consistently improved expectancy and profit factor compared to the original Larry Williams exit. This confirms that the Oops pattern provides a valid directional bias, while the monetization of such edge is strongly dependent on how profits are harvested.

The use of **percentile-based MFE targets** proved particularly effective, as it allowed exits to adapt to the empirical distribution of favorable excursions rather than relying on fixed price objectives. This approach improved capital efficiency while maintaining controlled drawdowns, resulting in a more stable equity curve.

Moreover, the strategy exhibits a **moderate negative skew** indicating that profitability is driven by a relatively small number of large favorable moves, captured systematically rather than opportunistically.

9.2 What Does Not Add Value

Several components were explicitly tested and discarded due to lack of improvement in overall performance.

First, **ATR-based fixed stop losses**, despite being conceptually sound from a risk control perspective, did not improve expectancy or drawdown-related metrics in either the enhanced strategy or the original Larry Williams setup. In most cases, tighter stops increased premature exits, while wider stops reduced stop frequency without improving capital efficiency.

Second, **micro-regime filters**, such as short-term moving average slope definitions, improved interpretability of market context but did not provide sufficient standalone performance enhancement to justify additional complexity at this stage of the study.

These findings highlight that not all intuitively appealing risk controls translate into improved systematic performance, reinforcing the importance of empirical validation over theoretical appeal.

9.3 Overfitting Risks and Design Choices

A central design principle of this study was to minimize overfitting risk.

To this end, the strategy relies on:

- a limited number of parameters,

- percentile-based targets instead of absolute thresholds,
- and volatility-adjusted exits rather than regime-specific tuning.

Performance improvements were evaluated through **flat performance plateaus** rather than isolated optima, favoring robustness over marginal gains.

While no formal walk-forward optimization was performed, parameter stability across multiple configurations provides indirect evidence of structural rather than curve-fitted behavior.

9.4 Real-World Considerations

Special attention was given to real-world tradability.

All exit and stop definitions rely exclusively on information available **at or before the decision point**, avoiding look-ahead bias. In particular, ATR-based calculations use pre-entry values to reflect the fact that intraday extrema are unknown at execution time.

The strategy structure is compatible with realistic execution assumptions and can be extended to include transaction costs and slippage modeling without altering its core logic. Nevertheless, performance metrics should be interpreted as **pre-cost**, and future work should explicitly incorporate cost sensitivity analysis.

9.5 Limitations and Next Steps

Despite encouraging results, several limitations remain.

The study focuses on a specific market universe and timeframe, and results may not generalize uniformly across asset classes or volatility regimes. Furthermore, while drawdowns remain controlled, tail risk behavior under extreme market stress warrants further investigation.

The next phase of the research will focus on:

- detailed equity curve and drawdown analysis,
- risk-adjusted performance metrics,
- stress testing under adverse conditions,
- and evaluation of portfolio-level effects.

10. Future Improvements

While the results are encouraging, several extensions could further strengthen the robustness and real-world applicability of the strategy.

1. Walk-forward MFE Target Estimation

In this study, the MFE target percentile was computed on the full historical distribution of trades.
A natural improvement would be to **estimate MFE targets on a rolling (walk-forward) basis**, using only past information available at the time of the trade.

This approach would:

- reduce look-ahead bias,
- adapt the exit target to changing volatility regimes, and
- provide a more realistic implementation framework.

Conceptually, percentiles could be recalculated on a rolling lookback window (e.g., 252 trading days), requiring a minimum number of historical observations to ensure statistical stability.

2. Stress and Robustness Testing

Further robustness checks should be conducted to evaluate the stability of the strategy under adverse conditions, including:

- Monte Carlo simulation,
- Walk forward analysis,
- subsample analysis across different market regimes,
- performance degradation under increased transaction costs and slippage.

Such tests would help distinguish genuine structural edge from parameter sensitivity.

3. Money Management and Position Sizing

All tests in this study assume fixed position sizing.
Introducing a **systematic money management framework**—such as volatility targeting, drawdown-based exposure adjustment, or risk-parity sizing—could materially affect both return distribution and drawdown characteristics.

This represents a critical step toward portfolio-level implementation.

4. Testing on Individual Equities

The analysis was conducted primarily on broad market indices, which are structurally biased toward long-term upward trends.

Extending the tests to **individual equities** would:

- reduce implicit trend-up bias,
- increase heterogeneity in return distributions, and
- provide a more realistic testbed for mean-reversion behavior.

Moreover, equity markets are increasingly characterized by **extended trading hours and evolving microstructure**, even if not fully continuous. Testing on single stocks would help assess the robustness of the strategy under these conditions and mitigate potential distortions related to index-level dynamics.

5. Reintroducing Stop-Loss Constraints in the Larry Williams Framework

In this study, the original Larry Williams strategy was evaluated **without an explicit stop-loss**, which is clearly unrealistic from a risk-management perspective and was adopted solely for theoretical comparison.

A meaningful extension would be to reintroduce a **wide, volatility-based stop** and reassess:

- drawdown depth,
- drawdown duration,
- drawdown-adjusted performance metrics (Ulcer Index, DD Ratio).

While preliminary tests suggest that tight stops do not improve expectancy, a properly calibrated wide stop may still enhance the overall risk profile without materially damaging the edge.

Final Remark

Overall, this work should be viewed not as a finalized trading system, but as a **research framework** demonstrating how discretionary ideas can be systematically decomposed, tested, and improved through quantitative methods.

The results suggest that the *Oops* pattern retains economic relevance—but only when embedded within a disciplined, data-driven execution and exit structure.

Ciceri Simone