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Quantitative Trading Strategy, Backtesting, and Performance Analysis Using Python: A Data - Driven Analysis

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Abstract

Background: The Nepal Stock Exchange (NEPSE) remains dominated by traditional trading behaviors, often driven by intuition and Fear of Missing Out (FOMO), rather than data or models. Despite global progress in algorithmic strategies, quantitative methods remain underutilized in Nepal's equity market.

Purpose: This study aims to design, implement, and evaluate a rule-based, long-only quantitative trading strategy tailored for NEPSE, comparing its performance to the standard Buy & Hold approach. The goal is to assess whether systematic models can improve capital protection and risk-adjusted performance in inefficient market settings.

Design/methodology/approach: A Python-based backtesting framework is developed, combining momentum and mean-reversion indicators such as the Z-score, Relative Strength Index (RSI), and a 240-day moving average to generate buy signals. Realistic trading constraints are incorporated, including dynamic position sizing based on risk, trade limits, and cool down periods. Performance is benchmarked against Buy & Hold using financial metrics such as CAGR, Sharpe Ratio, Sortino Ratio, Maximum Drawdown, Win Rate, Profit Factor, and Recovery Factor. Monte Carlo simulations, return distribution analysis, and sensitivity checks are applied to ensure robustness.

Results: The stategy outperform Buy & Hold in terms of raw daily returns; it also shows superior performance on risk-adjusted metrics. It achieves higher Sharpe and Sortino ratio and significantly lower drawdowns, cofirming better downside risk control and capital preservation.

Conclusions: The findings suggest that even simple, rule-based quantitative systems can offer tangible benefits in emerging markets, such as NEPSE by reducing behavioral noise and enhancing portfolio discipline. The study supports the broader adoption of systematic methods in local trading environments.

Keywords: Quantitative Trading, NEPSE, Risk Management, Algorithmic Strategy, Backtesting.

1. Introduction

A quantitative trading strategy is an organized, algorithm-driven approach to trading that usesstatistical methods and numerical data to inform buy and sell choices (Devapitchai et al., 2024). These techniques examine both historical and contemporary market data to identify trends and possibilities rather than depending solely on subjective assessment. They can fully automate operations like data processing, signal production, order placement, and performance evaluation because they are typically developed in languages like Python (Jansen, 2018). Quantitative trading minimizes emotional influence and improves the accuracy and consistency of investment decisions by implementing explicit, predetermined procedures (Gunawan, 2024). These tactics often use multiple quantitative indicators, machine learning techniques, factor analysis, and predictive modelling.

Over recent decades, quantitative trading has transformed global financial markets through the application of mathematical modeling, statistical analysis, and algorithmic execution (Chan, 2013). These rule-based, data-driven models process vast amounts of information rapidly, reducing emotional decision-making. While such approaches are standard in developed markets, their adoption in emerging markets, such as Nepal, remains limited (Acharya, 2023). The Nepal Stock Exchange (NEPSE), characterized by low liquidity, high volatility, and a dominant presence of retail investor, reflects an underdeveloped market where classical finance theories often fail to capture unique behavioral dynamics. Most investors rely on intuition, peer influence, and speculation rather than systematic, data-driven strategies (Acharya, 2023), resulting in persistent inefficiencies.

The Nepal Stock Exchange (NEPSE) is still lagging behind the global trend toward more sophisticated algorithmic and quantitative trading systems due to several technological, legal, and infrastructure constraints (KC et al., 2025). The ban on short sales, antiquated trading methods, and a broad ignorance of contemporary ideas such as risk-adjusted performance evaluation, are some of the main challenges. These obstacles prevent the market from implementing data-driven trading strategies, which are prevalent in many international financial markets. Acknowledging these difficulties, this study aims to bridge the current gap by developing, implementing, and assessing quantitative trading techniques that are especially suited to NEPSE's operational environment. By employing a strategic approach the study aims to show the usefulness, possible advantages, and general viability of incorporating quantitative trading frameworks into Nepal's developing financial market.

Traditional trading methods still play a major role in the Nepal Stock Exchange (NEPSE), where investor decisions are sometimes affected more by rumors, intuition, and FOMO than by empirical models or analytical tools (Kumar & Poudel, 2025). Although algorithmic and quantitative trading have become increasingly popular in international financial markets, Nepal's equity market has yet to fully utilize these data-driven strategies (Nepal et al., 2025). The market's ability to benefit from methodical decision-making, impartial risk assessment, and improved portfolio discipline is constrained by this lack of adoption. The current study aims to bridge this gap by developing, implementing, and thoroughly assessing a rule-based, long-only quantitative trading strategy tailored to NEPSE's market circumstances. The study investigates whether structured, algorithmic approaches can deliver better risk-adjusted returns and greater capital preservation in a comparatively inefficient and behavior-driven trading environment by comparing the model's results with those of the traditional buy-and-hold strategy.

Specifically, the research contributes by applying modern quantitative approaches mean reversion and momentum strategies using indicators like Z-score, 240-day moving average (MA240), and Relative Strength Index (RSI) comparing their performance with the traditional buy-and-hold approach through metrics such as CAGR, Sharpe ratio, Sortino ratio, and Maximum Drawdown and statistically validating results using Monte Carlo simulation, sensitivity analysis, Z-test, and the Kolmogorov-Smirnov test. Ultimately, this study demonstrates the feasibility of quantitative trading in a low-liquidity environment, such as NEPSE, and offers insights for policymakers, institutional investors, and regulators seeking to enhance market efficiency and transparency.

2. Literature Review

Theoretical Framework and Rationale for Strategy Design

Quantitative strategies in developed markets rely on data and algorithms to minimize emotional bias in trading (Chan, 2009). Foundational theories such as the Efficient Market Hypothesis (Fama, 1970) and the Random Walk Hypothesis (Malkiel, 1973) suggest that all available information is already reflected in prices, meaning that future returns cannot be reliably predicted from past prices. These ideas underpin passive strategies, such as Buy & Hold, which assume that consistent outperformance through active trading is statistically unlikely. Behavioral finance challenges this view by showing that investors are not perfectly rational. Cognitive biases, herd behavior, and emotional overreactions often distort prices, particularly in retail-dominated markets like NEPSE, creating inefficiencies such as momentum and mean reversion (Acharya, 2023; Barberis et al., 1998; Thaler, 1999). When such inefficiencies are systematically identified and exploited, they provide a theoretical basis for rule-based quantitative trading. Building on this behavioral foundation, the proposed strategy integrates both mean-reversion and momentum elements through the Z-Score, RSI, and the 240-day moving average (MA240). The Z-Score detects extreme deviations from the mean caused by panic or euphoria, while the RSI identifies overbought or oversold conditions reflecting investor exhaustion. The long-term market regime filters ensure that trades align with the broader trend and reduce premature entries. Together, these components form a disciplined system designed to exploit behavioral inefficiencies inherent in NEPSE's market structure. We hypothesize that this systematic approach, which involves buying in oversold conditions during uptrends and moving to cash in downtrends, will lead to superior risk-adjusted performance and improved capital preservation compared to passive investing.

Empirical Review

In emerging and developing markets, empirical studies are increasingly showing that market inefficiencies are not just theoretical but also observable and exploitable. Chaudhuri and Wu (2003) found that stock-price indexes in 17 emerging markets exhibited mean reversion, rejecting the random walk hypothesis. Rule-based strategies utilizing momentum and reversal indicators can offer better downside protection and higher risk-adjusted returns compared to traditional approaches.

In India, momentum and indicator-based strategies, such as the MACD, have been shown to outperform passive benchmarks in equity markets (Subramanian & Balakrishnan, 2014). Similarly, in Bangladesh, technical indicators, including the Relative Strength Index (RSI), MACD, and moving averages, demonstrated significant predictive power for stock price movements on the Dhaka Stock Exchange (Banik, 2014). Tadas et al. (2023) test a range of technical trading strategies (momentum, moving averages, etc.) on Indian large-cap stocks (Nifty 50 companies). They report that specific rules yield statistical out performance versus passive buy and hold in their sample period. This point supports the case that in emerging/retail-dominated markets, systematic rule-based approaches can add value. Studies reveal that trading strategies based on moving averages and RSI consistently beat buy-and-hold approaches on the Karachi Stock Exchange, especially when evaluated with risk-adjusted performance metrics (Khan, 2016).

Butt et al. (2021) revisit the momentum effect across 19 emerging market countries. They show that while momentum profits are present, they tend to be weaker than in developed markets; moreover, momentum returns are negatively impacted in down-market states and by higher investor risk aversion. The implication is that strategy design in emerging markets must account for higher crash risk, market fragility, and structural differences.

In the U.S. and other advanced markets, momentum-based trading strategies have been documented with consistent excess returns. For example, a study covering 12-month prior returns followed by a six-month holding period found that stocks with clearer prior trends delivered approximately 11.34% annualized returns, compared to 5.06% for standard momentum in the U.S. market (Asem & Tian, 2010). Another international study encompassing the U.S., U.K., Japan, and other developed markets shows that the size, value, and momentum strategies share a common risk-factor structure across geographies, confirming that momentum premia are robust even in highly efficient markets (Goyal et al., 2025).

While these markets share structural traits such as volatility, liquidity issues, and retail dominance, the Nepalese market, represented by NEPSE remains empirically underexplored. Most academic focus has been on macroeconomic variables such as remittance flows, interest rate impacts, or GDP correlations. Few studies, if any, have tested algorithmic or rule-based strategies, making NEPSE a prime candidate for testing simple but structured quantitative models.

Research Gap

Despite the growing body of empirical work in South Asian capital markets, NEPSE has remained largely excluded from rigorous analysis of quantitative trading models. The current literature on NEPSE is sparse in micro-level trading insights and almost entirely lacks algorithmic experimentation. Tools such as Z-score filters, RSI thresholds, dynamic position sizing, or Monte Carlo simulations have not yet been applied in a Nepalese context. However, these techniques are common in global quantitative research.

This gap is significant, especially given the behavioral nature of NEPSE's retail-dominated structure and the lack of regulatory support for advanced trading mechanisms such as short selling. Without empirical validation, local investors and institutions continue to operate on heuristics, speculation, and emotion rather than statistical evidence. Therefore, a structured, backtested, and statistically validated trading model for NEPSE fills an essential void in both academic and practical domains.

Conceptual Framework and Hypotheses

This study introduces a long-only quantitative trading strategy tailored for NEPSE, using a combination of RSI, Z-score, and a 240-day moving average (MA240). These indicators form the core signal-generation mechanism within a Python-based backtesting engine. The system incorporates realistic constraints such as trade cooldowns, risk-based position sizing, and capital preservation features. To validate this strategy, performance is compared to a Buy & Hold benchmark using Compound Annual Growth Rate (CAGR), Sharpe Ratio, Sortino Ratio, Profit Factor, Win Rate, Maximum Drawdown, and Recovery Factor. Statistical robustness is tested using Z-tests, the Kolmogorov-Smirnov test, and Monte Carlo simulations to evaluate consistency under uncertainty and noise. This framework brings a structured, data-driven approach to a market typically ruled by sentiment and speculation. It serves as a practical proof of concept for the feasibility of quantitative systems in frontier markets. Beyond the backtesting results, the study's conceptual model offers foundational groundwork for future academic inquiry, institutional adoption, and even regulatory reform in Nepal's evolving capital market landscape. The study investigates whether a rule-based quantitative trading strategy can achieve superior risk-adjusted performance compared to a traditional Buy and Hold approach in the Nepal Stock Exchange (NEPSE), a frontier market dominated by retail investors and characterized by low liquidity. Drawing on Modern Portfolio Theory and behavioral finance, the strategy capitalizes on temporary market inefficiencies resulting from overreaction and herding (Barberis et al., 2001).

- **H1:** There is a significant difference in the covariance structure of log returns between the Buy & Hold strategy and the Quantitative Strategy.
- **H2:** Quantitative approach is better than Buy & Hold in terms of risk-adjusted returns.

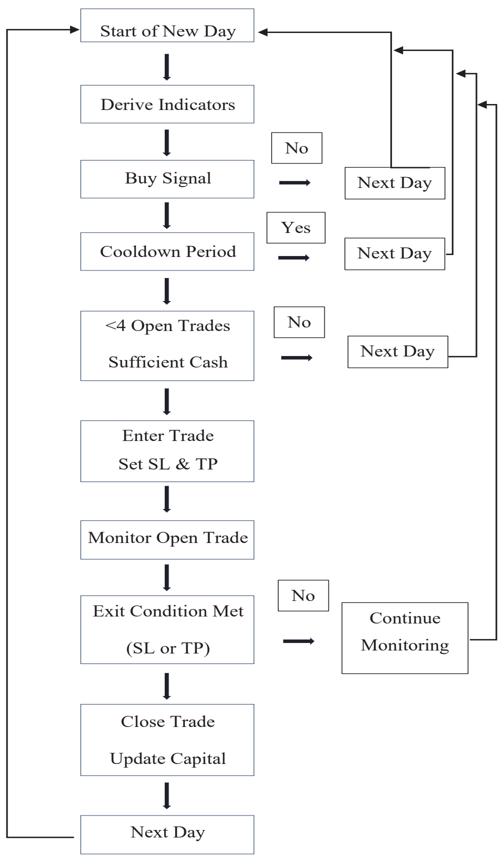
These hypotheses provide a formal framework for evaluating the system's performance in terms of risk-adjusted returns and capital preservation, grounding the study in established financial theory.

3. Methods

This study focuses on the Nepal Stock Exchange (NEPSE), the sole capital market of Nepal. It employs a quantitative, causal-comparative research design utilizing backtesting to assess the performance of a rule-based trading strategy on NEPSE index data. The research constructs a trading system based on technical indicators, including the Z-score, RSI, and the 240-day Moving Average, and compares its performance to a traditional Buy and Hold benchmark. In this study, the Z-score is employed as a normalized deviation indicator rather than a strict statistical measure of mean reversion. Its role is to identify short-term price extremes relative to recent historical behavior. Similar normalization techniques are widely used in rule-based trading systems where the objective is signal consistency rather than statistical inference (Chan, 2013; Kestner, 2003). The system incorporates realistic market constraints, including risk allocation, trade cooldowns, and maximum position limits. A fixed 0.25% execution adjustment was applied to all trade exits. Stop-loss exits were adjusted adversely, while take-profit exits incorporated price continuation effects. This adjustment serves as a simplified execution buffer rather than a microstructure-level slippage model. To compare the Quantitative Strategy with Buy & Hold, log returns are analyzed using the Kolmogorov–Smirnov test and a Z-test on Sharpe ratios to assess research hypotheses. Python is used as the primary tool for strategy development and testing, utilizing libraries like Pandas, NumPy, TA-Lib, Seaborn, and others.

Daily index price data for NEPSE is collected from July 1997 to March 2025, comprising 6,298 daily observations. The data, sourced from the ShareSansar website (Sharesansar.com.), covers multiple market regimes, including both bull and bear phases. Unit-root pre-testing is methodologically unnecessary in quantitative strategy research because modern, time-aware validation techniques already account for non-stationarity effects that traditional econometric tests aimed to detect (Schnaubelt, 2019). The study covers 28 years of NEPSE index data, from July 1997 to March 2025. This long horizon ensures that the strategy is exposed to a wide variety of market conditions. The backtesting is performed over this full period, while statistical metrics are computed to measure both average performance and risk behavior over time.

Figure 1: Algorithmic Backtesting Loop of Quantitative Strategy



4. Result

Descriptive Analysis

Buy and Hold trading strategy

Figure 2: Buy and Hold Strategy Equity Curve

Figure 2 represents the overall equity growth of the Portfolio. It almost reflects the market price movement, as all capital is invested at the beginning and held until the end of the data. The Buy and Hold Trading system is a traditional approach to trading in financial markets. The primary process involves investing all the capital in the given securities and holding them over time in the market while being in a drawdown and enjoying the entire bullish move of the given securities. There are no entry or exit criteria, nor is there effective risk management which leads investors to suffer the large drawdowns.

Quantitative trading strategy

Figure 3: Relative Strength Index of Close Price

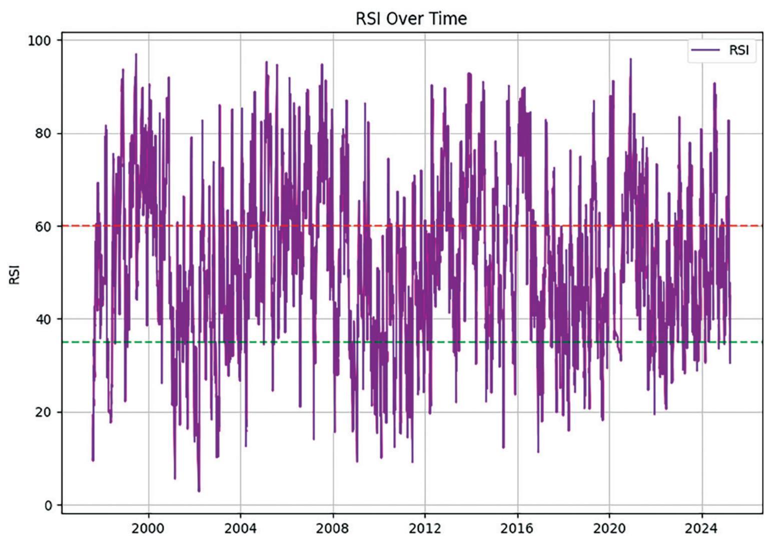


Figure 4 Z-Score Over Time of Close Price

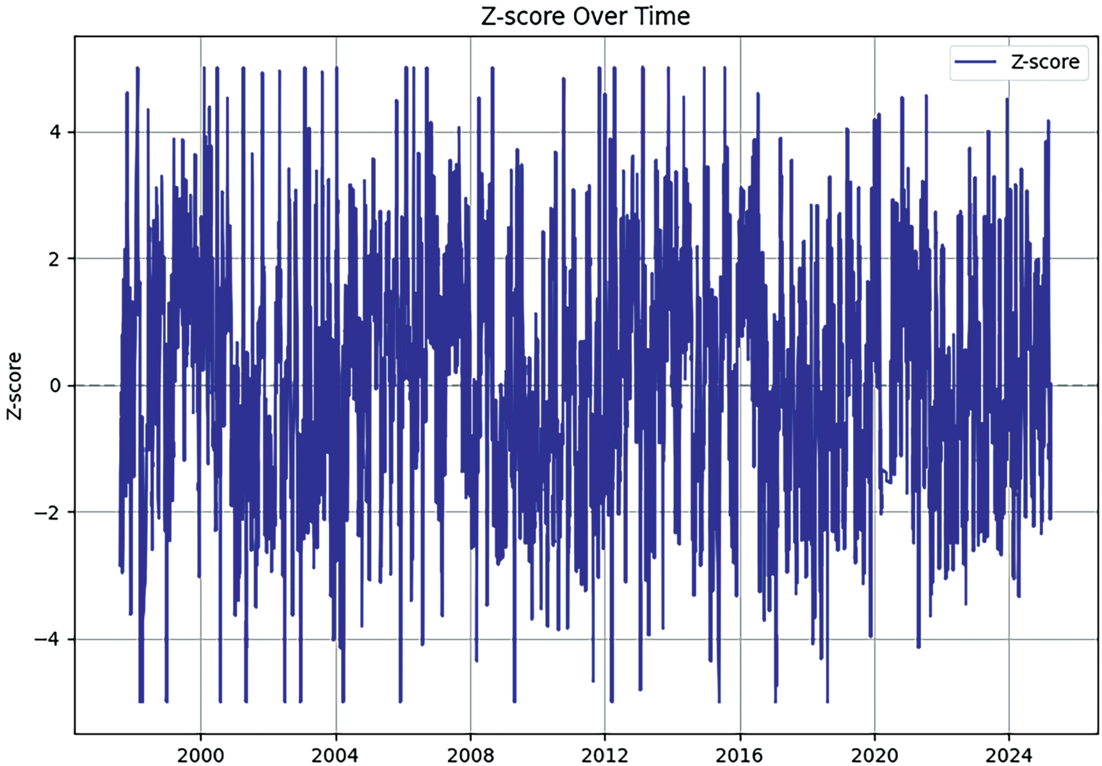


Figure 5: MA240 With Close Price of NEPSE Index

Analysis and Result

In this section, all outputs and results interpreted from the above strategies are shown. Both strategy performance is compared in terms of risk-adjusted returns. There are two types of performance analysis: first, comparisons are made with raw returns, and second, with log returns and statistical testing.

Raw Return Analysis

Figure 6: Equity curve of Quantitative and Buy and Hold Strategies

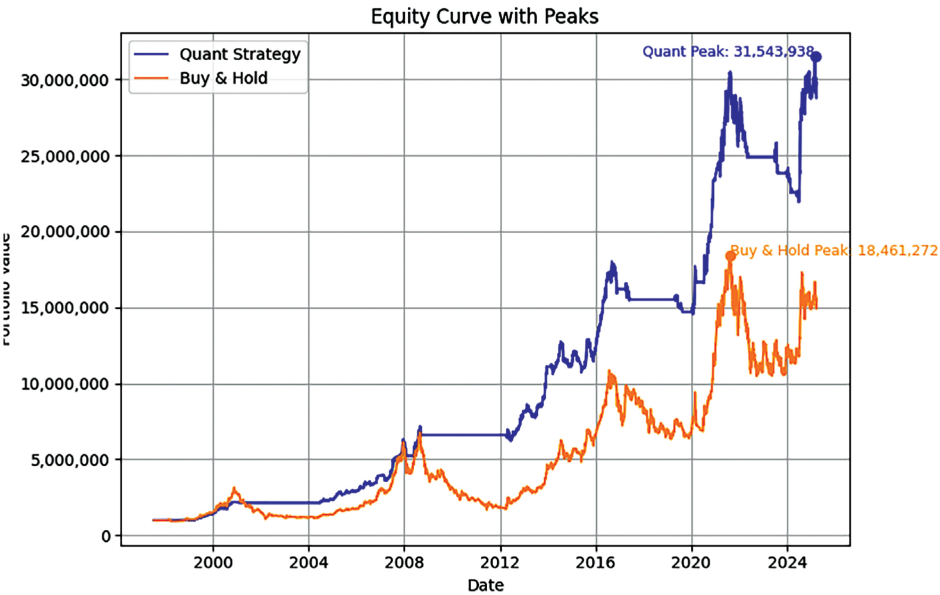


Figure 6, represents the portfolio equity curve for both strategies. The quantitative strategy has outperformed its benchmark in terms of the equity curve. The peak for the Quant strategy is Rs 31,543,938, while the Buy & Hold is Rs 18,461,272. After 2002, the quant curve is always above the Buy and Hold curve.

Figure 7: Maximum Drawdown of Buy and Hold and Quantitative Strategies

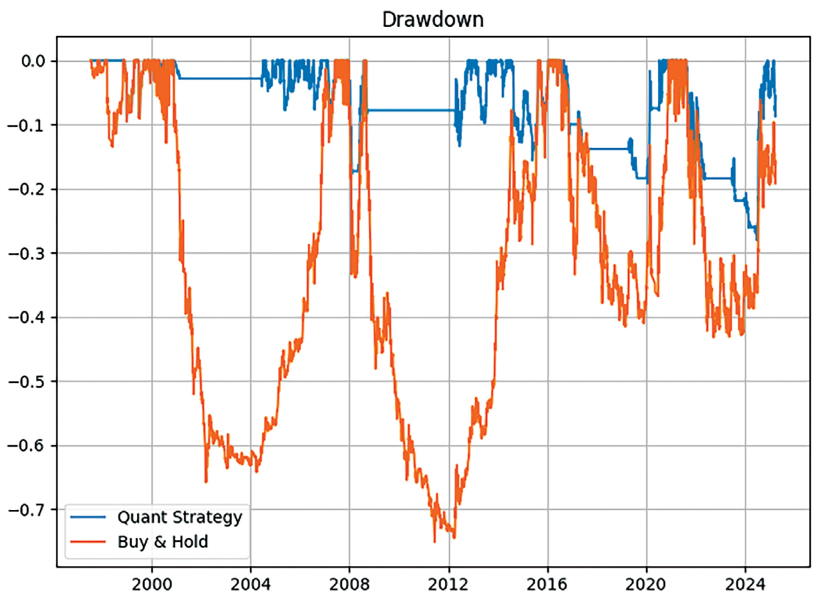
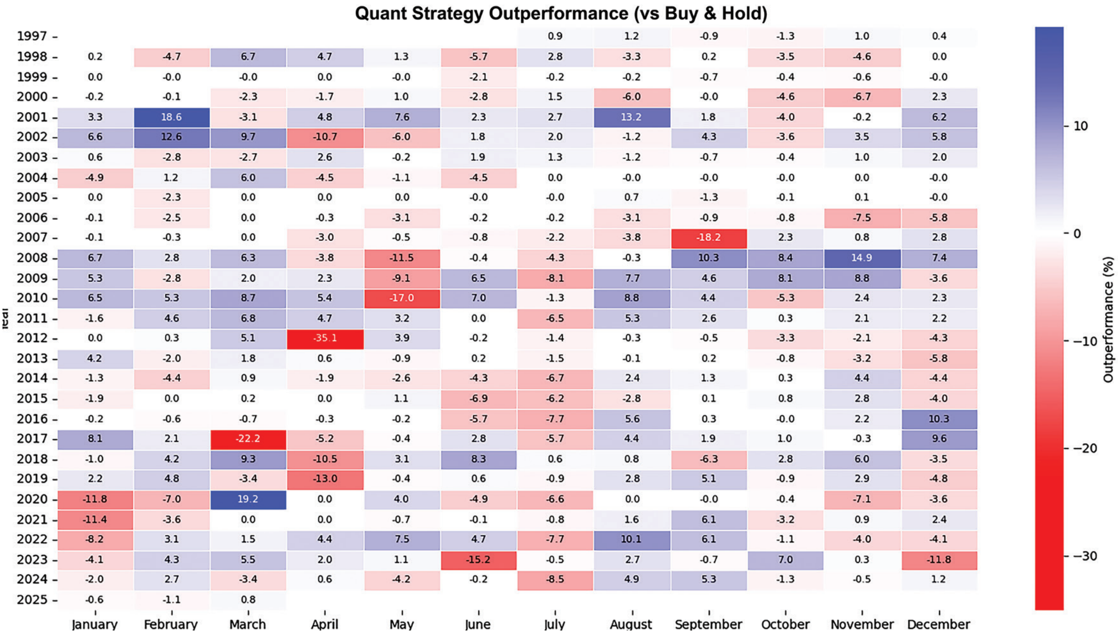


Figure 7, represents the maximum drawdown faced by both strategies. The quantitative strategy has outperformed its benchmark strategy in terms of drawdown. The maximum drawdown for the Quant strategy is 28.11% in 2024, while the Buy & Hold strategy has a drawdown of 75.16% in 2012.

Figure 8: Outperformance of the Quantitative strategy over the Buy and Hold strategy



The figure 8 illustrates the monthly outperformance of the quantitative trading strategy relative to the Buy and Hold benchmark between 1997 and 2025. Blue tones indicate months where the quant strategy outperformed, while red tones denote underperformance. The data reveals periods of consistent outperformance, such as in 2011, and isolated underperformance, notably in April 2012. This kind of calendar-based performance visualization is commonly used in financial strategy evaluation to identify seasonal patterns and anomalies (Kakushadze & Serur, 2018).

Figure 9: Distribution of Daily Returns with Stats Table

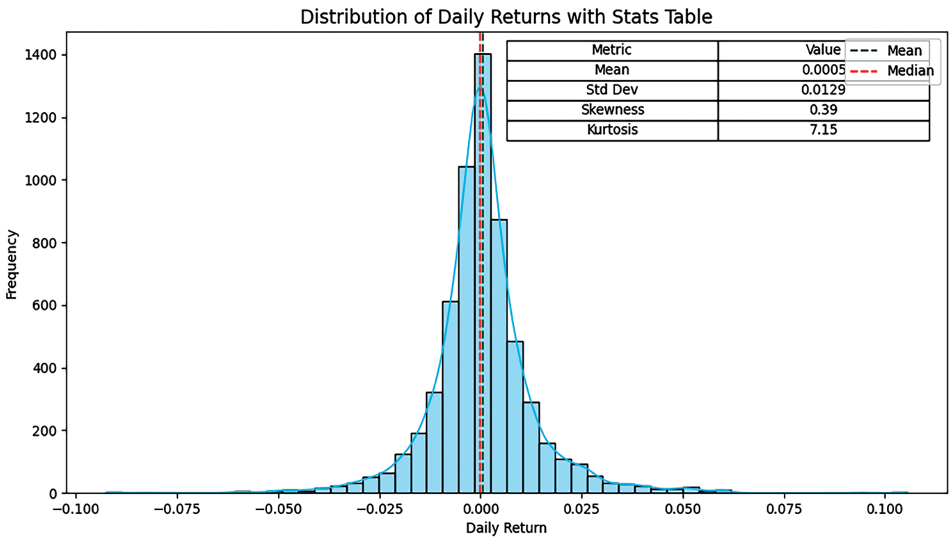


Figure 9 illustrates the distribution of daily returns from the dataset used in this study. The x-axis represents the daily returns, and the y-axis represents the frequency. The histogram displays the frequency of different return values that occurred in the given dataset, allowing us to examine the nature of the return distribution visually. The mean daily return is 0.0005, indicating that the strategy yields a small, consistent positive return on average each day. The standard deviation is 0.0129, which reflects the volatility or average fluctuation around the mean, showing moderate variability in daily returns. The skewness value of 0.39 suggests a positively skewed distribution, meaning there are more frequent small losses or gains, but occasionally large positive returns that extend the right tail.

The distribution of daily returns is not perfectly normal. Although it appears roughly bell-shaped, the positive skewness indicates that large positive returns are more likely than large negative ones. Moreover, the high kurtosis value of 7.15 suggests the presence of fat tails, implying that extreme return values, both positive and negative, occur more frequently than expected under a normal distribution. This observation is crucial for risk management, as it highlights the higher-than-anticipated probability of significant price movements (Cont, 2001).

Figure 10: QQ plot of Strategy Daily Returns

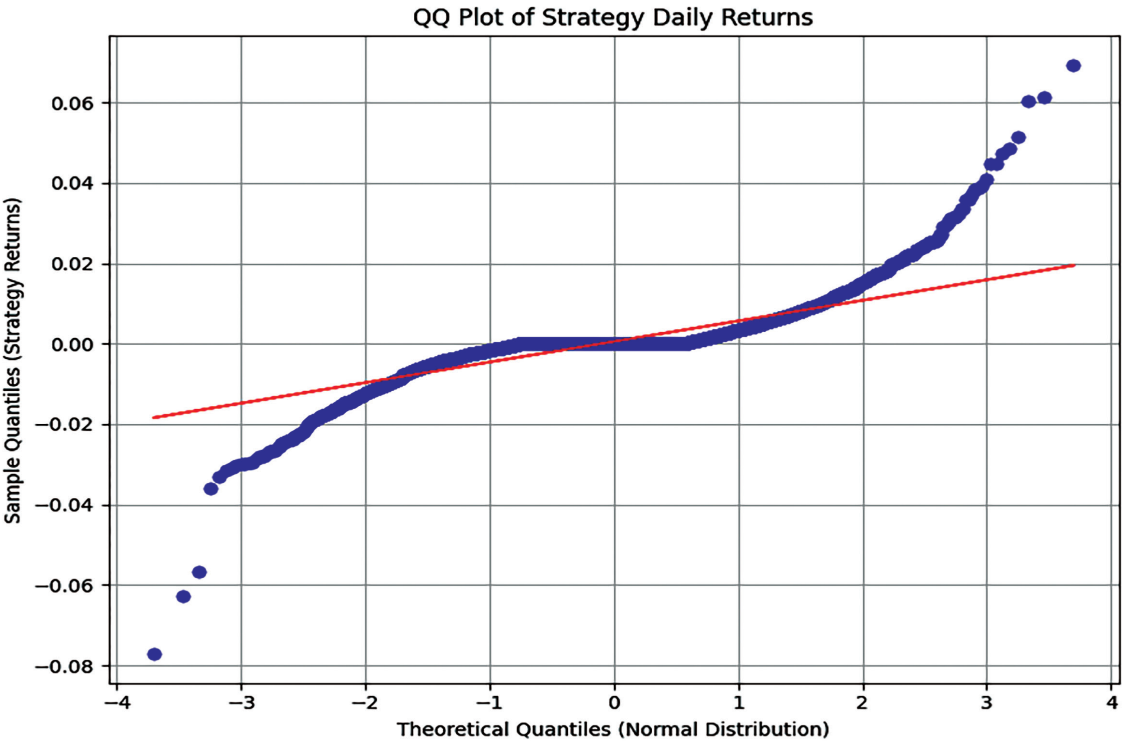


Figure 10, illustrates the QQ plot of strategy Daily Returns that compares a distribution of daily returns with a normal distribution. The fat tails observed indicate that the system is showing dynamic behavior by decreasing risk during losing streaks and adjusting position size based on prior capital performance. Centered around the red reference line, the plot's center shows the notable "fat tails" ends. The system's dynamic character is evident from the plot. The selected trade entry for the described strategy creates outliers, capturing extreme gains with an asymmetric reward-to-risk ratio of 1:4.5. Rather than a weakness, these variations highlight the system's resilience and willingness to accept large returns when conditions align, which lowers risk while strategically positioning it for high-probability swings. This aligns to minimize downside risk.

Figure 11: Capital Tracking for Quantitative strategies

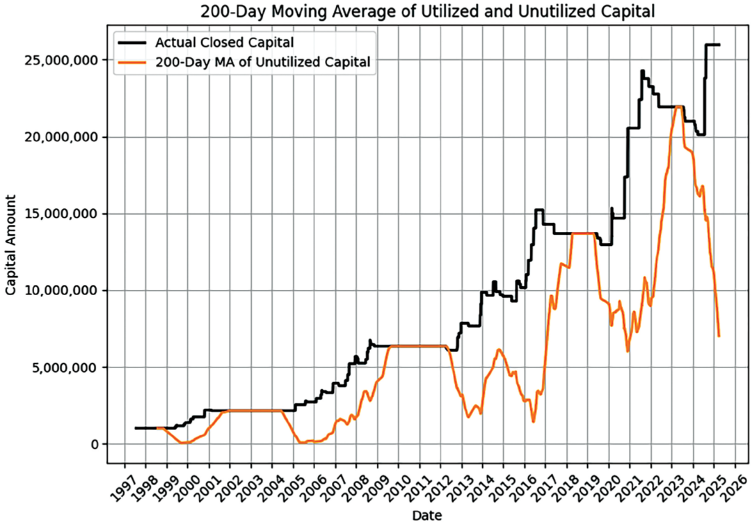


Figure 11 represents the capital tracking during backtesting period. The closed capital is always above the 200-Day MA of unutilized capital. Also, from 2002 to 2004, 2010 to 2012, 2018 to 2019, and 2023 to 2024, it is evident that the closed capital and unutilized capital are the same, which means the trades are not being taken. This is due to a bearish trend in NEPSE. The strategy follows rules by not taking trades in a bearish market, but it also shows that the capital is resting in cash and remains unutilized, which might affect the cost of opportunity.

Performance Summary

Table 1: Performance Summary of Quantitative and Buy & Hold Strategies

Type	Quant	Buy & Hold
Total Return	2877.27%	1454.38%
Max Drawdown	-28.11%	-75.16%
CAGR	14.38%	11.47%
Sharpe	1.39	0.64
Sortino	1.35	0.89

Table 1 presents a comparative performance summary between the quantitative strategy and the traditional Buy & Hold approach. The quantitative strategy achieved a significantly higher total return (2,877.27 %) and Compound Annual Growth Rate (CAGR) of 14.38%, compared to 1,454.38 % and 11.47%, respectively, for Buy & Hold. It also exhibited better risk-adjusted metrics, including a higher Sharpe ratio (1.39 vs. 0.64) and a lower maximum drawdown (−28.11% vs. −75.16%), indicating superior capital preservation and return consistency (Sharpe, 1966; Sortino & Price, 1994).

Active Days Performance Comparison

Table 2: Active Days Performance Comparison of Strategies

Type	Quant	Buy & Hold
Mean Daily Log Return	0.0011	0.0014
Sharpe Ratio	1.92	1.73
Max Drawdown	-29.84%	-40.3%

Days in Market: 3150 (49.5% of trading days)

Table 2 compares the performance of the quantitative strategy during its active periods to the Buy & Hold approach. Although Buy & Hold delivers a slightly higher mean daily log return (0.0014 vs. 0.0011), the quantitative strategy shows superior risk-adjusted outcomes, with a higher Sharpe ratio (1.92 vs. 1.73) and lower maximum drawdown (−29.84% vs. −40.3%). This supports the principles of Modern Portfolio Theory, which prioritizes the optimization of return per unit of risk rather than absolute returns. The strategy's selective market participation and reduced drawdowns also align with the concept of downside risk management and the idea of conditional market exposure, which can coexist with the Efficient Market Hypothesis: even in broadly efficient markets, systematic strategies can achieve better risk-adjusted outcomes by exploiting temporary inefficiencies or structural constraints. While these results do not propose a new financial theory, they demonstrate how established theories on risk-adjusted returns and capital preservation can manifest in an underdeveloped market context.

Additional Performance for Quantitative Strategy

Table 3: Additional Performance Metrics for Quantitative Strategy

Type	Result
Win Rate	53.64%
Average Win	Rs 676,702.26
Average Loss	Rs -231,301.33
Profit Factor	3.38
Recovery Factor	102.37

Table 3 summarizes the trade-level performance metrics of the quantitative strategy. The system maintained a win rate of 53.64%, with an average winning trade (Rs 676,702.26) significantly exceeding the average loss (Rs -231,301.33). The resulting profit factor of 3.38 indicates that the strategy generated over three times more gains than losses. Additionally, a recovery factor of 102.37 highlights the strategy's exceptional ability to rebound from drawdowns, underscoring its robustness in capital recovery (Kestner, 2003).

Sensitivity Analysis

This analysis involves adjusting parameter values to determine if the strategy aligns too closely with specific market conditions.

First condition.

When I changed the RSI level from 35 to 60 or 30 to 65, and adjusted the moving averages from MA240 to MA200 and from MA70 to MA60, which act as stop-losses for the mean-reversion approach, we obtained the following results.

Table 4: Performance of Quantitative Strategy Under First Condition for Sensitivity Analysis

Type	Result
Win Rate	53.15%
Average Win	Rs 653,469.61
Average Loss	Rs -237,346.05
Profit Factor	3.12
Recovery Factor	92.55
Total Return	2641.01%
Max Drawdown	-28.54%
CAGR	14.01%
Sharpe Ratio	1.32
Sortino Ratio	1.24

After modifying key parameters of the strategy, it continued to maintain strong performance. Table 4 shows that the win rate decreased slightly to 53.15% from 53.64%, and the total return decreased to 2641.01% from 2877.27%, with a CAGR of 14.01% from 14.38%, suggesting a minimal decrease in profitability. However, the maximum drawdown increased to -28.54% from -28.11%, and both the Sharpe Ratio (1.34) and Sortino Ratio (1.22) declined modestly, indicating a small trade-off in risk-adjusted performance.

The profit factor of 3.34 declined to 3.05, and the recovery factor of 99.23 declined to 84.13; however, both still reflect a high degree of efficiency in capturing gains relative to losses. This shows that the strategy is reasonably robust, though parameter tuning does influence its risk-reward dynamics, underscoring the importance of thorough backtesting (Lo et al., 2000).

Second Condition

When I changed the cooldown period of momentum from 4 to 5, Mean reversion from 3 to 4, Stop Loss level 4% to 5% below the entry level for momentum, Z-score window 15 to 20, and other things remaining the same, we get the following result:

Table 5: Performance of Quantitative Strategy Under Second Condition for Sensitivity Analysis

Type	Result
Win Rate	48.98%
Average Win	Rs 316,024.44
Average Loss	Rs-110,738.88
Profit Factor	2.74
Recovery Factor	32.37
Total Return	986.89%
Max Drawdown	-30.49%
CAGR	9.91%
Sharpe:	1.05
Sortino:	0.95

According to Table 5, the second scenario's test results show a lower win rate of 48.98% and a decrease in total return to 986.89%, with a CAGR of 9.91%, indicating reduced aggressiveness in trade selection. Despite this, the profit factor of 2.74 remains above the standard threshold of 1.5 for strong strategies (Chan, 2013), and the average win still significantly outweighs the average loss. However, the recovery factor drops to 32.37, and the Sharpe and Sortino ratios of 1.05 and 0.95, respectively, suggest a decline in risk-adjusted efficiency compared to more aggressive setups. Sensitivity Analysis showed that the quantitative trading strategy remains profitable and relatively resilient across simulations, even when the context is unfavorable. This shows that the model is resilient and configuration-agnostic as long as one of the few key inputs remains similar, such as the RSI range and moving averages. To sum up, the system does not overfit on a single, highly optimized parameter set, which broadens its applicability in the real world and reduces the risk of overfitting (Focardi & Fabozzi, 2007).

Inferential Analysis

Monte Carlo Simulation

Table 6: Results of Monte Carlo Simulation of Quantitative Strategy

Type	Result
Max Ending Capital:	60,695,262.29
Average Ending Capital:	11,039,102.31
Median Ending Capital	10,129,366.69
Worst Ending Capital	2,319,321.38
Simulations in Profit:	20000/20000
Simulations in Drawdown:	0/20000
Bankruptcies:	0
Average Max Drawdown	-0.1021
Worst Max Drawdown	-0.2717
Max Win Streak (AVG)	6.7800
Max Win Streak (Max)	19.0000
Max Loss Streak (Avg)	5.6000
Max Loss Streak (Avg)	16.0000

Table 6 shows the results of a Monte Carlo simulation, based on 20,000 randomized return paths of the quantitative strategy, demonstrating strong robustness and consistency. The average ending capital across all simulations was approximately NPR 11,039,102.31, while the median is NPR 10,129,366.69, indicating that most outcomes were positively skewed. The maximum ending capital observed was an impressive NPR 60,695,262.29, whereas the worst-case ending capital was still profitable at NPR 2,319,321.38. This indicates that, even in a random situation, with this sample of trades, the capital will end up being positive, which shows its resilience and potential to withstand different market conditions.

In terms of risk, the average maximum drawdown across simulations was only -10.21%, with the worst-case drawdown being -27.17%, which remains within acceptable limits for most risk-managed portfolios. Furthermore, the simulation recorded an average maximum win streak of 6.78 trades, with the longest streak reaching 19 consecutive wins. Similarly, the average maximum losing streak was 5.6 trades, with the most extended observed loss streak being 16 consecutive losses. Despite such potential streaks, the strategy managed to recover in every scenario, highlighting its resilience, risk control, and long-term profitability under various market conditions. There are more detailed graphs that provide further insight into Monte Carlo simulations.

Figure 12: Sample of Monte Carlo simulation Equity Curve

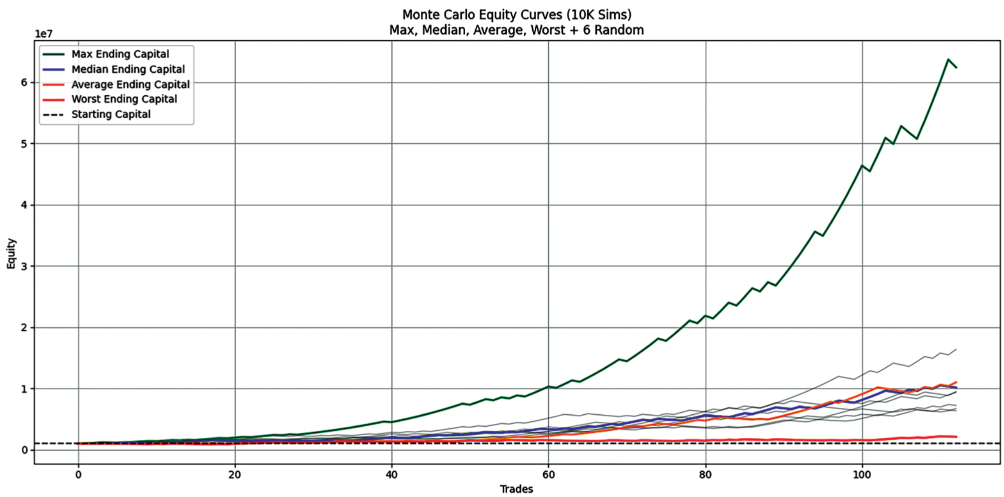


Figure 13: Histogram of Ending Capital of Monte Carlo Simulation

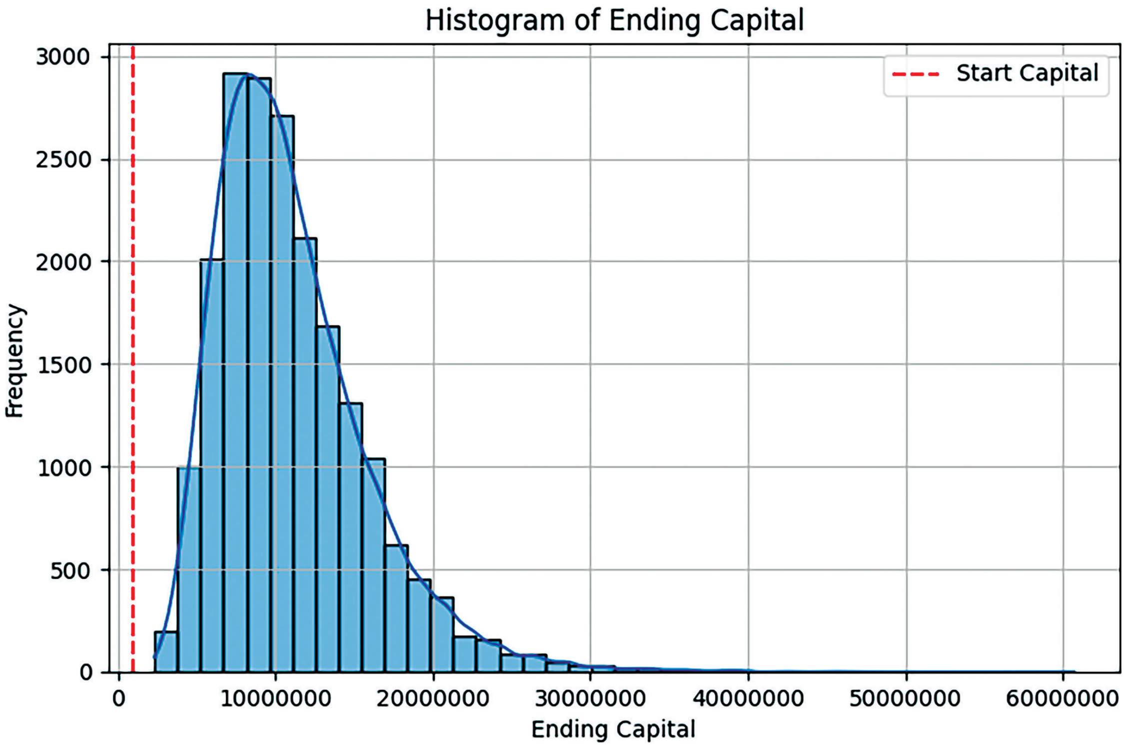
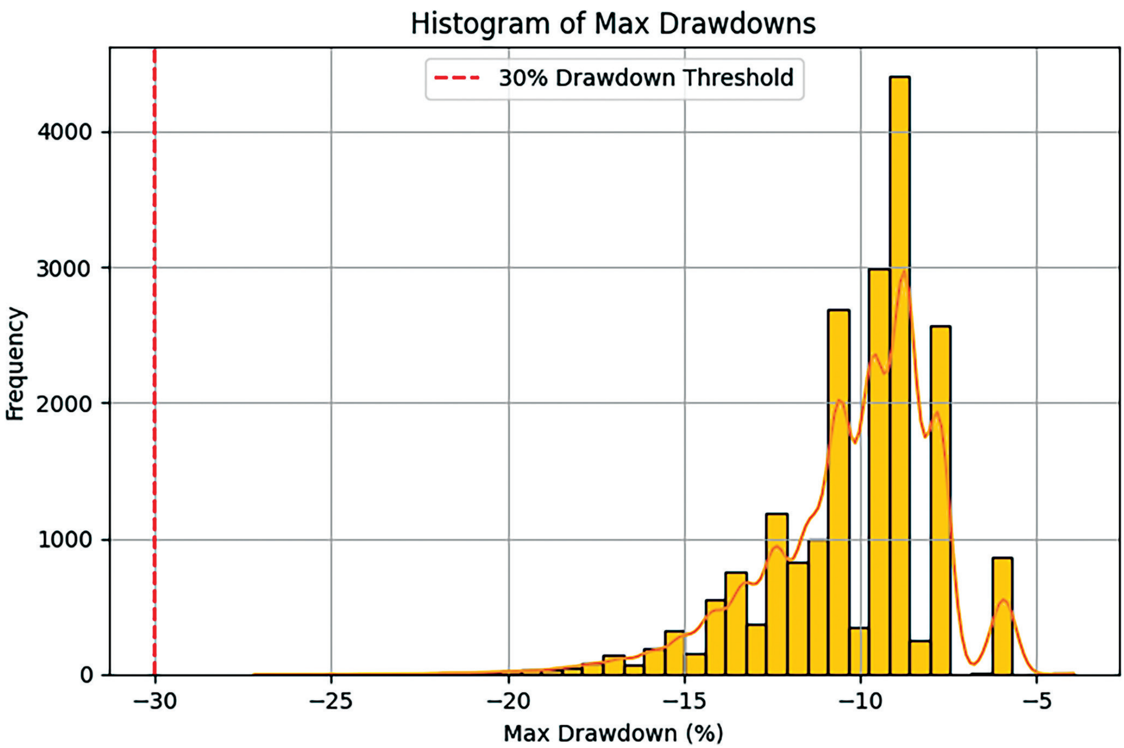


Figure 14: Histogram of Max Drawdowns of Different Simulations



Log Return Analysis

To evaluate the statistical characteristics and differences in performance between the Quantitative Strategy and the traditional Buy & Hold approach, two key statistical tests is conducted using log returns: the Kolmogorov-Smirnov (KS) test and a Z-test on Sharpe ratios.

Kolmogorov-Smirnov (KS) Test for Return Distribution

Table 7: Kolmogorov-Smirnov (KS) Test Result for Return Distribution

Type	Result
Quant Strategy	0.00053
Buy & Hold	0.00043
KS Statistic	0.26700
P-Value	0.0001
Interpretation	Significant Difference ($p < 0.05$)

The p-value is almost zero, far below the conventional 5% threshold ($\alpha = 0.05$). Thus, we reject the null hypothesis that the two return distributions are the same. This statistical analysis confirms that the log returns generated by the Quantitative Strategy are significantly different from those of the Buy & Hold strategy. Such divergence may reflect the strategy's filtering mechanisms, adaptive entries/exits, and risk controls, which collectively alter the return distribution structure (Cont, 2001).

Z-Test for Risk-Adjusted Return (Sharpe Ratio Comparison)

Table 8: Z-Test Result for Risk-Adjusted Return Using the Sharp Ratio

Strategy	Sharpe Ratio
Quant Strategy	0.0843
Buy & Hold	0.0339
Z-Statistic	4.0130
P-Value	0.0001
Interpretation	Statistically Significant ($p < 0.05$)

From Table 8, with a Z-statistic of 4.013 and a p-value well below 0.05, we reject the null hypothesis that the Sharpe ratios are equal, or the Quantitative approach is not better than Buy & Hold in terms of risk-adjusted returns. The data support the conclusion that the Quantitative Strategy provides a significantly higher risk-adjusted return. Although the absolute Sharpe values are modest, their relative difference demonstrates the effectiveness of the strategy's risk management and dynamic exposure techniques in producing more consistent returns (Lo, 2002).

5. Discussion

This study developed and evaluated a rule-based quantitative trading strategy specifically for the Nepal Stock Exchange (NEPSE), a frontier market characterized by low liquidity, limited institutional participation, and largely manual trading operations. Unlike developed markets where algorithmic strategies are widely adopted (Chan, 2013), NEPSE remains dominated by passive Buy & Hold behavior, creating an environment where price inefficiencies may arise due to investor overreaction and herding. This context provided an opportunity to test whether a disciplined, data-driven system could outperform traditional approaches on a risk-adjusted basis. The strategy combined three well-established technical indicators: the Z-score, to exploit mean-reversion opportunities; the Relative Strength Index (RSI), to detect oversold conditions; and the 240-day Simple Moving Average (MA240), to align trades with prevailing long-term trends. Trade execution incorporated robust risk management, including dynamic position sizing, a maximum of four active trades, a cooldown period to prevent overtrading, and a 1:4.5 risk-reward ratio to favor asymmetric payoff potential. These design choices reflected principles from Modern Portfolio Theory and contemporary risk management literature (Tharp, 2006; Kissell, 2014; Murphy, 1999; Gatev, Goetzmann, & Rouwenhorst, 2006).

Backtesting on daily NEPSE index data from July 1997 to December 2024 supported the study's formal hypotheses. The Compound Annual Growth Rate (CAGR) of 14.38% vs 11.48% for Buy & Hold. The Maximum Drawdown (-28.11% vs. -75.16%), Sharpe Ratio (1.39 vs. 0.64) and Sortino Ratio (1.35 vs. 0.89) demonstrated more efficient returns per unit of risk, the quantitative strategy achieved superior risk-adjusted performance, confirming H1. Additional metrics, including a Profit Factor and a high Recovery Factor, illustrated resilience in adverse market conditions (Magdon-Ismail et al., 2004).

Statistical validation reinforced the robustness of these findings. The Augmented Dickey-Fuller test confirmed the need to use log returns due to non-stationarity in raw prices (Dickey & Fuller, 1979). Monte Carlo simulations with 10,000 randomized trade sequences showed that the strategy maintained its edge under varied market conditions, ruling out overfitting or randomness as explanations for its performance (Glasserman, 2004). Sensitivity analysis revealed the system remained effective across a broad range of Z-score and RSI thresholds, highlighting adaptability to changing market dynamics (Saltelli et al., 2008). Return distribution analysis indicated lower skewness and kurtosis compared to Buy & Hold, consistent with more stable, less extreme outcomes (Cont, 2001). Moderate volatility further confirmed consistent performance.

Importantly, NEPSE's long-only regulations did not impede the strategy's effectiveness, demonstrating that disciplined, rule-based approaches can generate meaningful advantages even in structurally constrained, retail-dominated markets. Overall, the results align with Modern Portfolio Theory and behavioral finance principles, demonstrating that systematically exploiting momentum and mean-reversion signals can enhance risk-adjusted returns in markets prone to inefficiencies, even without introducing new financial theories.

6. Conclusion

This research investigated whether a rule-based quantitative trading strategy can offer superior risk-adjusted returns compared to the traditional Buy and Hold approach in the context of the Nepal Stock Exchange. By designing a custom system rooted in technical analysis and reinforced with disciplined risk management, the study addressed the gap between passive investment behavior and the potential of systematic trading in an underdeveloped market. The strategy demonstrated that even within the limitations of a long-only environment and a frontier market structure, it is possible to achieve consistent performance while reducing exposure to large drawdowns. Adaptive elements, such as dynamic position sizing, cooldown periods, and capital-based trade filtering, contributed to its robustness. Comprehensive backtesting and simulation confirmed the system's practicality and resilience under varying market conditions.

A key limitation identified was the inability to execute short trades due to NEPSE's permanent ban on short selling, which often prevented the strategy from capitalizing on bearish signals and reduced its overall efficiency. These extensions aim to strengthen the strategy's predictive power further and demonstrate the growing relevance of data-driven and AI-enhanced approaches for investment decision-making, even in markets where such methods are not yet mainstream.

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