Strategy Building Documentation Layout

# INTRODUCTION

The pursuit of building **alpha-generating trading strategies** lies at the heart of quantitative research. While many strategies look impressive on paper, they often fail in live markets because they overlook the **real-world challenges of execution, biases, and robustness**. My goal in this project was to bridge that gap: to create strategies that not only show strong historical performance but are also designed with the **practical realities of live trading** in mind.

To maintain focus and realism, I confined my work to the **cash segment** of the equity markets. This allowed me to carefully model **capital allocation, transaction costs, liquidity constraints, and execution delays**, all of which play a critical role in determining whether a strategy can truly survive outside the backtesting environment.

The journey I document here is not a straight line from idea to implementation—it is a process of **hypothesizing, testing, failing, and pivoting**. Along the way, I systematically explored several dimensions of strategy development:

1. **Hypothesis Development** – Every strategy begins with a market intuition or theory. I started by formulating testable hypotheses around price behavior, momentum persistence, and trend confirmation, aiming to ground my ideas in both empirical evidence and practical intuition.
2. **Indicator Selection** – The financial markets offer an abundance of technical indicators and statistical tools. Choosing the right ones requires balancing simplicity, explanatory power, and robustness. I documented how I shortlisted indicators, rejected noise-generating ones, and combined them to create composite signals.
3. **Backtesting Realism** – A key objective was to simulate the **true execution environment**. This meant accounting for order execution delays, slippage, and capital allocation rules, rather than relying on “perfect hindsight” assumptions. In effect, the backtests were designed to answer: *How would this strategy have actually performed if I had deployed it in the past?*
4. **Bias Management** – One of the most dangerous pitfalls in strategy research is falling prey to hidden biases. I placed particular emphasis on eliminating **look-ahead bias** (using only past information available at the time), **survivorship bias** (ensuring delisted securities are accounted for), and **overfitting** (avoiding cherry-picked results). Preserving a **proprietary edge** while being mindful of these biases was central to my methodology.
5. **Signal Construction & Relative Testing** – Rather than committing to a single signal, I built multiple variants and tested them against each other. This comparative framework made it easier to identify what truly added value versus what was redundant or curve-fitted.
6. **Hyperparameter Tuning** – Finally, I addressed the challenge of parameter selection. Instead of optimizing for the best static parameters (which often leads to overfitting), I experimented with **rolling-window and walk-forward methods**, ensuring that the strategy adapts dynamically to changing market conditions.

This documentation is, therefore, not just a record of a finished trading strategy, but a **comprehensive narrative of the research journey**—highlighting the **decisions, challenges, and refinements** that shaped the end result. By focusing equally on the *process* and the *outcome*, the intention is to reflect the mindset of professional quantitative research, where rigor, skepticism, and adaptability matter as much as raw performance.

# 2. Research & Ideation

When building strategies in the **cash segment**, one of the most effective approaches is to measure performance relative to a **benchmark index**. This provides a realistic yardstick against which alpha can be evaluated. For this project, I selected the **Nifty 50 Index** as my benchmark.

The **Nifty 50** is widely regarded as the most liquid and representative equity index in India, making it an ideal choice for strategy development. Some of its key advantages include:

* **High Liquidity** – constituent stocks are among the most traded in the Indian markets, which reduces slippage and improves execution quality.
* **Diversification** – the index spans multiple sectors, ensuring that performance is not driven by a single industry.
* **Market Representation** – it reflects the overall health of the Indian equity market, making it an excellent base for benchmarking strategies.
* **Stability** – index constituents are regularly reviewed, which maintains relevance while avoiding excessive churn.

**Initial Approach: Long–Short Market Neutral Strategy**

My first idea was to design a **long–short market-neutral strategy**, with the objective of generating alpha while reducing market risk. The key benefits of such a strategy include:

* **Reduced Systematic Risk** – by taking both long and short positions, exposure to overall market movements is minimized.
* **Pure Alpha Capture** – returns are primarily driven by stock selection rather than market direction.
* **Hedging Capability** – short positions naturally provide a hedge during downturns.

The initial framework involved identifying the **top 10 upward-trending stocks** to go long on, and simultaneously shorting the **bottom 10 underperforming stocks**, thereby creating a balanced, relative-value structure.

**The Challenge: Real-World Constraints**

While the theoretical design looked promising, incorporating **real-world execution constraints** quickly highlighted critical issues. The Indian cash market does not allow overnight short-selling. The only way to maintain short exposure is via a **stock borrowing and lending mechanism (SLBM)**, where traders borrow securities and sell them in the market with the obligation to return them later. *(For a detailed explanation, see: NSE SLBM Mechanism)*

However, in practice, this introduced two major challenges:

1. **Additional Borrowing Costs** – maintaining short positions through SLBM significantly increased expenses.
2. **Erosion of Profitability** – transaction costs, slippage, and borrowing fees outweighed the incremental profits generated by the short side of the strategy.

As a result, the **advantages of market neutrality were overshadowed by the real-world frictions** of short-selling in the Indian market.

**The First Pivot: Focusing on Long-Only Strategies**

Recognizing that the short leg was more costly than beneficial, I made my **first major pivot**: transitioning from a **long–short framework** to a **long-only strategy**. While this reduced the hedging benefits of market neutrality, it allowed me to:

* Simplify execution and capital allocation.
* Eliminate unnecessary borrowing and shorting costs.
* Focus on extracting alpha from the strongest upward-trending opportunities.

This pivot reflects one of the key realities of strategy building: while theory may suggest elegant solutions, **practical constraints often dictate which ideas survive and evolve**. By narrowing the scope to long-only strategies, I set the stage for building a more realistic and implementable framework in the Indian cash market.

# 3. Initial Strategy Design

Before diving into indicator selection and coding, I first focused on setting **realistic expectations** for how my strategy should behave across different **market regimes**. This step was crucial to avoid over-expecting, to recognize inherent limitations, and to acknowledge potential vulnerabilities in advance.

**Framing Practical Expectations**

* **Uptrending Markets:**  
  The strongest edge of my hypothesis lay in rising markets. In such phases, most stocks tend to perform positively, and by applying a **filtering mechanism to capture only the strongest upward trends**, I expected my portfolio to outperform the index significantly. This was the environment where I anticipated maximum alpha generation.
* **Sideways/Range-Bound Markets:**  
  Initially, I expected the strategy to remain relatively neutral in sideways conditions. However, my backtests revealed a **critical drawback**: the model underperformed heavily in range-bound markets.
  + The root cause was **mean-reversion dynamics** inherent in sideways markets.
  + My signals, designed to capture emerging trends, frequently mistook short-lived price movements for genuine trends.
  + As prices reverted back within the range, the strategy incurred **repeated whipsaw losses**, leading to negative performance.
* **Downtrending Markets:**  
  Since the pivot had already restricted me to a **long-only framework**, I did not expect the strategy to perform well in bear phases. The expectation was for it to stay largely inactive, generating minimal trades rather than significant losses. Backtests aligned with this assumption—the system was less active, thereby limiting downside exposure, though not immune to losses.

**Assumptions Underpinning the Design**

To make the strategy workable under **data and computational constraints**, I had to make a few simplifying assumptions:

1. **Daily Timeframe Execution**
   * Due to limited access to high-quality intraday data and computational resources, I resorted to designing the strategy on a **daily timeframe**.
   * While this limited short-term responsiveness, it provided stability in testing and execution.
2. **Closing Price Assumption for Entry**
   * The major assumption was that trades would be executed **at the closing price** once signals were generated.
   * In practice, this creates a challenge, as executing trades exactly at the closing price is not feasible in live markets.
   * A practical workaround would be to use **near-closing data (e.g., 5 minutes before market close)**, assume that as the closing signal, and place trades in the remaining time before market close to mimic real-world execution more accurately.

**Expected Behavior of the Strategy**

* Strong performance in **bullish, trending phases**, where stock momentum amplifies portfolio growth.
* Neutral to weak performance in **sideways phases**, with a high likelihood of whipsaw losses due to mean-reversion.
* Low activity in **bearish regimes**, which limits drawdowns but also restricts opportunity.

By articulating these expectations upfront, I was able to build a clear framework for evaluation—measuring whether the strategy was behaving **as expected across regimes** rather than merely chasing returns. This mindset helped me identify weaknesses early (e.g., sideways market performance) and set the stage for refinements in subsequent iterations.

4. Indicators , Signal Generation & Execution

**4.1 Indicators Used**

In designing the strategy, the choice of indicators was critical, as they form the foundation of both signal generation and filtering mechanisms. After evaluating multiple alternatives, I relied on a blend of classic momentum/trend indicators (RSI, MACD, ADX) and incorporated modifications (slope of MACD and ADX) to capture trend strength and reduce lag. Below is a detailed explanation of each indicator and its role in the strategy.

**4.1.1 Relative Strength Index (RSI)**

**Definition & Purpose:**  
The Relative Strength Index (RSI) is a momentum oscillator that measures the magnitude of recent price changes to evaluate overbought or oversold conditions, with values ranging between 0 and 100.

* RSI > 70 → Typically considered overbought.
* RSI < 30 → Typically considered oversold.

**Use in Strategy:**

* I did not rely on RSI as a contrarian signal (buy oversold / sell overbought), but rather as a **trend confirmation filter**.
* Stocks with RSI sustaining above the midline (50) indicated strong bullish momentum and were prioritized for long entries.
* Conversely, RSI drifting below 50 was considered a sign of weakening momentum, even if other indicators aligned.

**Rationale:**  
This helped filter out “false positives” from MACD or ADX by ensuring that selected stocks were backed by genuine buying pressure.

**4.1.2 Moving Average Convergence Divergence (MACD)**

**Definition & Purpose:**  
MACD is a trend-following momentum indicator that measures the relationship between two moving averages of price:

* MACD Line = (Short-term EMA – Long-term EMA)
* Signal Line = EMA of the MACD Line

Crossovers between the MACD line and Signal line indicate momentum shifts.

**Use in Strategy:**

* **Buy Signal:** MACD line crossing above the signal line, ideally above zero.
* **Sell Signal:** MACD line crossing below the signal line, ideally below zero.

**Rationale:**  
MACD acted as the **primary trigger** for entry and exit. Since it reacts relatively quickly to changes in trend, it helped capture early movements in uptrending stocks.

**4.1.3 Average Directional Index (ADX)**

**Definition & Purpose:**  
The Average Directional Index measures the **strength of a trend**, regardless of its direction, with values ranging from 0 to 100.

* ADX < 20 → Weak/sideways market.
* ADX > 25–30 → Strong, trending market.

**Use in Strategy:**

* A rising ADX confirmed that any MACD-based crossover was occurring in a strong trend environment.
* Only trades with ADX above a minimum threshold (≈ 20–25) were considered valid.
* This filter prevented excessive whipsaws in sideways markets, where MACD often gives misleading signals.

**Rationale:**  
ADX served as a **trend-quality filter**, ensuring that positions were taken only when directional strength supported them.

**4.1.4 Slope of MACD (Modification)**

**Definition & Purpose:**  
While traditional MACD looks at crossovers, it often suffers from lag. To reduce this delay, I introduced the **slope (rate of change) of the MACD line** as an additional dimension.

**Use in Strategy:**

* A positive and steepening slope indicated strong bullish momentum, giving early confirmation of an uptrend.
* A flattening or negative slope signaled weakening momentum, even before an official crossover happened.

**Rationale:**  
By tracking the **momentum behind the MACD itself**, I could anticipate potential reversals earlier, thereby improving entry timing and reducing false entries.

**4.1.5 Slope of ADX (Modification)**

**Definition & Purpose:**  
Standard ADX measures trend strength but reacts slowly. To improve responsiveness, I analyzed the **slope of ADX**, which indicates whether the trend is strengthening or weakening in real time.

**Use in Strategy:**

* Rising slope → Trend strength accelerating → higher confidence in continuing with existing trades.
* Falling slope → Trend weakening → early warning to tighten stop-losses or prepare for exit.

**Rationale:**  
The slope of ADX added a **dynamic layer of validation**, ensuring that I stayed with trends only when they were gaining strength, rather than holding through periods of stagnation.

**4.1.6 Combined Interpretation**

In practice, these indicators were not used in isolation but in combination:

* **MACD** provided the core buy/sell trigger.
* **RSI** confirmed momentum above the neutral level.
* **ADX** validated the existence of a strong trend.
* **MACD slope** improved timing of entries.
* **ADX slope** guided position management and exits.

This multi-layered approach allowed the strategy to be more selective, filtering out weaker setups and prioritizing stocks with both momentum and trend strength.

**4.2 Signal Generation**

The most crucial aspect of any systematic strategy lies in defining **how and when trading signals are generated**. Signals act as the actionable triggers that convert raw market data and indicator values into buy, sell, or exit decisions. The process of designing these signals can range from simple rule-based conditions to multi-layered, constraint-driven logic.

In this strategy, I adopted an **iterative refinement approach**: beginning with a baseline signal-generation framework and then progressively incorporating additional constraints to improve robustness and reduce false positives. Ultimately, I developed and tested **four signal-generation models**, each with increasing complexity and stringency. These models were then evaluated against performance metrics such as **Sharpe Ratio, CAGR (Compounded Annual Growth Rate), and Maximum Drawdown (Max DD)**, enabling an evidence-based ranking of their effectiveness.

**Signal 1: Baseline Model (MACD + ADX + DI Confirmation)**

The first model established the **core structure** of the strategy. It combined trend-following and strength-confirmation indicators to avoid noisy trades:

* **Buy Signal** was triggered when:
  + MACD line > MACD Signal line (bullish momentum),
  + ADX > 30 (indicating strong trend),
  + MACD > 0 (trend direction is positive),
  + +DI > –DI (bullish directional movement).
* **Sell Signal** was triggered under the mirror conditions:
  + MACD line < MACD Signal line,
  + ADX > 30,
  + MACD < 0,
  + –DI > +DI (bearish dominance).
* **Exit Logic:** Positions were exited when:
  + Opposite MACD crossover occurred, or
  + ADX weakened below 25, suggesting trend exhaustion.

This baseline model captured strong directional trends but lacked safeguards against overbought/oversold traps.

**Signal 2: Incorporating RSI Filters**

The second model introduced **RSI constraints** to address one of the weaknesses of Signal 1—late entries in overextended markets. RSI helped in screening out trades where momentum was strong but already at risk of reversal.

* **Additional Conditions:**
  + Long entry only allowed if RSI < 70 (avoiding overbought entries).
  + Short entry only allowed if RSI > 40 (avoiding oversold conditions).

This filtering mechanism helped reduce false signals and enhanced entry selectivity, particularly in volatile markets.

**Signal 3: Trend Slope & Composite Confirmation**

The third model represented a **refinement in trend-quality assessment** by incorporating:

* **ADX Slope:** Ensuring not just a strong trend (ADX > 30), but one that is **accelerating** (ADX slope > 0). This constraint aimed to capture emerging strength rather than stagnant or fading trends.
* **Combined Score (custom metric):** An aggregated measure synthesizing multiple indicator inputs into a composite signal. Trades were allowed only when the score was positive (for longs), adding another layer of confirmation.

This version prioritized quality over quantity, trading fewer but stronger setups compared to earlier models.

**Signal 4: Final Enhanced Model (Full Constraint Integration)**

The fourth and most comprehensive signal-generation framework combined **all the refinements**:

* MACD crossover + direction check.
* ADX > 30, with a **positive ADX slope** (accelerating trend).
* +DI/–DI confirmation.
* RSI filter (RSI < 70 for longs, RSI > 40 for shorts).

Exit rules remained consistent with earlier models, with positions liquidated upon MACD reversal or weakening ADX (<25).

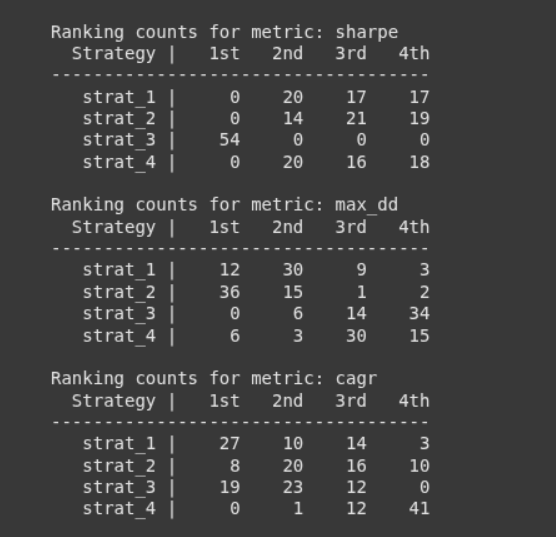
This model was the most stringent, allowing trades only when multiple dimensions of confirmation aligned: momentum, strength, acceleration, and exhaustion protection.

**Comparative Evaluation**

Each signal generation model was backtested across multiple stocks and time horizons, and their results were systematically compared. The evaluation focused on three key metrics:

* **Sharpe Ratio:** To measure risk-adjusted returns.
* **CAGR:** To capture absolute growth over the test horizon.
* **Max Drawdown:** To evaluate downside protection and capital risk.

By ranking these models across the above metrics, I could empirically infer which signal-generation logic provided the most **robust and reliable** framework for real-world execution.



| **Criteria** | **Strategy 1: Baseline (MACD + ADX + DI)** | **Strategy 2: RSI-Filtered Model** |  | **Strategy 3: ADX Slope + Composite Score** | **Strategy 4: Full Constraint Model** |
| --- | --- | --- | --- | --- | --- |
| **Sharpe Ratio (Risk-Adjusted Return)** | Moderate – mostly 2nd–3rd rank, rarely best | Average – consistent mid-ranks |  | **Outstanding – ranked 1st in all tests** | Weak – usually bottom half |
| **Max Drawdown (Risk Control)** | Strong – ranked top 2 in 42/54 cases | **Best – ranked 1st in 36 cases** |  | Weak – worst performer, 4th in 34 cases | Poor – often 3rd or 4th |
| **CAGR (Growth Potential)** | Fairly strong – 27 first-place finishes | Moderate – competitive but not dominant |  | Strong – 19 first-place finishes | **Weakest – 4th in 41 cases** |
| **Strengths** | Balanced, decent growth, good downside control | Excellent drawdown protection, filters false signals |  | **Unmatched Sharpe, strong CAGR potential** | Very strict filtering, avoids many false trades |
| **Weaknesses** | Rarely top in Sharpe, may miss strong alpha | Conservative – misses some big trends |  | **High drawdown risk, volatile** | Over-constrained, kills profitability |
| **Best Use Case** | **Balanced / Moderate Risk** strategy | **Risk-averse investors** prioritizing capital preservation |  | **Aggressive alpha seekers** with strong risk overlays (stop-loss, position caps) | Not recommended – overly strict, underperforms |

**Final Conclusion**

* **Best Overall Performer:**  
  **Strategy 3** (ADX Slope + Composite Score) — unmatched Sharpe Ratio, good CAGR. However, it carries **significant drawdown risk**, meaning it requires **stop-loss integration** and **capital allocation discipline** to be viable in real-world trading.
* **Safest Strategy (Defensive Choice):**  
  **Strategy 2** (RSI-Filtered Model) — best at **limiting drawdowns** while still producing competitive growth. This is the most **robust and risk-averse option**, though less aggressive in alpha generation.
* **Balanced Middle Ground:**  
  **Strategy 1** (Baseline Model) — provides decent CAGR and stable drawdown performance. A good compromise if one prefers simplicity.
* **Not Recommended:**  
  **Strategy 4** (Full Constraint Model) — over-constrained, consistently underperforms in growth and drawdown.

**4.3 Execution Logic**

**1) Filtering Candidates**

On each trading day, the strategy first filters stocks based on a **buy signal** generated by the indicator layer. Only those stocks that satisfy conditions like **MACD crossovers, ADX strength, and DI confirmation** are shortlisted. This ensures that the scoring system is applied only to candidates with genuine technical backing.

**2) Scoring Buy Candidates**

Shortlisted candidates are ranked through a z-score based scoring system. For each indicator, the raw value is standardized over a rolling 35-day lookback window:

* RS Score: Standardized measure of relative strength (RS).
* EMA Score: Standardized slope of the Exponential Moving Average, capturing trend direction and steepness.
* ADX Score: Standardized Average Directional Index, reflecting trend strength.

The final score is a weighted combination of these standardized metrics:

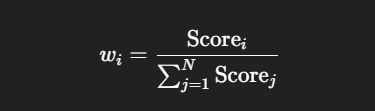


This ensures the model balances momentum (RS), directionality (EMA slope), and strength (ADX), while giving slightly more weight to trend direction (EMA).

**3) Weighting and Position Assignment**

From the scored list, the **top N stocks** are selected. Their combined scores are normalized into portfolio weights:

This ensures that stronger opportunities receive larger allocations, while diversification is maintained.



* If a stock is **newly added**, the allocated capital is invested at the current price.
* If the stock is **already in the portfolio**, allocations are topped up, and the entry price is recalculated as a **weighted average**.
* A **max price tracker** is maintained for each stock to support stop-loss monitoring.

**4) Portfolio Monitoring and Trailing Stop Loss**

Each open position is checked daily for exits:

* **Trailing Stop Loss**:
  + After entry, the **maximum price** reached by the stock is tracked.
  + The stop-loss threshold is set as:

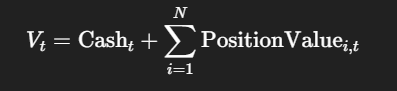


* + If the stock’s closing price falls below this trailing stop, the position is closed.
  + This ensures that **profits are locked in** as the stock rises, while limiting downside risk.
* **Exit Signals**:  
  If the indicator layer generates a sell/exit flag, the position is liquidated regardless of stop-loss level.

All exits account for **transaction and slippage costs**, ensuring realistic portfolio tracking.

**5) Daily Portfolio Valuation**

At the end of each day, the portfolio value is updated as:



Here, each position’s value is adjusted based on its entry price and current close. The resulting daily portfolio values form the **equity curve**, which is later analyzed for performance metrics like **CAGR, Sharpe ratio, and Max Drawdown**.

5. Hyperparameter Tuning and Backtesting

**1) Hyperparameter Tuning (best\_params\_fast)**

The first step was to systematically **search for the optimal parameters** of the technical indicators and portfolio construction rules.

* **Parameters Tuned**:
  + **MACD Long EMA**: [24, 26, 28]
  + **MACD Short EMA**: [11, 13, 15]
  + **Signal Line EMA**: [8, 9, 10]
  + **ADX Period**: [13, 15]
  + **Number of Stocks (no\_of\_stocks)**: best *n* stocks to include in each rebalance.
* **Indicator Initialization Requirement**:  
  Since MACD and ADX rely on moving averages, at least **3 months of prior data** are required before valid signals can be generated.  
  -This means that if the intended testing window is from *t* to *T*, the actual dataset must begin from *(t − 3 months)* to ensure indicators are correctly initialized.

The **Sharpe Ratio** was chosen as the primary metric since it balances return and volatility.

* **Output**:  
  The parameter combination yielding the **highest Sharpe Ratio** was stored as the best set.

**2) Rolling Backtesting Framework (backtest function)**

Instead of tuning parameters just once, I implemented a **rolling window framework**, which mimics how a live strategy would continuously adapt to changing market conditions.

* **Train-Test Split Design**:
  + A **12-month rolling training window** is used to find the best parameters.
  + These parameters are then **applied forward for the next 6 months** of trading (out-of-sample).
  + The window then rolls forward by 6 months, and the process repeats until the end of the dataset.
* **Data Handling**:
  + Each training and test set includes a **3-month buffer** for indicator initialization.
  + Yahoo Finance errors are handled by retrying until fewer than 5 tickers fail.
* **Execution Flow**:
  1. Tune parameters on the training year.
  2. Apply the best parameters to simulate the following 6-month test period.
  3. Store portfolio values across rolling windows in final\_portfolio.
* **Performance Visualization**:  
  Equity curves are plotted across the entire backtest horizon, showing cumulative portfolio evolution.

**3) Importance of this Rolling Design**

* **Realism**: Parameters are never chosen using future data. The rolling approach ensures decisions are based only on what was known up to that point.
* **Adaptability**: Financial markets evolve. The 12m → 6m scheme allows the model to **adapt to regime shifts** while not overreacting to short-term noise.
* **Risk Control**: Regularly re-selecting **no\_of\_stocks** prevents over-diversification or over-concentration as market leadership changes.
* **Avoiding Overfitting**: Splitting into repeated train-test cycles creates many out-of-sample validations, reducing the chance of lucky parameter fits.

## 6. Evaluation and Comparison with Market Index



Below is a direct comparison of the key performance metrics of Strategy 2 versus the Market Portfolio, accompanied by detailed commentary for each metric.

| **Metric** | **Market Portfolio** | **Strategy 2** | **Commentary** |
| --- | --- | --- | --- |
| Sharpe Ratio | 0.8108 | 1.0934 | Strategy 2 exhibits a higher Sharpe Ratio, indicating superior risk-adjusted returns. For every unit of risk, Strategy 2 generates more excess return compared to the market. This suggests better risk management or enhanced alpha generation. |
| Sortino Ratio | 0.9307 | 1.6463 | The Sortino Ratio, which considers only downside volatility, is much higher for Strategy 2. This means Strategy 2 not only delivers better risk-adjusted returns, but also protects against harmful drawdowns far more effectively than the market. |
| Profit Factor | 1.1697 | 1.2199 | A higher Profit Factor implies that the total gains created by Strategy 2 significantly outweigh the losses, making it a more robust and stable approach in the long run compared to the market portfolio. |
| Max Drawdown | -38.47% | -25.15% | Strategy 2 demonstrates a substantially lower maximum drawdown. This indicates improved capital preservation and lower portfolio stress in worst-case scenarios, which is especially valuable for risk-averse investors. |
| CAGR | 14.36% | 21.13% | The Compound Annual Growth Rate (CAGR) for Strategy 2 is notably higher, showcasing its superior compounding power and potential to grow capital more rapidly than merely tracking the market. |
| Total PnL | 10,472,000 | 17,964,330 | Strategy 2 generates significantly higher total profits over the backtest period, directly reflecting its ability to capitalize on market opportunities more effectively. |

## **6.1) Practical Implications and Usefulness**

* Superior Risk-Adjusted Returns:  
  Strategy 2’s higher Sharpe and Sortino ratios mean it offers both better average returns per unit risk and stronger performance during downturns. This makes it highly attractive for investors seeking to outperform the market without incurring excessive risk.
* Reduced Downside, Greater Stability:  
  The major improvement in Max Drawdown demonstrates Strategy 2 is less prone to deep portfolio losses, enabling investors to stay invested during turbulent periods and avoid panic selling, which is often a source of long-term underperformance.
* Improved Compounding:  
  With a CAGR substantially above the market, Strategy 2 is more suitable for long-horizon investors aiming to maximize wealth through consistent compounding rather than passive index exposure.
* Higher Absolute Returns:  
  The Total PnL outperformance means that investors following Strategy 2 could have achieved larger portfolio balances over the same duration, justifying the effort and discipline required for this rules-based approach.

## **6.2) Conclusion**

Overall, Strategy 2 outperforms the market index across virtually all key statistics, mainly by delivering higher returns with less risk and less severe losses. Practically, this translates to a more robust, actionable, and psychologically sustainable equity strategy for real-money investors—striking a compelling balance between risk management and long-term return generation.

If implemented with proper trading discipline and realistic execution assumptions, such a strategy could offer tangible improvements over passive index investing, especially for those with moderate risk tolerance seeking to preserve capital while generating enhanced growth.

## 7.Drawbacks, Causes, and Strategic Pivot

While the initial long-only strategy produced strong results during sustained uptrends, it consistently underperformed—and, in some cases, generated negative returns—during sideways and downtrending market conditions. This regime sensitivity significantly impacted overall portfolio performance and risk.

## **7.1) Drawbacks and Causes**

* Underperformance in Sideways/Downtrending Markets:  
  The long-only bias led to repeated trade entries even when market conditions were unfavorable. In both non-trending and declining regimes, the strategy’s long trades frequently hit stop-loss levels, leading to a string of small losses.
* Impact of Transaction and Slippage Costs:  
  Frequent stop-outs in choppy or declining conditions, coupled with inevitable transaction and slippage expenses, eroded any limited profits that were captured in minor upswings. Over time, these costs materially dragged down the portfolio’s net results.
* Mean-Reversion Trap in Sideways Markets:  
  Sideways markets often exhibited mean-reverting characteristics. My momentum-focused model would identify potential uptrends and enter trades, but the regime would frequently revert, triggering stop-losses and compounding losses. This “false breakout” cycle penalized returns each time the sideways regime persisted.
* Regime Sensitivity:  
  The strategy’s strong dependency on market directionality became evident: while it excelled in clear bull phases, it was highly vulnerable to whipsaw and drawdown in all other regimes.

## **7.2) Strategic Pivot**

To address these regime-related drawbacks and substantially improve portfolio resilience, I reengineered the approach with the following key pivots:

* Regime Detection Overlay:  
  I incorporated a market regime detection mechanism to actively classify periods as uptrending, sideways, or downtrending. The core trend-following logic was then applied only during identified uptrend periods—while completely avoiding trade entries in sideways and downtrend regimes.
* Capital Preservation in Challenging Regimes:  
  By abstaining from trading during unfavorable market climates, the strategy avoided unnecessary stop-outs and minimized the portfolio drag from excessive transaction costs and whipsaws. During these periods, the system shifted to capital preservation rather than forced participation.
* Opportunity for Mean-Reversion Strategies:  
  With capital idle during non-trending periods, an additional benefit emerged: the flexibility to deploy unallocated resources into separate, mean-reverting strategies that are actually optimized for sideways markets. This not only reduces drawdowns but also creates new avenues for positive return in otherwise challenging environments.

## **7.3) Advantages of the Pivot**

* The portfolio is now protected from the repeated penalization of sideways and bear regimes, thanks to selective participation based on regime detection.
* Transaction and slippage costs are reduced by trading less frequently and only when odds are favorable.
* There is potential for further diversification and return enhancement through the deployment of mean-reverting tactics during “rest periods” of the primary strategy, maximizing capital efficiency.

This strategic pivot resulted in a more robust and adaptable investment process, tailored to the realities of market cycles, with improved risk management and capital utilization across different environments.

## 8. Market Regime Strategy: Features, Operation, and Performance Analysis

## **8.1) Additional Filters: Supertrend Indicator**

The Supertrend indicator is a popular trend-following tool used to identify whether a market is in a bullish or bearish phase. It is calculated using the average true range (ATR) to measure market volatility and sets a dynamic trailing stop level above or below price, depending on the trend direction.

* When the price closes above the Supertrend line, it signals a bullish trend, suggesting that buying pressure dominates and upward momentum is likely.
* Conversely, when the price closes below the Supertrend line, it signals a bearish trend, indicating potential downward momentum.

The Supertrend’s main advantage is its ability to adapt to changing volatility and price trends in real-time, providing clear and timely buy or sell signals.

In this strategy, the Supertrend is applied to market-level data (specifically, the Nifty 50 index) to classify the overall market regime as bullish or bearish. Whenever the Supertrend indicates a bearish regime, the portfolio is fully liquidated (all positions closed), and the strategy holds cash until a bullish signal appears again. This prevents holding or acquiring long positions during unfavorable market conditions, reducing downside risk and excess trading during non-trending phases.

## **8.2) Working of the Strategy (Code Explanation)**

The function run\_strategy\_regime orchestrates the strategy execution combining price data, market regime filtering, position management, and trading rules:

* Initialization:
  + Starts with an initial cash balance.
  + Positions are tracked in a dictionary with allocation, entry price, max price since entry, and entry date.
* Unified Trading Calendar:
  + Constructs a comprehensive set of trading dates by merging dates from all stocks and the market regime data, ensuring synchronized processing.
* Daily Iteration:
  + Each date in the trading calendar is processed sequentially.
* Step 0: Check Market Trend
  + The market regime is checked using the market trend dataframe (e.g., Supertrend signals).
  + If the current date has no market data, the strategy defaults to an uptrend assumption.
* Step 1: Forced Exit During Bearish Market
  + If the market is not in an uptrend and there are open positions, all are liquidated at the current price, accounting for transaction and slippage costs.
  + The portfolio is moved to cash to avoid risk exposure in bearish regimes.
* Step 2: Trade Entry During Uptrend
  + Only if the market is in an uptrend does the function evaluate stocks for buy signals.
  + Stocks with a ‘buy’ signal and a valid combined score are considered, and the top candidates are selected based on their score.
  + Capital is allocated among selected stocks, updating position details for new or existing holdings.
* Step 3: Manage Portfolio and Exits
  + The portfolio value is updated daily considering price changes.
  + Positions are monitored for exit conditions:
    - Explicit exit signals.
    - Trailing stop losses set at a percentage below the maximum price achieved.
    - Maximum holding days to limit exposure duration.
  + Positions meeting exit conditions are sold, and cash balance updated net of costs.
* Tracking and Reporting:
  + Tracks days without trading activity and days missing data for transparency.
  + Returns the portfolio value over time, final cash balance, and remaining open positions at the end of the backtest.

## **8.3) RESULTS, ANALYSIS AND CONCLUSION 8.3.1) Comparative Table**

| **Metric** | **Market Portfolio** | **Long-Only Strategy** | **Market Regime Strategy** |
| --- | --- | --- | --- |
| Sharpe Ratio | 0.8108 | 1.0934 | 1.2518 |
| Sortino Ratio | 0.9307 | 1.6463 | 1.4502 |
| Profit Factor | 1.1697 | 1.2199 | 1.3340 |
| Max Drawdown | -0.3847 | -0.2515 | -0.1449 |
| CAGR | 14.36% | 21.13% | 16.67% |
| Total PnL | 10,472,000 | 17,964,330 | 12,738,320 |

## **8.3.2) Analysis & Insights**

* Risk-Adjusted Returns (Sharpe/Sortino Ratios):
  + Both custom strategies deliver much higher Sharpe and Sortino ratios than the market, meaning you earn more return for each unit of risk.
  + The Market Regime Strategy achieves the highest Sharpe ratio (1.25), indicating maximized overall risk-adjusted performance.
  + The Long-Only Strategy edges out on Sortino Ratio, signaling better performance specifically in limiting downside risk, but the Market Regime approach still excels over the market.
* Profit Factor:
  + The Market Regime Strategy’s profit factor (1.33) is highest, showing most consistent net positive trades relative to losses, which reflects superior trade selection and risk control.
* Drawdown:
  + The Market Regime Strategy slashes maximum drawdown to -14.5%, the lowest among all. This is crucial for real investors: less severe losses mean less psychological and financial pain, and greater resiliency in volatile markets.
  + The Long-Only Strategy also improves over the market, but not as dramatically.
* Growth Rate (CAGR):
  + The Long-Only Strategy produces the highest CAGR (21.13%), reflecting very strong capital compounding in bullish conditions.
  + The Market Regime Strategy’s CAGR (16.67%) is lower, but still outpaces the market index by a wide margin (14.36%) and comes with significantly lower risk.
* Absolute Returns (Total PnL):
  + The Long-Only Strategy shows the highest absolute profit, due to aggressive participation in uptrends.
  + The Market Regime Strategy’s absolute profit is lower but demonstrates a much smoother ride with smaller drawdowns.
  + Both strategies outperform the index in total profit

## **8.3.3) Practical Takeaways**

* Market Regime Strategy is Most Balanced:  
  Although not always maximizing absolute returns, the inclusion of regime filtering delivers the best blend of high risk-adjusted return (Sharpe), minimized drawdown, and consistent profit factor—all highly prized by professional investors.
* Long-Only Wins in Bulls, Loses in Choppy/Down Markets:  
  The long-only approach benefits handsomely from strong bull markets but suffers in sideways and declines, inflating drawdowns and oftentimes leading to larger psychological stress on investors.
* Market Regime Strategy for Real-World Use:  
  For most practical investors, the market regime approach wins decisively for its smoother equity curve, lower drawdowns, more reliable risk control, and flexible capital deployment.  
  In periods of trend clarity, it participates; when markets turn indecisive or bearish, it prioritizes capital preservation or opens the door to alternative, regime-suited tactics.
* Compared to Buy-and-Hold:  
  Both custom strategies far exceed the index portfolio on virtually every metric, showing the value of active strategy and regime awareness.

In summary:  
If absolute maximum growth is your sole objective—and you’re comfortable enduring higher drawdown—the pure Long-Only Strategy has merit. However, if you want high returns with sleeker risk, better drawdown control, and a strategy more sensitive to real market structure and investor psychology, the Market Regime Strategy is a clear improvement and the most practical solution for sophisticated, risk-aware investors.