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Empirical Investigation of Abnormal Returns through Technical Analysis in the Nepalese Stock Market

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Abstract

This study comprehensively assesses the potential superiority of a technical trading strategy compared to the conventional buy and hold approach in the Nepalese stock market, where prior research is limited. It investigates the effectiveness of three widely recognized technical analysis indicators, both individually and in combination, using a 12-year historical dataset of 75 stocks, and 25.65-year NEPSE (Nepal Stock Exchange) index data. The back testing procedure evaluates the profitability and viability of the technical analysis strategy relative to buy and hold. The results show that, when factoring in trading-related costs, the technical trading strategy does not consistently outperform buy and hold. However, when trading fees are excluded, the technical strategy exhibits statistically significant outperformance. Future research can explore alternative technical rules and strategies to gain a more nuanced understanding of trading dynamics.

Keywords: *NEPSE, Technical Analysis, Backtest, Bootstrap, Abnormal Return*

1. Introduction

Abnormal returns, the divergence between actual and expected returns, have been a central focus in financial research, gaining prominence alongside the evolution of modern portfolio theory and the efficient market hypothesis (EMH) (Fama, 1970). The mid-20th century marked a critical juncture with the formulation of the EMH, positing that asset prices reflect all available information, challenging the conventional wisdom of consistently achieving abnormal returns (Fama, 1965). The subsequent development of abnormal return studies aimed to understand market efficiency and the complexities of consistently outperforming the market (Malkiel, 1973).

In parallel, technical analysis emerged as a counterpoint to the EMH, offering a different lens through which to view market dynamics. Rooted in the examination of historical price and volume patterns, technical analysis provides practitioners with tools such as chart patterns, trend lines, and technical indicators to uncover potential abnormal returns (Lo et al., 2000).

In the course of examining the historical progression of abnormal returns, it becomes imperative to discern and acknowledge the pivotal milestones associated with the assimilation of technical analysis into this overarching paradigm. Advancements in computational tools and the availability of vast historical market data have played a pivotal role in refining technical analysis methodologies (Brock et al., 1992).However, the journey through abnormal returns is not without its criticisms. Detractors argue that technical analysis is subjective and may lead to the identification of patterns due to random chance (Fama & Blume, 1966). Moreover, the rise of algorithmic trading poses new challenges for technical analysts,

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necessitating continuous adaptation and refinement of their analytical approaches (Hendershott et al., 2011).

The discourse surrounding technical analysis in the Nepalese trading community exhibited limited engagement before 2015. Before this, with the exception of a minority of commodity traders who applied technical analysis, it remained a subject of marginal consideration. The initially tepid reception of technical analysis in Nepal may be attributed to the absence of readily accessible charting platforms. During this era, market participants had to manually extract data from the NEPSE website and rely on external software, such as Meta Stock, for charting. Nevertheless, the subsequent availability of more accessible charting platforms from 2015 onwards marked a transformative period, sparking a notable surge in the adoption of technical analysis.

Divergent perspectives exist among Nepalese stock traders and investors with regard to the efficacy of technical analysis. While some practitioners find it to be a valuable tool for making informed investment decisions, others remain skeptical of its utility. Notably, there exists a notable dearth of comprehensive research on this subject within the specific context of the Nepalese stock market. The prevailing trend among researchers has been to independently back-test individual technical tools, often overlooking the practical reality where traders frequently combine multiple indicators to refine their trading strategies.

In both established and emerging stock markets, including the NEPSE, debates and criticisms concerning the efficacy of technical analysis have persisted as a recurrent theme. Against this backdrop, this research endeavors to conduct an assessment of the profitability of a technical trading system within the Nepalese equity market, addressing and scrutinizing the reservations frequently articulated by academicians and fundamental investors. This study introduces a novel approach, denoted as the "combined trading strategy," which integrates three distinct technical indicators. In recognition of the limited body of work examining the profitability of technical analysis indicators in Nepal, this research endeavors to address this knowledge gap. By collectively evaluating the three technical indicators in the form of a holistic trading strategy, this study aims to conduct a thorough back-testing analysis to ascertain the overall performance of the proposed technical strategy.

2. Literature Review

Brock et al. (1992) conducted a comprehensive study to assess the effectiveness of moving average and range break strategies. Their research yielded substantial empirical support for the viability of technical strategies, thus challenging established financial models. Importantly, their findings contradicted the assumptions of the random walk theory, AR (1), GARCH-M, and Exponential GARCH models, indicating that the returns generated by these strategies deviated from the expectations set by these traditional models. In addition, their research revealed that buy signals outperformed sell signals, and buy-signal-generated returns exhibited lower volatility than those following sell signals.

Mills (1997) conducted an insightful analysis of different straightforward technical trading rules, employing daily data from the London Stock Exchange FT30 index spanning the years 1935 to 1994. The research demonstrated that, during certain sub-periods (1935-1954 and 1955-1974), trading strategies based on these rules would have generated significantly higher returns compared to a straightforward buy-and-hold strategy. However, during another sub-period (1976-1994), there was no compelling evidence to support the utility of these trading rules in generating useful signals for price movements, as their effectiveness waned, particularly in the early 1980s when the FT30 experienced significant growth following a prolonged period of stability.

Chong & Ng (2008) performed a comprehensive analysis of the profitability of two oscillators, specifically the Moving Average Convergence Divergence (MACD) and the Relative Strength Index (RSI), spanning a 60-year timeframe. The authors partitioned their sample into three extended sub-periods: 1935-1954, 1955-1974, and 1975-1994, with results indicating that both RSI and MACD rules generally outperformed the buy-and-hold strategy, particularly within the 1975-1994 sub-period, which yielded the highest number of statistically significant returns.

Subsequently, a notable study conducted by Park (2016) aimed to evaluate the performance of technical trading rules in contrast to the buy and hold strategy within the Australian financial markets. Upon conducting rigorous statistical analyses, the research results failed to establish statistically significant evidence supporting the superiority of technical trading rules over the buy and hold strategy within these markets.

Ansary et al. (2017) made significant observations in the context of emerging market data, emphasizing that technical analysis strategies outperformed the buy and hold strategy across various time horizons, encompassing the short term, long term, bull markets, bear markets, and periods both before and after the Egyptian revolution. Similarly, Kay (2019) corroborated the notion of market efficiency, asserting that trend-following strategies typically underperformed the traditional buy and hold strategy in a majority of scenarios. Notably, Kay's research highlighted that technical trading rules offered the advantage of mitigating downside risk relative to conventional buy and hold strategies.

The study conducted by Karki et al. (2023) provided insights into the overall effectiveness of technical analysis within the Nepal Stock Exchange (NEPSE). Notably, the analysis identified an exception in the relative strength index, which yielded negative returns. Furthermore, the study's application of bootstrap techniques raised doubts regarding the forecasting capability of technical strategies within the NEPSE, prompting a reevaluation of their performance within the Nepalese stock market.

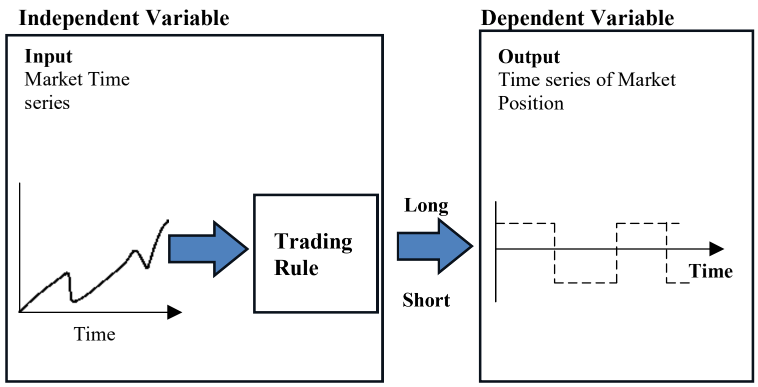
In summary, these studies collectively contribute to the existing body of knowledge concerning the efficacy of technical analysis in financial markets. They present a nuanced perspective, highlighting both the potential advantages and limitations associated with the utilization of technical trading rules.

3. Research Methodology

3.1 Conceptual Framework

In Figure1, the diagram depicts the relationship among the original market time series, a trading strategy, and the resulting time series of market positions. The passive return obtained by simply holding the market time series is commonly known as the buy-and-hold return. The returns generated through the application of a technical trading strategy serve as the dependent variable in this context.

Figure 1: Conceptual Framework of a Technical Trading Strategy.



Source: Aronson, 2007

Conversely, the trading strategy itself functions as an independent variable, with returns being contingent on the specific parameter configurations within the indicator. It's worth noting that the trading strategy's return can also be influenced by market trends and the selected time frame, thereby introducing these factors as additional independent variables.

3.2 Population and Data Sampling

In strategy backtesting, historical data is utilized since obtaining data for the entire population of all possible observations is either impractical or impossible. Aronson (2007) highlights that when testing a technical analysis (TA) rule, the population encompasses all conceivable daily returns that would be generated by the rule's signals over the immediate practical future (Aronson, 2007, p. 190). He argues against assuming infinite profitability of a trading rule into the future, emphasizing that profitability is expected to persist only within a finite timeframe, as long as the profits compensate for the researcher's efforts.

To tackle the challenge of limited data availability, this study employs the moving block bootstrap method for sampling. This approach involves resampling with replacement to create artificial price series. One notable advantage of using the bootstrap method is its capacity to preserve the autocorrelation structure of the data, enabling accurate and realistic analysis by maintaining the original data's distributional properties, even non-normal features.

3.3 Sample Selection

For historical back testing, the sample consists of 75 stocks listed on the Nepal Stock Exchange (NEPSE). The data spans from November 2010 to March 2023. Companies that listed later are included from their first trading day after the IPO. The selection criteria are based on the turnover of companies in the stock market, with the companies that traded for less than 80% of the days when the NEPSE was open are not included in the sample as they are comparatively illiquid. Source of the data is the official website of NEPSE.

In addition, the historical closing prices of the NEPSE index from 7/20/1997 to 3/9/2023 are considered for generating bootstrap price series. For statistical testing purposes, the study employs the bootstrap sampling method to obtain robust samples, especially when dealing with a small sample size, as suggested by Aronson (2007).

3.4 Method of Analysis

The research was conducted in two phases. In the first phase, the rule was deployed on historical price to observe the past performance of technical rule, while in the second phase, the strategy's statistical significance was assessed using the bootstrap method. In the historical backtest each stock was tested separately to analyze its performance in the historical data. On the contrary, for bootstrap method, two separate price series were used to generate bootstrapped average return of the rule. One being the price series formed using average daily returns of 75-equally weighted stocks' portfolio and another being 25.65-year historical data of the NEPSE index. During the back-testing process, the buying and selling rules were established according to the guidelines of Kirkpatrick & Dahlquist (2015). The standard Relative Strength Index (RSI) with a period of 14, Moving Average (MA) with a period of 20, and Moving Average Convergence divergence (MACD) with periods of 12, 26, and 9 were considered. Initially, a single trading strategy that combined these three technical indicators was tested. Subsequently, each indicator was individually tested using historical price data. For the purpose of hypothesis testing, only the combined trading strategy was considered. In the historical back testing the entire data set was divided into three parts. The first part, from November 2011 to August 2016, represents a strong bullish market with the Nepse index surging over 500%. The second part, spanning from September 2016 to March 2023, encompasses a ranging market with significant fluctuations. The third part being the full sample starting from November 2011 to March 2023.

Dividing the back testing time series into three segments gives an idea of how the technical strategy performs in a lengthy and stable bull market and during highly volatile times. In the first phase several new companies did not have enough history to back test hence such 26 companies were not considered. Only 58 companies were taken into consideration for the first part back testing.

3.5 Trading Rule

In this study, three technical indicators are tested individually and combinedly. When all three indicators satisfy the buying condition, it's a buy signal for a combined trading strategy. A long trade is taken and held until all indicators signal selling. When one of the indicators indicates buying while the other two have turned bearish, the trade is still held until all indicators turn bearish. As short selling is not allowed in the Nepalese market, this strategy is long-only.

Moving Average-20

Buying Rule: The buy signal is generated when price of the security is above the moving average. Selling Rule: The sell signal is generated when the price of the security is below the moving average.

Moving Average Convergence/Divergence (12,26,9)

Buying Rule: The buy signal is generated when MACD line is above the signal line.

Selling Rule: The sell signal is generated when MACD line is below the signal line

Relative Strength Index (14)

Buying Rule: The buy signal is generated when the RSI level is above 50.

Selling Rule: The sell signal is generated when the RSI level is below 50.

During the research, the Nepal Stock Exchange (NEPSE) had a settlement cycle of t+2 days, meaning that shares couldn't be sold until two days after purchase. For simplicity, this factor was disregarded in the study, and shares were occasionally sold on the day after purchase. When a trading signal emerged on day t, shares were purchased at the closing price on day t, assuming it was the same as the opening price on day t+1. While it's practically challenging to buy at the exact closing price, this assumption generally holds true when there are no overnight news events impacting the market.

The broker commission of 0.37% was imposed on both buy and sell trades. The SEBON commission and Depository Participant (DP) charge of 0.015% was deducted for each respectively with total fees and commission amounting to 0.40%. The capital gain tax of 5% was deducted from the profitable trades.

Data snooping and data mining bias

The amalgamation of trading strategy and individual indicator rules employed in this study is noteworthy for its methodological rigor. It is crucial to emphasize that these rules were not devised through data-mining; instead, standard and widely accepted parameters were utilized for each indicator. Moreover, the rules under examination have not been previously tested on the specific instruments scrutinized in this study, and deliberate efforts were eschewed to manipulate indicator parameters with the aim of enhancing the strategy's profitability. This adherence to established parameters aligns with Aronson's (2007) recommendation, advocating for the necessity of testing single rules free from data-mining bias.

To safeguard against data snooping bias, a concern that arises when potentially spurious relationships are identified due to chance, the study employs bootstrapping. By subjecting the combined trading strategy to bootstrapped price series, this research ensures that any observed patterns or relationships are statistically significant and not merely a product of random variation. Bootstrapping involves the generation of numerous simulated datasets, allowing traders and investors to assess the robustness of their strategies. This iterative process enhances confidence in the strategy's ability to perform effectively in real-world market conditions, aligning with best practices in quantitative research methodology.

4. Results

Table 1: Historical Back testing Result Summary of Combined Trading Strategy

Back test	Market Phase	Time period	No. of stocks	Average B&H CAGR	Average Rule CAGR	Rule -B&H
1	Bull market	2010-2016	58	41.37%	18.90%	-22.47%
2	Sideways Market	2016- March 2023	75	5.51%	9.80%	4.29%
3	Long term bull and bear	2010- March 2023	75	16.06%	12.63%	-3.43%

Combined trading strategy: 2010-2016 (Bullish Period)

The first back testing was done on a trading rule that combined MA-20, RSI-14, and MACD on a 58-equally weighted portfolio which covered the highly bullish time period starting form 2010 – 2016. Of the 58 stocks that were considered, only 1 was able to outperform the buy and hold in terms of annual return after factoring trading costs. The average annual buy and hold return of 58 stocks was 41.37% while the average trading rule return was 18.90%. Average annual buy and hold standard deviation was 37.36% while the strategy standard deviation was 40.19%.

Combined trading strategy: 2016- March 2023 (Bull and Bear Mixed Period)

During this period market experienced major bullish and bearish trends. 50 out of 75 stocks outperformed buy and hold strategy after trading fees. Average annual buy and hold return of 75 stocks was 5.51% while the average annual strategy return was 9.8%. Average outperformance 58 was 4.29%. Average annual buy and hold standard deviation was 37.64% in case of buy and hold while it was 43.19% as per strategy.

Combined trading strategy: 2010 - March 2023 (Full Sample)

Combined trading strategy was applied in full sample data starting from 2010 to March 2023. The average outperformance produced by 75 stocks during the backtest period was -3.43%. Average return from the buy and hold and strategy are 16.06% and 12.63% respectively. Average standard deviation for the passive approach and trading rule are 38.30% and 43.37% respectively.

Table 2: Back testing Result Summary of Individual Indicators

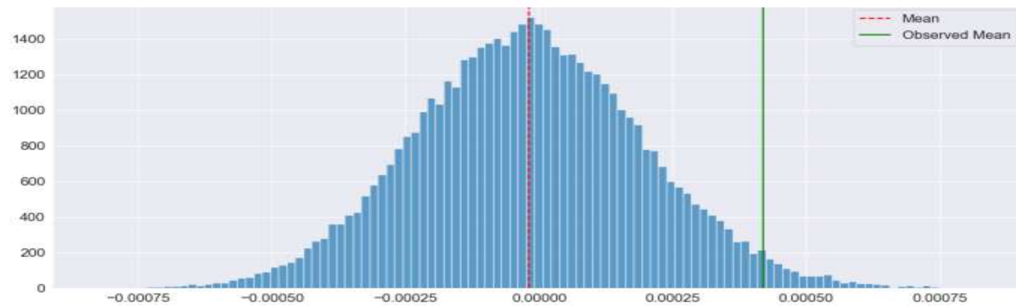
Back test	Indicators	Time period	No. of stocks	Average B&H CAGR	Average Rule CAGR	Rule -B&H
1	Moving Average	2016- March 2023	75	16.06%	6.11%	-9.95%
2	MACD	2016- March 2023	75	16.06%	7.83%	-8.23%
3	RSI	2010- March 2023	75	16.06%	5.10%	-10.96%

Three indicators, MA-20, MACD, and RSI is tested individually in full sample data set. The average annual outperformance of 75 stocks on MA-20, MACD, RSI is -9.95%, -8.23%, and - 10.96% respectively. The average annual standard deviation of MA-20, MACD, and RSI trading rules are 41.27%, 39.97%, and 41.22% respectively. Karki et al.'s (2023) study align with this study, showing that RSI underperformed buy and hold between 2012 and 2022. While Karki et al. (2023) found that MACD outperformed buy and hold without considering transaction costs, this study indicates that MACD does not outperform buy and hold when transaction costs are accounted for during the same period.

Bootstrap Results

Three bootstrap sampling tests were done in the study. In the first two, 50,000 average daily outperformance samples were generated to calculate p-value. In the third boostrap, 10,000 price series were created on the basis of 75-equally weighted portfolio and eventually rules were backtested on those price series.

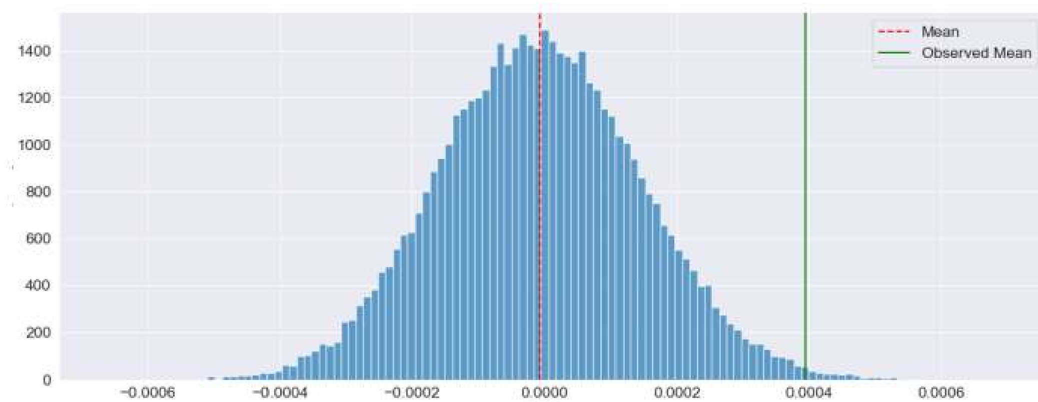
Figure 2: Bootstrap Distribution of Average Daily Rule Return – Buy and Hold Return Based on 75 Stocks Equally Weighted Portfolio



Source: Author's own calculation using Plotly in Python

The combined trading strategy was applied on equally weighted portfolio of 75 stocks and it generated average daily outperformance of 0.04%. When 50,000 bootstrapped average daily outperformance data were obtained, the p-value of 0.0271 was obtained at 95% confidence interval, resulting in rejecting null hypothesis that difference between strategy return and buy and hold return is less than or equal to zero. The trading costs were not considered due to impracticability to include it on daily return.

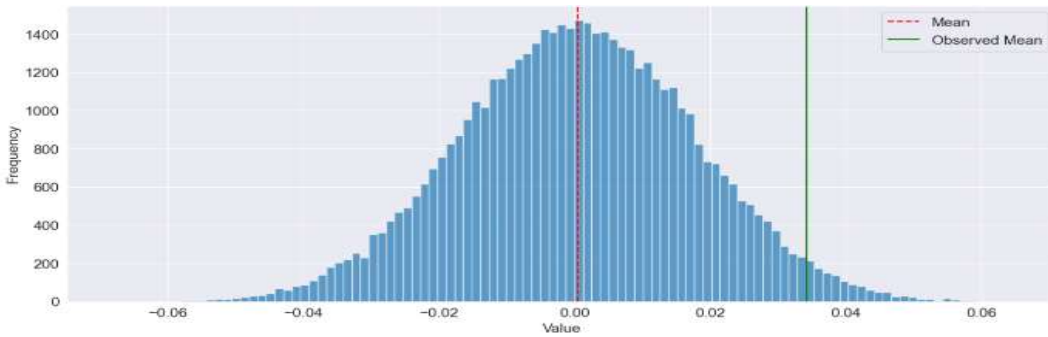
Figure 3: Bootstrap Distribution of Average Daily Rule Return – Buy and Hold Return Based on NEPSE Index



Source: Author's own calculation using Plotly in Python

In this test 25.65 years of historical NEPSE index data was used for getting bootstrapped average daily outperformance samples. While combined trading strategy was applied on historical index data the average daily rule return – buy and hold return obtained was 0.039%. The p-value was 0.0056, rejecting the null hypothesis that difference between strategy return and buy and hold return is less than or equal to zero. The trading costs were not considered due to impracticability to include it on daily return.

Figure 4: Bootstrap Distribution of 10,000 Strategy CAGR – Buy and Hold CAGR (Including Trading Costs)



Source: Author's own calculation using Plotly in Python

Out of 10,000 tests conducted, 7,100 tests (71%) demonstrated superior performance compared to the buy-and-hold strategy. The observed annual outperformance was 7.20%. The p-value was 0.0573 failing to reject null hypothesis that the strategy returns minus buy and hold returns is less than or equal to zero. The p-value was slightly higher than 0.05. The trading costs were included in this bootstrap method as it is different from the above two. This approach was computer intensive.

Notably, this study contradicts Brock et al.'s (1992) findings supporting the profitability of technical analysis and aligns with PARK's (2016) conclusion that technical trading strategies do not outperform buy and hold strategies, especially in efficient markets. These results suggest that the Nepalese stock market adheres to the concept of weak-form efficiency, as posited by the Efficient Market Hypothesis (EMH), where historical market data is rapidly incorporated into current asset prices, making it challenging for technical analysis strategies to consistently outperform a simple buy-and-hold approach. Thus, this study provides evidence that the Nepalese stock market is generally efficient in terms of the prompt assimilation of past market data into stock prices, aligning with EMH principles.

5. Conclusion

In conclusion, the performance of the combined trading strategy manifests variability across different market conditions. Notably, it lags behind the buy and hold method during strong bullish markets and markets where bullish periods predominate over bearish ones, but outperforms in markets characterized by substantial bull and bear phases. On an individual basis, the combined trading strategy exhibits superior performance compared to individual indicators, indicating that the amalgamation of these indicators into a unified strategy enhances overall effectiveness. This study demonstrates that trading costs have a significant impact on the profitability of technical trading strategies.

By broadening the scope of investigation, incorporating various indicators and parameter settings, future researchers and practitioners are recommended to explore alternative technical trading rules and test the profitability of different technical strategies.

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