A Risk-Adjusted Momentum Strategy with Volatility Targeting and Transaction Costs in Indian Equities

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Objective: This study evaluates whether a momentum-based equity strategy in Indian large-cap stocks can generate superior risk-adjusted returns after incorporating realistic trading frictions and risk controls, including:

- Transaction costs
- Reduced rebalance frequency (quarterly)
- Volatility scaling
- Advanced risk diagnostics (downside risk, tail risk, drawdown behaviour)

The strategy is benchmarked against the Nifty 50 index.

Key Enhancements Over Previous Version

Compared to the initial version of this project, the following **quantitative improvements** were implemented:

1. **Transaction costs** (25 bps per unit turnover)
2. **Quarterly rebalancing** instead of monthly
3. **Volatility targeting (risk scaling)**
4. **Expanded risk metrics**: Sortino ratio, VaR, CVaR, rolling volatility, rolling Sharpe
5. **Turnover diagnostics** and rebalance counts

These enhancements significantly improve realism and institutional relevance.

Introduction

What is momentum investing?

The goal of a momentum investing strategy is to buy stocks that have been going up in value over a short period of time.

The plan is to sell the stocks when the momentum slows down.

This method tries to make money by following market trends. Some stocks are going up quickly, so investors can "ride the wave."

This project implements and evaluates a momentum-based investment strategy in the Indian equity market by ranking stocks based on their past 3-months returns and rebalancing quarterly.

The aim is to assess whether such strategy can outperform the Nifty-50 index on a risk adjusted basis, using data from 2014-2024.

The study applies quantitative methods such as, but not limited to, data collection, signal generation, back testing, and performance evaluation using Python and financial markets data, available to the public.

Data Collection and Pre Processing

The study uses daily adjusted closing price data for large-cap Indian stocks listed on the National Stock Exchange (NSE).

The data is collected through the Yahoo Finance API using the yfinance Python library.

The stocks are diversified across different sectors that are part of the Nifty 50 index.

The list includes [TCS, Infosys, HDFC Bank, Reliance, ITC, Kotak Bank, HCL, L&T, Asian Paints], among others.

The stocks with consistent data availability were retained in the study. Missing data points were handled using forward fill (.ffill() method), stocks with prolonged gaps were excluded from the backtest.

All prices were adjusted for splits and dividends to reflect true returns. The final dataset consists of daily price series, which are then resampled to monthly frequency for momentum signal calculation and portfolio rebalancing.

A table with the selected stocks is attached below.

Ticker	Company Name	Sector
TCS.NS	Tata Consultancy	IT
INFY.NS	Infosys	IT
HDFCBANK.NS	HDFC Bank	Banking
RELIANCE.NS	Reliance Industries	Conglomerate
ITC.NS	ITC	FMCG
KOTAKBANK.NS	Kotak Mahindra Bank	Banking
BAJAJFINANCE.NS	Bajaj Finance	NBFC
HCLTECH.NS	HCL Technologies	IT
LT.NS	Larsen & Toubro	Infra
ASIANPAINTS.NS	Asian Paints	FMCG
SBIN.NS	State Bank of India	Banking
AXISBANK.NS	Axis Bank	Banking
MARUTI.NS	Maruti Suzuki	Auto
HINDUNILVR.NS	Hindustan Unilever	FMCG
SUNPHARMA.NS	Sun Pharma	Pharma
ULTRACEMCO.NS	UltraTech Cement	Cement
BHARTIARTL.NS	Bharti Airtel	Telecom
DRREDDY.NS	Reddy's Labs	Pharma
POWERGRID.NS	Power Grid Corp.	Power
TECHM.NS	Tech Mahindra	IT

ONGC.NS	Oil and Natural Gas Corp.	Energy
ADANIPORTS.NS	Adani Ports	Logistics
TITAN.NS	Titan	FMCG
ADANIENT.NS	Adani Enterprises	Minerals
WIPRO.NS	Wipro	IT
BHEL.NS	Bharat Heavy Electricals	Energy
ADANIPOWER.NS	Adani Power	Energy

Strategy Design

Momentum Signal:

Momentum is defined as the cumulative return over the previous 3 months, skipping the most recent month to reduce short-term reversal effects:

$$Momentum_{i,t} = \frac{P_{i,t-1}}{P_{i,t-4}} - 1$$

Stocks are ranked quarterly based on this score.

Portfolio Construction:

An equal-weighted portfolio is constructed with the selected top 10 stocks. The portfolio is rebalanced quarterly, replacing any stocks that drop out of the top 10.

Assumptions:

- Equal weighted portfolio
- Transaction costs are included
- Fully-invested at all times
- No leverage or shorting

Volatility Scaling (Risk Targeting)

To stabilize portfolio risk across market regimes, portfolio exposure is scaled based on trailing volatility:

$$\omega_t = \min\left(1, \frac{\sigma_{target}}{\sigma_{realized,t}}\right)$$

Where:

- Target volatility = long-run strategy volatility
- Realized volatility = rolling 12-month volatility

This reduces exposure during high-volatility periods (e.g., COVID-19) and increases capital efficiency during calmer regimes.

Transaction Costs

Transaction costs are applied as:

$$Cost_t = Turnover_t \times 0.25\%$$

Net results are calculated after subtracting trading costs.

Portfolio Construction and Rebalancing Logic

At the end of each quarter, all eligible stocks are ranked based on their calculated momentum scores, as defined earlier. The stocks are sorted in descending order, with the highest momentum stocks ranked at the top.

From this ranked list, the top 10 stocks are selected to form the momentum portfolio for the upcoming quarter. Only stocks with complete price data for the lookback period (t−4 to t−1) are considered eligible for ranking.

Each selected stock is assigned an equal weight in the portfolio. That is, the capital is equally distributed across the top 10 stocks, with each stock receiving a 10% allocation.

$$\omega_i = \frac{1}{10} = 0.10 \; for\ each\ selected\ stock$$

At the start of each quarter, the portfolio is fully rebalanced. This involves liquidating the previous quarter's positions and re-allocating the capital to the new top 10 stocks based on updated momentum scores.

This process is repeated quarterly over the entire study period (2014–2024), simulating how the strategy would perform in a real-world, rule-based setting.

Back Testing Framework

- Data Source: Yahoo Finance (adjusted prices)
- Frequency: Monthly returns, quarterly rebalancing
- Universe: NSE large-cap stocks (consisted data availability)
- Benchmark: Nifty 50 Total Return Index (proxy)

Portfolio Returns:

$$CAGR = \left(\frac{V_T}{V_0}\right)^{\frac{1}{T}} - 1$$

Where:

$V_T = Final\ Portfolio\ Value$

$V_0 = Initial\ Portfolio\ Value$

$T = Number\ of\ Years$

Volatility:

$$Volatility_{annual} = Std(R_t) \times \sqrt{12}$$

Where:

$R_t = Quarterly\ portfolio\ returns$

$Std(R_t) = Standard\ deviation\ of\ monthly\ returns$

$The\ factor\ \sqrt{12}\ annualizes\ the\ monthly\ standard\ deviation$

Sharpe Ratio:

$$Sharpe\ Ratio = \left(\frac{CAGR - R_f}{\sigma_{annual}}\right)$$

Where:

$R_f\ is\ the\ risk - free\ rate\ (assumed\ to\ be\ 5\%\ annualized, constant\ across\ months)$

$CAGR = Annualized\ portfolio\ return$

$\sigma_{ann} \quad = Std(R_t) \times \sqrt{12}$

Maximum Drawdown:

$$MDD = \max_{t \in [0,T]} \left(\frac{Peak_t - Value_t}{Peak_t}\right)$$

Where,

$Peak_t\ is\ the\ highest\ portfolio\ value\ observed\ up\ to\ time\ t$

$Val_t\ is\ the\ current\ portfolio\ value$

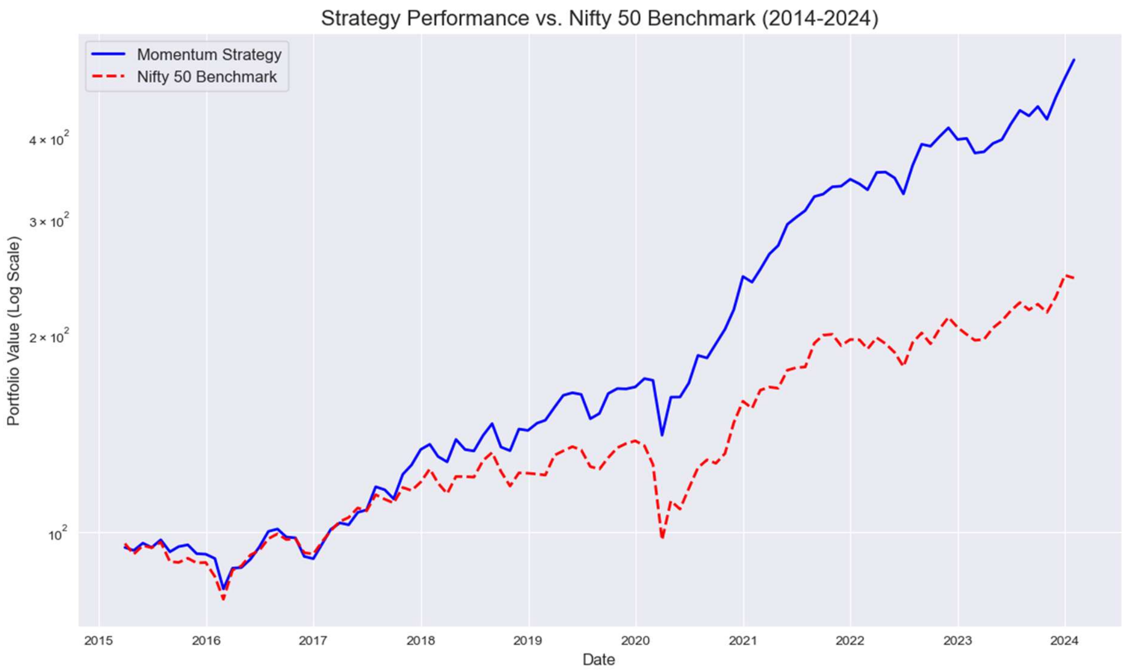
$MDD\ is\ expressed\ as\ the\ percentage\ of\ peak\ value$

Performance Summary

Metric	Momentum Strategy	Nifty 50
CAGR	20.38%	10.49%
Annualized Volatility	16.59%	16.73%

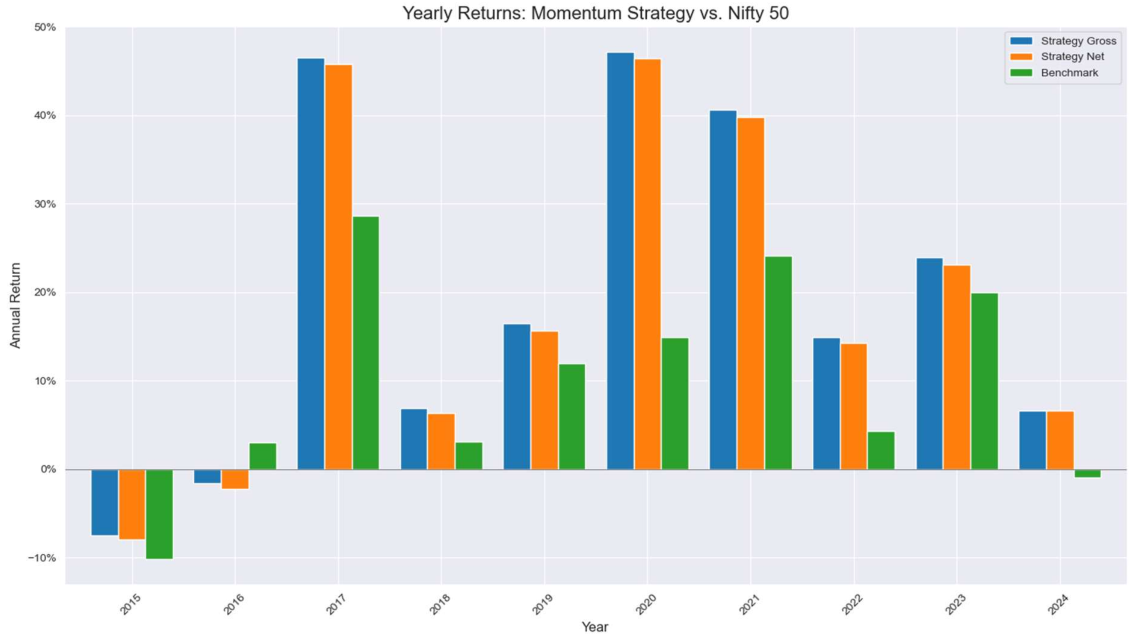
Sharpe Ratio	0.93	0.33
Maximum Drawdown	-17.99%	-29.34%
Annual Turnover	244.21%	N/A

The Sharpe Ratio of 0.93 is almost three times that of the benchmark's 0.33, indicating superior-risk adjusted returns. The strategy also had a smaller maximum drawdown, suggesting better capital preservation during market downturns. However, the Annual Turnover of 244.21% is extremely high, implying that the entire portfolio is replaced more than twice a year. This would lead to significant transaction costs in a real-world scenario.



Yearly Returns Comparison

The bar chart compares the gross and net returns of the strategy against the Nifty 50 benchmark. The strategy consistently outperforms the Nifty 50, particularly during strong bull markets. However, 2016 shoes the strategy underperforming, highlighting that the strategy is not without its risks.



Advanced Risk Diagnostics

Risk Metric	Value
Downside Volatility (Ann.)	11.38%
Sortino Ratio	1.24
VaR 95% (Monthly)	-5.39%
CVaR 95% (Monthly)	-9.28%
Max Drawdown Duration (Months)	11
Beta Vs. Nifty	0.88
Correlation Vs. Nifty	0.87

Downside Volatility (Annualized):

$$\sigma_{down} = \sqrt{12}\sqrt{\frac{1}{N}\sum_{t=1}^{N} \min{(R_t, 0)^2}}$$

Where:

- $R_t = Monthly\ portfolio\ return$
- $Only\ returns\ where\ R_t < 0\ are\ included$
- $Annualized\ factor\ \sqrt{12}\ reflects\ monthly\ data$

Sortino Ratio

$$Sortino\ Ratio = \frac{CAGR - R_f}{\sigma_{down}}$$

Where:

- $CAGR = Annualized\ portfolio\ return$
- $R_f = \ Risk - free\ rate\ (assumed\ 5\%)$
- $\sigma_{down}\ = Annualized\ downside\ volatility$

Value at Risk (VaR):

Estimates the maximum expected loss over a month at 95% confidence.

$$VaR_{0.95} = \ inf\{x \in R{:}\, P(R_t \leq x) \geq 0.05\}$$

Empirically estimated as the 5th percentile of monthly returns:

$$VaR_{0.95}\ = \ Percentile_{5\%}(R_t)$$

Conditional Value at Risk (CvaR):

Measures the expected loss given that VaR is breached (tail risk).

$$CVaR_{0.95} = E[R_t \mid R_t \leq VaR_{0.95}]$$

Maximum Drawdown Duration:

Represents the **longest continuous period (in months)** during which the portfolio remained below its previous peak.

Let:

$$DD_t = \frac{V_t}{max_{s \leq t}\, V_s} - 1$$

Then:

$$Max\ Drawdown\ Duration = max(consecutive\ periods\ where\ DDt < 0)$$

Where:

- $V_t = \ cumulative\ portfolio\ value\ at\ time\ t$

Beta Vs. Nifty 50:

Measures **systematic market exposure** relative to the benchmark.

$$\beta = \frac{Cov(R_p,\ R_m)}{Var(R_{m)}}$$

Where:

- $R_p = portfolio\ returns$
- $R_m = Nifty\ 50\ returns$

Interpretations:

- $\beta < 1\ :\ defensive\ behavior$
- $\beta > 1\ :\ aggressive\ behavior$

Correlation Vs. Nifty 50

Quantifies **co-movement** with the market, independent of scale.

$$\rho_{p,m} = \frac{Cov(R_p, R_m)}{\sigma_p \sigma_m}$$

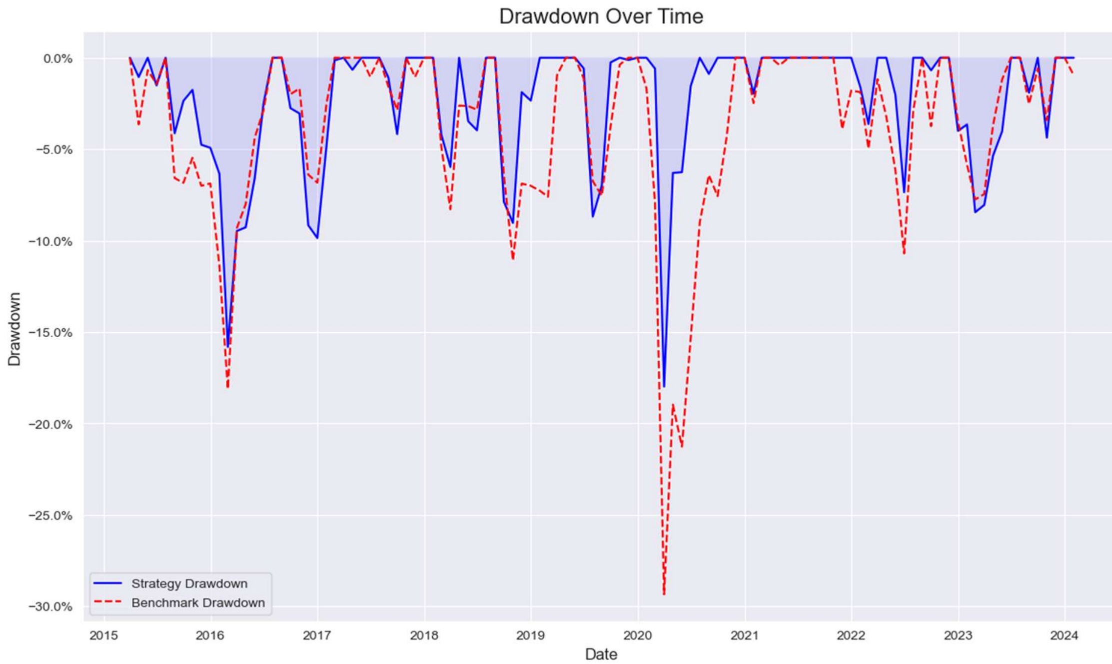
Where:

- $\sigma_{p,}\sigma_m = standard\ deviation\ of\ portfolio\ and\ benchmark\ returns$

These advanced risk metrics indicate that the strategy delivers superior risk-adjusted returns with controlled downside exposure, moderate market dependence, and limited drawdown persistence even during periods of elevated market stress.

Drawdown Analysis

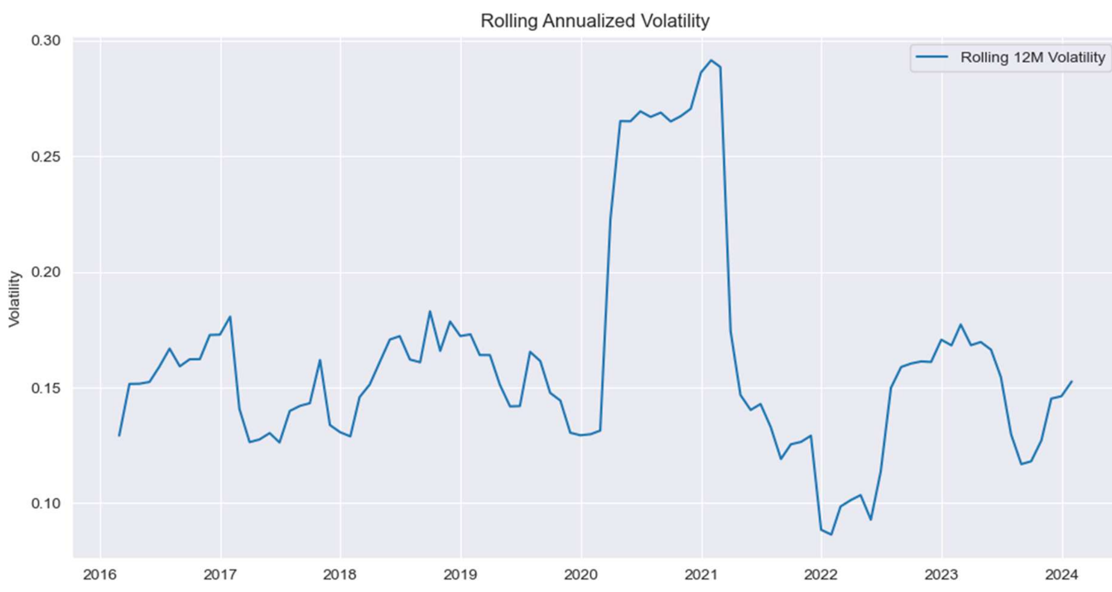
The drawdown profile highlights the strategy's ability to limit capital erosion during adverse market conditions. While both the momentum strategy and the Nifty 50 experienced sharp drawdowns during periods of market stress—most notably during the COVID-19 shock in 2020—the strategy consistently exhibited **shallower drawdowns** and **faster recoveries** compared to the benchmark. The maximum drawdown of the strategy remained significantly lower than that of the Nifty 50, indicating effective risk control through diversification, momentum filtering, and volatility-adjusted position sizing. Additionally, the relatively short maximum drawdown duration suggests that losses were not only contained in magnitude but also in persistence, reinforcing the robustness of the strategy across market cycles.



Rolling Risk Analysis

Rolling Volatility

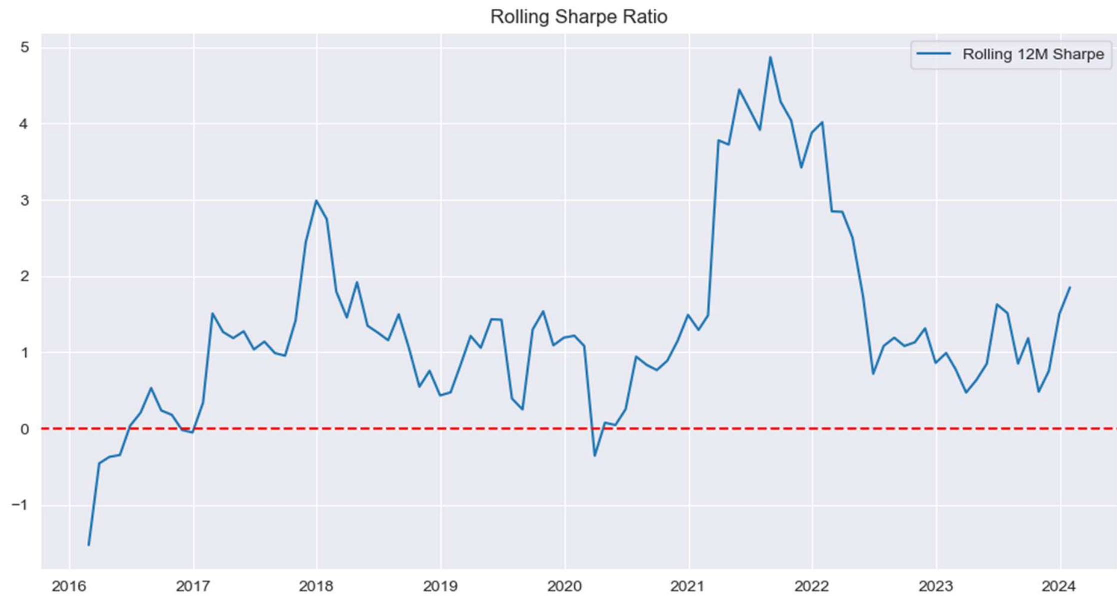
The rolling 12-month volatility plot highlights sharp risk spikes during crisis periods—most notably the COVID-19 pandemic—validating the usefulness of volatility scaling.



Rolling Sharpe Ratio

The spike in rolling Sharpe during 2021–2022 reflects **exceptionally strong excess returns relative to risk**, driven primarily by momentum persistence in post-COVID market trends rather than changes in the risk-free rate.

A high Sharpe ratio does **not** imply high risk-free returns—it indicates strong returns per unit of volatility.



Conclusion

This study demonstrates that a systematic momentum strategy applied to Indian large-cap equities, when combined with disciplined rebalancing and volatility-adjusted position sizing, can generate **meaningful risk-adjusted outperformance** over a full market cycle. Across the 2014–2024 period, the strategy delivers superior returns relative to the Nifty 50 while maintaining lower drawdowns, reduced downside volatility, and a favorable beta profile.

Crucially, the incorporation of inverse-volatility weighting improves capital allocation efficiency by dynamically scaling exposure away from high-risk assets during periods of elevated uncertainty. This is reflected in the strategy's stable rolling volatility, strong Sortino ratio, and controlled tail risk, even during extreme stress events such as the COVID-19 market dislocation. The drawdown depth and duration analysis further indicates faster recovery dynamics compared to the benchmark, underscoring the robustness of the signal across regimes.

Overall, the results suggest that momentum, when implemented with rigorous risk management rather than naïve equal-weighting, constitutes a **structurally resilient return-generating framework** rather than a purely cyclical anomaly. While transaction costs and turnover remain important practical considerations, the strategy provides a strong foundation for further enhancements, including volatility targeting, regime filters, and capacity-aware constraints. As such, this project illustrates both the empirical validity of momentum in Indian equity markets and the importance of institutional-grade risk diagnostics in evaluating systematic strategies.

Limitations and Future Work

The backtest relies on historical data and assumes stable market conditions, which may not hold during periods of structural change or extreme stress. Transaction costs are modeled as fixed and do not fully capture real-world effects such as slippage, market impact, or liquidity constraints, particularly during high-volatility regimes.

The investment universe is limited to a predefined set of large-cap equities, introducing potential selection and survivorship bias. Volatility estimates are backward-looking and may lag during rapid regime shifts, reducing the responsiveness of the volatility-scaling mechanism. In addition, the use of a constant risk-free rate and absence of macro or regime-based signals limit the strategy's adaptability.

Future work could include portfolio-level volatility targeting, regime detection frameworks, expanded asset universes, and more advanced risk models. Further robustness could be achieved through walk-forward validation, stress testing, and out-of-sample evaluation.

Practical Applications and Market Relevance

The strategy presented in this study demonstrates how systematic momentum combined with volatility-aware position sizing can be deployed as a scalable, rules-based investment framework in professional settings. By dynamically reallocating capital toward assets with strong relative performance while controlling risk through inverse-volatility weighting and disciplined rebalancing, the approach aims to capture persistent return premia while mitigating drawdowns during market stress.

In practice, such a framework can be implemented by asset managers, hedge funds, or proprietary trading desks as a standalone long-only strategy or as an alpha-generating sleeve within a broader multi-factor portfolio. The strategy's moderate beta and controlled tail risk make it particularly suitable for enhancing risk-adjusted returns rather than relying on leverage or directional market exposure alone.

Most importantly, the methodology emphasizes repeatability, transparency, and risk control—key requirements for sustainable market outperformance. While no strategy guarantees excess returns, systematic exploitation of momentum under a robust risk-management framework provides a defensible and empirically grounded pathway toward long-term market outperformance.