



# Performance Evaluation of Technical Analysis in the Nepalese Stock Market: Implications for Investment Strategies

Dipendra Karki<sup>1</sup> , Rewan Kumar Dahal<sup>1\*</sup> , Ganesh Bhattarai<sup>1</sup> , Sudeep Balla<sup>2</sup> ,  
Arun Lama<sup>3</sup> 

<sup>1</sup> Nepal Commerce Campus,  
Tribhuvan University, Kathmandu,  
Nepal

<sup>2</sup> Global Panacea Pvt. Ltd., Lalitpur,  
Nepal

<sup>3</sup> CMT Association, New York City  
(NYC)

\*Corresponding email:  
[rewan.dahal@ncc.edu.np](mailto:rewan.dahal@ncc.edu.np)

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## Abstract

**Purpose:** This study aims to examine the performance of five widely used technical indicators on Nepal Stock Exchange (NEPSE) indexes. Specifically, the study evaluates indicators such as the simple moving average, moving average convergence and divergence, relative strength index, stochastic oscillator, and Bollinger Band.

**Design/Methodology/Approach:** The study utilizes a descriptive and quantitative research design. Daily closing index data of NEPSE and its six sub-indices are analyzed for a substantial period, ranging from 1st September 2012 to 31st August 2022. The performance of the technical indicators is examined through modeling, backtesting, and statistical analysis. The technical trading rules of each indicator are incorporated into the modeling process, and the results are analyzed using different performance metrics. Furthermore, the predictability of the indicators is tested through standard statistical analysis and bootstrap techniques utilizing a random walk model.

**Findings:** The results of the study reveal that the technical strategies, as represented by the analyzed indicators, generally support the effectiveness of technical analysis in the NEPSE. However, the relative strength index stands out as an exception, generating negative returns. The second stage of the analysis indicates that the simple moving average, relative strength, and Bollinger band fail to generate significant returns in certain indices. The findings from the bootstrap techniques further contradict the forecasting ability of technical strategies in the NEPSE, raising questions about their real performance in the Nepalese stock market.

**Practical Implications:** This research provides valuable insights for investors, traders, and market participants in understanding the nuances and limitations of technical analysis in the context of the NEPSE. The findings suggest that technical indicators, notably the relative strength index, should be interpreted cautiously and that investing decisions should take into account additional factors. The study contributes to the ongoing discussion on the effectiveness of technical analysis in the Nepalese stock market, assisting practitioners to make informed decisions and better understand market dynamics.

**Paper Types:** Research Paper

**Keywords:** Technical Analysis, Moving Average, Back testing, Bootstrap

## Introduction

Technical analysis (TA) has been a part of financial practice for many years (Lo et al. 2000). Early market analysis research concentrated on relative strength trading strategies that buy recent winners and sell recent losers. According to Levy (1967), a trading strategy that purchases equities at prices that are higher than their average values over the previous 27 weeks generates notable anomalous returns. Technical trading rules (TTRs) are frequently used in practice to buy/sell signals from historical data (Gehrig & Menkhoff, 2006). Despite its extensive application in the financial industry, TA has not received the same level of acceptance and academic scrutiny as more established fields such as fundamental analysis (FA). Technical analysis is a comparatively recent development in the Nepalese Stock Market, primarily due to the Nepal Stock Exchange (NEPSE) establishment in 1993. In recent years, the digitalization of NEPSE trading has played a crucial role in increasing the participation of retail investors in the equity market. As the Number of investors in the Nepalese stock market has increased, there has also been an increase in interest in technical analysis as it is perceived as easier to understand compared to fundamental analysis. Although technical analysis has grown in popularity, most investors still have a poor grasp of its foundational concepts. In Nepal, only a few significant studies have been conducted regarding different aspects of technical analysis. Vaidya (2018) documented that many investors are interested in ‘New Hi-Lo price’ and ‘trade volume indicators’ rather than ‘candlestick charts’ and ‘resistance and support level’, indicating that most investors are still unaware of the actual performance of the technical analysis. This showed that people are following the popularity hype, and thus more research is required to conclude the effectiveness and significance of technical analysis in the Nepalese equity market.

Despite the widespread use of Technical Analysis by stock market participants to create trading strategies, the existing literature remains highly controversial and inconclusive. This study aims to explore the relevance and predictability of technical analysis by conducting rigorous backtesting to recognize the research gap regarding the application of technical analysis. The study mainly focuses on examining five commonly used technical indicators, namely Simple Moving Average (SMA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Stochastic Oscillator, and Bollinger Bands (BB) in NEPSE and its six sub-indices. By analyzing various aspects of technical analysis that influence its performance, this study aims to enable investors to understand the usability and accuracy of different technical indicators in the Nepalese stock market.

## Literature Review

Brock et al. (1992) examined technical indicators of the Dow Jones Industrial Index 30. They contributed valuable insights into the field by testing 26 rules of two technical indicators using daily data from 1897 to 1986. The study employed a framework that utilized t-tests for statistical significance and reporting the findings, which has since become the norm in the literature. In addition, a parametric bootstrap methodology was presented to conduct additional significance testing to overcome the unfavorable properties of financial data. The technique involved choosing the best-fitting “null model” for the data, using substitutes to draw residuals, and then substituting the residuals to generate different price sets with similar statistical features as the original data. Although this approach provided insights, it introduced an approximation element and may have influenced the results.

In contrast to their approach, Liu and Singh (1992) independently presented the moving block bootstrap approach, which divides the original data set into overlapping blocks of fixed length and resamples with replacement from these blocks. Unlike the residual bootstrap method, the moving block bootstrap preserves the original structure of the financial time series. However, the emphasis of these studies on the statistical significance of technical indicators may not fully capture the practical implications of these indicators in real-world trading scenarios.

In light of these limitations, subsequent studies attempted to address the gaps and challenges encountered in past research. For instance, Azhara's (2010) research delved into the performance of various technical indicators, including the moving average and relative strength index. Their findings demonstrated that these indicators outperformed a simple buy-and-hold strategy, indicating their potential usefulness in trading. Metghalchi et al. (2013) discovered that technical analysis could outperform the Swedish market, even considering transaction costs. This is noteworthy because technical analysis is generally assumed to have less explanatory power in developed and emerging markets. The findings of Tharavanij et al. (2015) further support this proposition. Their study demonstrated that technical analysis performs well in Thailand's developing equity market but does not exhibit the same effectiveness in Singapore's developed market. These contrasting outcomes highlight the importance of considering market characteristics.

Furthermore, Nithya and Thamizhchelvan (2014) investigated the effectiveness of technical analysis in the banking sector of the equity market. They discovered that while it can help investors make significant gains using technical indicators, it works best with fundamental analysis. Previous studies have shed light on the relationship between technical indicators and investment decision-making. For instance, Esha (2015) surveyed Indian firms with particular mention of CNX Nifty. She found that capital structure and relative strength index have the highest beta coefficient value, referring to the most effective tools in the investment decision-making process. The two indicators, the relative strength index and moving averages, can minimize the risk in the equity market by identifying the conditions of oversold, overbought, and trend reversals.

Similarly, Khan et al. (2017) found that compared to average daily sell day returns, daily mean buy day returns were positive and statistically significant when testing technical analysis in Karachi Stock Exchange. The study also found that price prediction is improved, mainly when using the general regression neural network technique. In addition, the study discovered that trading rules could forecast future price changes.

Additionally, Radovanov, Marciki, and Fakulta (2017) conducted a study on technical trading rules in the Balkan stock market. They employed bootstrap methodologies, i.e., moving block and residual method and t-statistics, to test the effectiveness of trading rules. These methods were used 'with' as well as 'without' the transaction costs. Even after adjusting for data snooping biases, the analysis showed that we could reject the null hypothesis that trading rules do not beat the benchmark at the 5 % significance level for five different stock indexes. The study's findings provided compelling evidence favoring the analyzed technical trading rules.

Using evolutionary approaches to analyze financial markets, Macedo (2018) discovered varying degrees of efficiency across different markets. Notwithstanding, the study's findings documented that technical analysis can lead to profitable trading opportunities in some markets and at certain periods. However, it highlighted the inconsistency of these gains over time, emphasizing the need for further investigation into the dynamics of technical analysis. Patel (2019), in his study of technical analysis employing hybrid predicting models on the indices of the national stock exchange of India, found that the hybrid models always outperformed the standalone models, irrespective of the attributes of the stock indices. The Artificial Neural Networks (ANN) based hybrid models performed significantly better than the Wavelet-ARIMA-based (Autoregressive Integrated Moving Average) models (90% of the time) when first-ranked models are considered. Muruganandan (2020) tested the profitability of technical indicators, i.e., RSI and MACD, on different market cycles of BSE Sensex, where the findings showed that, even before accounting for trading expenses, the RSI trading rule could not produce a positive return. Yet, throughout the Bear market period, the sell signal produced by MACD trading rules beat both the mean return and the unconditional mean return of the buy signal, but it could neither help with market timing nor a reduction in losing trades. So, the study concluded that a trader in the Indian market cannot consistently generate abnormal returns using the RSI and MACD.

Vaidya (2020) examined NEPSE using one of the popular technical indicators, i.e., MACD and discovered that the NEPSE return was consistent throughout a short time frame. The study suggested that an investor with a fundamental understanding of moving averages might find the MACD results useful in the context of the NEPSE. Based on the MACD analysis of daily returns from the NEPSE over 20 years (up to 2019/20), the study concluded that the NEPSE was extremely unstable and offered a volatile investment market. In a subsequent study, Vaidya (2021) claimed that the Bollinger Bands were useless for interpreting the NEPSE Index’s data since the market’s divergence from the upper and lower bands was so modest during the brief market volatility. While several factors influence stock prices and trigger market over- or under-reactions (Karki, 2020), technical analysis is often employed to counteract behavioral biases in investment decision-making. Despite the significant contributions made by past research, the reliability of technical analysis in guiding investment decisions has been controversial. Given these research gaps, this article aims to contribute to a more comprehensive study of technical analysis within the Nepalese context.

### Conceptual Framework

Based on literature reviews and incorporating the theoretical foundation of market efficiency anomalies, this study proposed a conceptual framework that provides a structured approach to analyze the performance of technical analysis in stock markets. In this study, various performance metrics were used to study the entire cycle of the backtesting period. Figure 1 depicts the conceptual framework for the study.

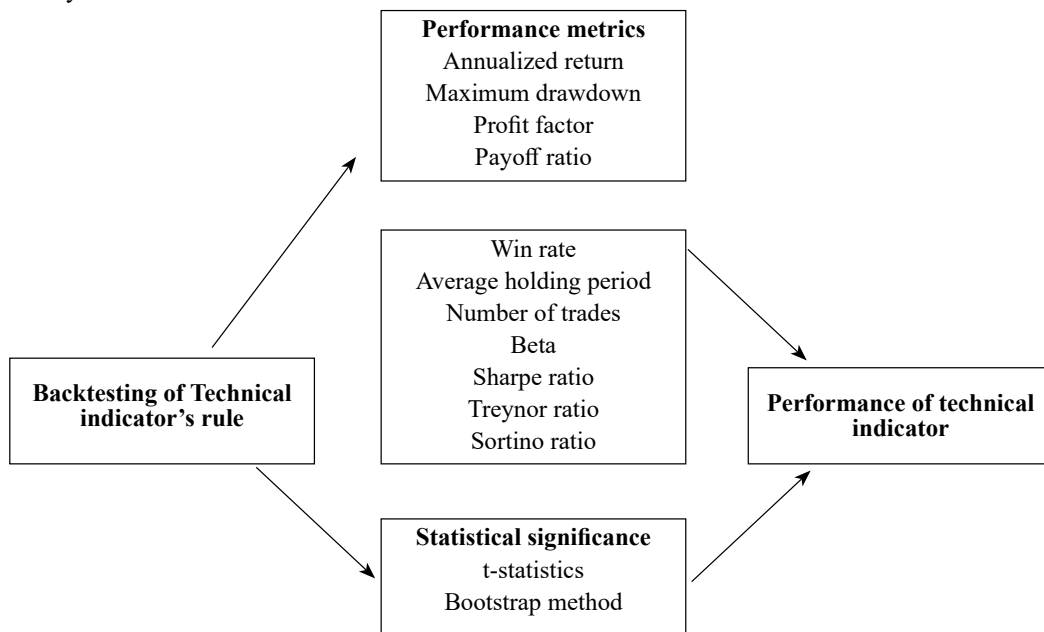


Figure 1. Conceptual Framework

### Operationalizing the variables

We used different metrics to test the performance of technical indicators. They are Annualized return, Maximum drawdown, Profit factor, Payoff ratio, Win rate, Average holding period, Number of trades, Beta, Sharpe ratio, Treyner ratio, and Sortino ratio.

## ***Annualized Return***

An annualized return is an investor's equivalent annual return over a given period. The return accounts for all the losses and gains over time, which are averaged to calculate the annual compounded return. The annualized return formula calculates how much an investor would make over time if the annual return were compounded.

$$R_{\text{Annual}} = \left( I_E / I_i \right)^{1/n} - 1$$

Here,

$R_{\text{Annual}}$  = Annualized return

$I_E$  = Investment at the end of the period

$I_i$  = Initial Investment

$n$  = no. of year in the observation period

*Maximum drawdown*: It is the maximum drop in equity line from the initial capital invested. While the maximum drawdown is the worst drop from the equity peak, for the sake of simplicity drop from the initial capital is considered here.

## ***Profit Factor***

The profit factor is the gross profit to gross loss ratio over the entire trading period. Profit per unit of risk is measured by this performance metric, where values larger than one indicate a profitable system. Though a value larger than one is a profitable system, a value greater than two is considered a very good profit factor as it will have a significant margin of safety.

$$P_F = \frac{GP}{GL}$$

Here,

$P_F$  = Profit factor

$G_p$  = Sum of profits in winning trades

$G_L$  = Sum of losses in losing trade

## ***Payoff Ratio***

The payoff ratio for a trading system is calculated as the average winner per trade divided by the average loser per trade. The performance of the trading system improves with a greater payoff ratio. Consequently, it will indicate whether our average winner is greater than our average loss (or not).

$$POR = \frac{AP}{AL}$$

Here,

POR = Payoff Ratio

AP = Average profits in winning trades = ( GP ) /  $N_{WT}$

AL = Average losses in losing trades = ( GL ) /  $N_{LT}$

GP = Sum of profits in winning trades

GL = Sum of losses in losing trades

$N_{WT}$  = No. of winning trades

$N_{LT}$  = No. of losing trades

### **Win rate**

The win rate indicates the percentage of profitable trades. It is critical to understand that the win rate is not as important as commonly assumed, as the most profitable trend-following strategies win only about 30% of the time. Conversely, overfitting can be expected to result in a win rate greater than 90%. A win rate of 50% or higher is considered satisfactory.

$$WR = \frac{N_{WT}}{N_T}$$

Here,

WR = Win rate

$N_{WT}$  = Number of winning trades

$N_T$  = Total number of trades

### **Average holding period:**

The average holding period is the average length of time any script is kept or the average duration between buying and selling the script. It is the sum of the total holding period across all trades divided by the number of trades.

$$AHP = \frac{THP}{N_T}$$

Here,

AHP = Average Holding Period

THP = Total Holding Period

$N_T$  = Total no. of trades

### **Number of Trades**

The number of trades refers to the total no. of the buy-hold-sell cycle. The trades can be winning or losing trades, which will sum to the total number of trades during the observation period.

$$N_T = N_{WT} + N_{LT}$$

Here,

$N_T$  = Total no. of trades

$N_{WT}$  = No. of winning trades

$N_{LT}$  = No. of losing trades

### **Beta**

The volatility of a stock in proportion to the market as a whole is measured by its beta. By definition, the market has a beta of 1.0. A stock with a beta above 1.0 fluctuates more than the market over time. Usually, low-beta stocks carry less risk but have lower potential returns and vice versa.

$$\beta_A = \frac{Cov(r_A, r_M)}{Var(r_M)}$$

Here,

$\beta_A$  = Beta of Assets

Cov = Covariance

Var = Variance

$r_A$  = Expected rate of returns on Asset A

$r_M$  = average expected rate of returns on the market

### ***Sharpe Ratio***

The Sharpe Ratio is one of the earliest benchmarks for return-to-risk evaluation tools introduced by Sharpe (1966). The ratio establishes a relationship between the asset's return deviation from a predefined benchmark (often a risk-free asset) and the standard deviation (i.e., risk) in order to evaluate an investment's return to its risk.

$$S_A = \frac{E(R_A - R_F)}{\sigma(R_A)}$$

Here,

$S_A$  = Sharpe Ratio of Asset A

$R_A$  = Returns of Asset A

$R_F$  = Return of a Risk-Free Asset

$\sigma$  = Standard deviation of asset's return

### ***Treynor Ratio***

Treynor Ratio is a performance measure to determine the abnormal returns produced for every unit of risk the portfolio considers. This risk is systematic risk, which is quantified by the beta of the portfolio.

$$T_A = \frac{E(R_A - R_F)}{\beta_A}$$

Here,

$T_A$  = Treynor's ratio

$R_A$  = Returns of Asset A

$R_F$  = Return of a Risk-Free Asset

$\beta_A$  = volatility of asset A with the market

### ***Sortino Ratio***

The sortino ratio measures the risk-adjusted return of a portfolio, an investment asset, or a strategy. It is a variant of the Sharpe ratio that penalizes just returns that fall short of a user-specified target or required rate of return instead of penalizing both upward and downward volatility equally.

$$SR_A = \frac{E(R_A - R_F)}{\sigma_d(R_A)}$$

Here,

$SR_A$  = Sortino Ratio of Asset A

$R_A$  = Returns of Asset A

$R_F$  = Return of a Risk-Free Asset

$\sigma_d$  = Downside Standard deviation of the asset's return

## **Methodology**

This study used descriptive and causal-comparative research design to evaluate the performance of different technical analysis tools. For the analysis of this study, price-adjusted closing price data of NEPSE and its six sub-indices, i.e., commercial bank, development bank, hydropower, life insurance, non-life insurance, and finance, were used. The period of data ranges from 1st September 2012 to

31st August 2022. The basic reason to consider this data period is to correspond with data availability and consistency in the NEPSE. Further, this data period provides sufficient length, market stability, relevance to the current context, and practicality, all of which contribute to the validity and reliability of the study's findings.

In this research, we examined the performance of some of the indicators in the NEPSE, and for that, we modelled it in Excel to process the data based on the trading rules of the indicators. We explain the employed rules below:

### ***i) Simple Moving Average (SMA)***

SMA is one of the simple technical analysis tools that smooth the price data by averaging the price over a specific period. Schulmeister (2008) and many others evaluated the predictability and profitability of SMA. The value of the SMA will be:

$$SMA = \frac{\sum_{i=1}^n P_{t-i+1}}{n}$$

Here, n= number of time-period for average; t= latest time of observation; P= Price of stock

- When the SMA value of the fast curve surpasses the SMA value of the slow curve after the occurrence of crossover, the trend shifts upward, indicating a long position and vice versa.

### ***ii) Moving Average Convergence Divergence***

MACD indicator illustrates the dynamics between two price moving averages. Appel (1999) was the original publisher of the work. The MACD and the Signal line curves in this indicator produce, buy and sell signals. The difference between the EMAs of 12 and 26 days is used to determine MACD. The signal line is derived from a 9-day moving average of the MACD.

$$EMA_t = (P_t - EMA_{t-1}) \cdot k + EMA_{t-1}$$

Here,

$EMA_t$  = Exponential Moving Average at the time t

t= latest time of observation

$P_t$  = price at the time t

$EMA_{t-1}$  = Exponential Moving Average at the time (t-1)

k= smoothing constant =  $\frac{2}{1+n}$ ,  $0 < k < 1$

n= number of time-period for average

$$MACD_t = EMA_{12 \text{ day}} - EMA_{26 \text{ day}}$$

$$Signal_t = EMA_{9 \text{ day}} \text{ of } MACD$$

$MACD_t$  = MACD at the time t

$Signal_t$  = Signal value at the time t

- When the MACD value breaks out above the signal line after the crossover, a buy signal is generated (indicates long position) and vice versa.

### ***iii) Relative Strength Index***

RSI is a technical indicator that is used to evaluate the condition of the market, i.e., an overbought and oversold situation of the market. This is a widely known momentum oscillator developed by Wilder (1978). The index value fluctuates between zero and 100; if the value is above 70, we consider that the stock is overbought, and if the value is below 30, we consider the stock is oversold.



$$RSI = 100 - \frac{100}{1 + RS}$$

$$RS = \text{Relative Strength} = \frac{\text{Average Gain during look-back period}}{\text{Average loss during look-back period}}$$

$$\text{Average gain} = \frac{\sum_{i=1}^n U_{t-i+1}}{n} \quad \text{Average loss} = \frac{\sum_{i=1}^n D_{t-i+1}}{n}$$

Here,

$U_{t-i+1}$  = price variation of observation day (if the closing is greater than the prior day else, zero)

$D_{t-i+1}$  = price variation of observation day (if the closing is lesser than the prior day else, zero)

n= number of days in the look-back period

t= latest time of observation

- A sell signal is generated when the RSI's ascending value crosses the upper bound (i.e., 70), and a short position is opened and maintained until the RSI signal breaches the lower bound value during a decline.

- A buy signal is generated when the RSI's falling value crosses the lower bound (i.e., 30), and a long position is held until the RSI signal breaks the upper bound value while rising.

#### ***iv) Stochastic Oscillator***

The stochastic oscillator looks at the relationship between the stock's closing price and its range of prices over a given time frame. Lane (1984) created this set of momentum indicators. There are two indicators; one is %K, sometimes referred to as the fast stochastic indicator, and another is %D, sometimes referred to as the slow stochastic indicator.

$$\%K = \frac{C_t - L_{t,t-n+1}}{H_{t,t-n+1} - L_{t,t-n+1}} \times 100$$

$$\%D = EMA_{3 \text{ day}} \text{ of } \%K$$

Here,

t= latest time of observation

n= number of time-period

$C_t$  = Closing price at time t

$L_{t,t-n+1}$  = Lowest closing price from time t to time (t-n+1)

$H_{t,t-n+1}$  = Highest closing price from time t to time (t-n+1)

- When the %K value surpasses the %D value after the occurrence of crossover, it indicates a long position, so we buy the stock.

- When the %D value surpasses the %K value after the occurrence of crossover, it indicates a short position, so we sell the stock.

#### ***v) Bollinger Bands***

Bollinger Bands are another commonly used instrument for technical analysis. These kinds of indicators are frequently employed in breakout trading strategies. According to Bollinger (2001), BB is created using a simple moving average with a lag of n days and a confidence interval. This gives three values i.e., Moving average, Lower Bollinger Band, and Upper Bollinger Band.

$$BB = SMA_{t,n} \pm k. \sigma_{t,n}$$

Here,

$t$  = latest time of observation

$SMA_{t,n}$  = Simple moving average at time  $t$  with a lag of  $n$ -day

$k$  = constant

$\sigma_{t,n}$  = Standard deviation at time  $t$  with a lag of  $n$ -day

- In upward movement/trend, if the price crosses the Upper Bollinger Band, then the long position is signaled, and we will sell the stock.
- In downward movement/trend, if the price crosses the Lower Bollinger Band, then the short position is signaled, and we will buy the stock.

In the second stage, the bootstrap method was used to analyze the predictability of technical indicators. Developed by Efron (1979), the bootstrap seemed as a method to evaluate an estimator's precision. A bootstrap approach uses repeated replacement sampling from the real data to describe the characteristics of estimators.. Bootstrap techniques are more adaptable than traditional statistical techniques, which may be analytically challenging or useless if the right assumptions are not made.

Brock et al. (1992) used this method in their research to compare the returns between the strategies incorporating different models such as the RW model, AR model, GARCH-M model, and EGARCH model. We used the RW model in this research to estimate the returns of the strategies. The bootstrap technique for this model contains the following five iterations:

Calculate the logarithmic return of daily price data from an index

$$r_t = Y_t - Y_{t-1}$$

Resample the data using a replacement from the original series to produce a series of bootstrapped returns  $rt^*$ .

Create bootstrap dependent variables, i.e., price, by adding the returns of the fitted values.

$$Y_t^* = Y_{t-1}^* + r_t^*$$

Estimate the RW model's bootstrap parameters (which have been discussed further in the data analysis plan).

Re-do step 2 and repeat up to step 4 a total of  $B$  times.

The null model is replicated 500 times for each simulation (i.e.,  $B = 500$ ). This should provide a reasonably close approximation of the null model's distribution of returns.

## Data Analysis and Result

In the first stage of analysis, the significance of the returns from using the indicators was tested using different techniques and metrics to test the results. This section presents the results from the strategies used in backtesting the 10-year-period value index and sub-indices of the stock market. A total of 2294 observations were generated during this period. Modeling of strategies and the model analysis were done using Excel Software. Table 1 depicts the annualized returns of different technical indicators to different sectors.

**Table 1 Annualized Return from Different Strategies in Different Sectors**

| Scripts    | NEPSE  | Com. Bank | Hydro  | Dev. Bank | Life Insurance | Non-Life Insurance | Finance |
|------------|--------|-----------|--------|-----------|----------------|--------------------|---------|
| B&H return | 16.09% | 13.91%    | 8.85%  | 29.55%    | 28.70%         | 26.79%             | 19.32%  |
| SMA return | 21.33% | 16.50%    | 14.90% | 32.32%    | 38.51%         | 36.77%             | 27.34%  |

| Scripts                      | NEPSE  | Com. Bank | Hydro  | Dev. Bank | Life Insurance | Non-Life Insurance | Finance |
|------------------------------|--------|-----------|--------|-----------|----------------|--------------------|---------|
| MACD return                  | 23.64% | 20.13%    | 22.68% | 29.80%    | 44.09%         | 38.80%             | 23.97%  |
| RSI return                   | -4.81% | -4.79%    | -6.49% | 0.60%     | -9.95%         | -9.39%             | -5.50%  |
| Stochastic Oscillator return | 44.00% | 45.35%    | 39.43% | 49.41%    | 69.77%         | 65.72%             | 33.43%  |
| BB return                    | 18.05% | 12.90%    | 15.03% | 27.83%    | 33.24%         | 32.92%             | 22.64%  |

Table 1 shows the annualized return of different strategies from different indices, where the maximum return can be seen from the Stochastic oscillator in life insurance. In contrast, RSI generated a negative return as high as 9.95%. According to Table 1, the sub-index life insurance has the highest annualized return of 69.77% through the Stochastic oscillator among all the strategies used in all the indices, whereas the same sub-index, i.e., life insurance has the lowest annualized return of -9.95% through RSI among all the strategies used in the indices. All indicators, except RSI, were found profitable, with returns exceeding the NEPSE benchmark.

In order to evaluate the performance of various technical indicators, this study developed different performance metrics. These metrics were used to assess the effectiveness of different trading strategies compared to a simple buy-and-hold strategy. Table 2 presents the performance metrics obtained from analyzing these trading strategies.

**Table 2 Performance Metrics of Different Trading Strategies over Buy-and-Hold Strategy (NEPSE)**

| Scripts                | SMA    | MACD   | RSI    | Stochastic Oscillator | BB     |
|------------------------|--------|--------|--------|-----------------------|--------|
| Annualized Return      | 21.33% | 23.64% | -4.81% | 44.00%                | 18.05% |
| Maximum Drawdown       | 26.28% | 21.10% | 48.15% | 11.67%                | 27.17% |
| Profit Factor          | 3.86   | 2.97   | 0.66   | 2.56                  | 12.19  |
| Payoff ratio           | 3.31   | 2.57   | 0.44   | 2.82                  | 9.75   |
| Wins (%)               | 53.85% | 53.62% | 57.69% | 47.40%                | 55.56% |
| Average Holding period | 33.31  | 17.16  | 39.81  | 4.41                  | 130.44 |
| No. of Trades          | 39     | 69     | 26     | 327                   | 9      |
| Beta                   |        |        |        |                       |        |
| Sharpe ratio           | 0.65   | 0.77   | -0.68  | 1.80                  | 0.49   |
| Treynor ratio          |        |        |        |                       |        |
| Sortino ratio          | 0.97   | 1.14   | -1.00  | 2.68                  | 0.72   |

Table 2 shows different performance metrics of different technical trading strategies over the buy-and-hold strategy (NEPSE). We can see that the Stochastic oscillator shows good values of metrics, whereas RSI shows the complete opposite.

To evaluate each technical indicator's performance, we concentrated on the measure of returns generated during the study period. This method permits a thorough evaluation of the efficacy of these indicators on the Nepalese stock market. Table 3 summarizes the daily market returns for the NEPSE and six sub-indices.

**Table 3 Summary Statistics**

| Scripts  | NEPSE   | Com. Bank | Hydro    | Dev. Bank | Life-Insurance | Non-Life Insurance | Finance   |
|----------|---------|-----------|----------|-----------|----------------|--------------------|-----------|
| N        | 2293    | 2293      | 2293     | 2293      | 2293           | 2293               | 2293      |
| Mean     | 0.0651% | 0.0568%   | 0.0370%  | 0.1129%   | 0.1100%        | 0.1035%            | 0.0770%   |
| Std.     | 1.3019% | 1.4140%   | 1.8637%  | 1.5664%   | 1.8402%        | 1.8355%            | 1.5516%   |
| Skewness | 0.27    | 0.69      | 0.60     | 0.87      | 0.53           | 0.48               | 0.70      |
| Kurtosis | 3.33    | 4.68      | 2.83     | 5.38      | 4.24           | 3.05               | 7.19      |
| JB       | 39.35** | 450.36**  | 142.08** | 827.24**  | 253.90**       | 89.84**            | 1863.66** |

\*\* Correlation is significant at the 0.01 level (2-tailed)

\* Correlation is significant at the 0.05 level (2-tailed)

Table 3 illustrates different statistics of the indices. The result shows some skewness in the data, with all positively skewed. Hydropower has a kurtosis of 2.83 which means it has platykurtic distribution. Non-life insurance has a kurtosis of 3.05 which means it has mesokurtic distribution. All the other indices are leptokurtic. The results show that the data failed the normality test.

**Table 4 Results for Various Trading Strategies Using NEPSE**

| Strategy              | N(buy)  | N(sell) | $R_t(\text{buy})$ | $R_t(\text{sell})$ | $R_t > 0(\text{buy})$ | $R_t > 0(\text{sell})$ | Buy-Sell  |
|-----------------------|---------|---------|-------------------|--------------------|-----------------------|------------------------|-----------|
| SMA                   | 1221.00 | 1049.00 | 0.001584          | -0.000580          | 0.5332                | 0.4395                 | 0.002164  |
| MACD                  | 1124.00 | 1122.00 | 0.001888          | -0.000758          | 0.5231                | 0.4563                 | 0.002646  |
| RSI                   | 1068.00 | 1179.00 | -0.000462         | 0.001500           | 0.4466                | 0.5293                 | -0.001962 |
| Stochastic Oscillator | 1113.00 | 1164.00 | 0.003276          | -0.001921          | 0.5624                | 0.4227                 | 0.005197  |
| BB                    | 1174.00 | 948.00  | 0.001414          | -0.000450          | 0.5324                | 0.4378                 | 0.001863  |

Table 4 includes five technical trading strategies with statistics on the sample data of NEPSE. Though computational analyses have been performed with all the sub-indices, only the result of NEPSE is presented. The first column lists the five technical tools used in this study. The second and third columns are the number of buy and sell signals generated when using these strategies on the data. The next two columns are  $R_t(\text{buy})$  and  $R_t(\text{sell})$ , the mean return generated from the buy/sell signal.  $R_t > 0(\text{buy})$  and  $R_t > 0(\text{sell})$  represent the fraction of the buy and sell returns that are greater than 0. All except RSI (0.4466) have  $R_t > 0(\text{buy})$  greater than 0.5, and all except RSI (0.5293) have  $R_t > 0(\text{sell})$  less than 0.5. This implies that all the technical indicators except RSI perform well and beat the market benchmark. The last column is the buy-sell spread which is the difference between the buy and sell returns with the largest difference from the stochastic oscillator with a value of 0.005197.

**Table 5 Testing of Differences Between Trading Strategy Mean of Buy Signal and Unconditional Mean**

| Strategy              | NEPSE | Com. Bank | Hydro | Dev. Bank | Life-Insurance | Non-Life Insurance | Finance |
|-----------------------|-------|-----------|-------|-----------|----------------|--------------------|---------|
| SMA                   | 2.02  | 1.52      | 1.31  | 1.94      | 2.38           | 2.39               | 2.13    |
| MACD                  | 2.61  | 2.11      | 2.23  | 2.23      | 3.29           | 3.02               | 2.11    |
| RSI                   | -2.31 | -1.94     | -1.41 | -1.81     | -3.07          | -2.89              | -2.26   |
| Stochastic Oscillator | 5.52  | 5.62      | 4.10  | 4.19      | 5.61           | 5.38               | 3.26    |
| BB                    | 1.63  | 0.97      | 1.17  | 1.24      | 1.61           | 1.72               | 1.72    |

We can see some trading strategies still failed to reject the null hypothesis that the buy signal cannot generate a significantly greater return than the unconditional mean (using the right-tailed t-test). We can see from Table 5 that SMA failed to reject the null hypothesis for commercial banks, hydropower, and development bank. Similarly, BB failed to reject the null hypothesis for NEPSE, commercial bank, hydropower, development bank and life insurance. As we can observe from previous results, RSI has failed to reject the null hypothesis for all the indices as it had generated negative returns.

**Table 6 Testing of Differences Between Trading Strategy Mean of Sell Signal and Unconditional Mean**

| Strategy              | NEPSE | Com. Bank | Hydro | Dev. Bank | Life-Insurance | Non-Life Insurance | Finance |
|-----------------------|-------|-----------|-------|-----------|----------------|--------------------|---------|
| SMA                   | -2.54 | -1.93     | -1.52 | -2.33     | -2.71          | -2.65              | -2.46   |
| MACD                  | -2.97 | -2.62     | -2.35 | -2.12     | -3.23          | -2.83              | -2.03   |
| RSI                   | 1.82  | 1.60      | 1.29  | 1.54      | 2.68           | 2.65               | 2.05    |
| Stochastic Oscillator | -5.49 | -5.31     | -3.75 | -4.22     | -5.27          | -5.07              | -3.11   |
| BB                    | -2.19 | -1.62     | -1.58 | -1.53     | -2.27          | -2.38              | -1.74   |

Table 6 shows similar results to that of Table 5 as some of the trading strategies have failed to reject the null hypothesis that the sell signal cannot generate a significantly greater return than the unconditional mean (using the left-tailed t-test).

In the second stage, test statistics and bootstrap methodologies were used. If expected stock prices are based on current buy-sell information, technical trading rules provide undeniable evidence of stock price prediction capability. The projected returns of buy and sell signals, or buy/sell signals created by technical trading rules, must be compared with the returns of a buy-and-hold strategy to evaluate the validity of such a connection. The following calculations provide the t-test of differences between the arithmetic means of two subsamples, which is the obvious choice for this purpose:

The t-statistics for the buy/sell is

$$t = \frac{\bar{R}_{b/s} - \bar{R}}{\sqrt{\frac{\sigma^2}{N_{b/s}} + \frac{\sigma^2}{N}}}$$

The t-statistics for the buy-sell spread is

$$t = \frac{\bar{R}_b - \bar{R}_s}{\sqrt{\frac{\sigma^2}{N_b} + \frac{\sigma^2}{N_s}}}$$

Here,

$\bar{R}_{b/s}$  = mean return following the buy or sell signals

$\bar{R}$  = unconditional mean return (i.e., buy and hold strategy)

$\sigma^2$  = variance of unconditional mean return

$N_{b/s}$  = number of buy or sell signals

$N$  = overall number of observed data

The outcomes of the t-test are predicated on a stationary, independent, and asymptotically normal distribution. These presumptions frequently fail to describe the financial time series accurately. Thus, this study used bootstrap techniques to tackle this problem as guided by Brock (1992) and other authors

after him. The use of bootstrap techniques is justified due to the limitations of traditional statistical assumptions, such as stationarity, independence, and asymptotic normality, which often do not hold in financial markets. The bootstrap experiment also helps analyze appraisal biases brought on by data snooping.

Further, this study employed Random Walk (RW) bootstrap model as it is considered superior to others. The RW bootstrap model assumes that future price movements follow a random walk, which is a widely accepted representation of market dynamics. It preserves the serial dependence observed in financial time series data. It takes into account the autocorrelation and time-varying patterns that exist in stock market data. By maintaining the original structure of the time series, the RW bootstrap approach allows for a more accurate representation of market behavior. To formulate the comparative effectiveness of this trading rule  $k$  at time  $t$  in comparison to the benchmark buy-and-hold strategy or always-long position at the same time, i.e., for the buy period, the following formula is used;

$$f_{k,t} = R_{k,t} - R_t$$

Alternately, the relative performance equals the returns provided by trading rule  $k$  when the benchmark is constantly in a neutral position, i.e., for the sell-period, the following formula is used;

$$f_{k,t} = R_{k,t}$$

Then, obtain the p-values as per the next indicator function:

For buy signals,

$$p = \begin{cases} 0 & \text{if } f_{k,t} > 0 \\ 1 & \text{if } f_{k,t} \leq 0 \end{cases}$$

For sell signals,

$$p = \begin{cases} 0 & \text{if } f_{k,t} < 0 \\ 1 & \text{if } f_{k,t} \geq 0 \end{cases}$$

**Table 7 Testing of Differences for Trading Strategy Buy-Sell Spread**

| Strategy              | NEPSE | Com. Bank | Hydro | Dev. Bank | Life-Insurance | Non-Life Insurance | Finance |
|-----------------------|-------|-----------|-------|-----------|----------------|--------------------|---------|
| SMA                   | 3.95  | 2.98      | 2.44  | 3.69      | 4.41           | 4.36               | 3.97    |
| MACD                  | 4.82  | 4.08      | 3.94  | 3.75      | 5.63           | 5.05               | 3.58    |
| RSI                   | -3.57 | -3.05     | -2.32 | -2.89     | -4.97          | -4.79              | -3.73   |
| Stochastic Oscillator | 9.52  | 9.45      | 6.79  | 7.28      | 9.41           | 9.04               | 5.50    |
| BB                    | 3.28  | 2.24      | 2.37  | 2.38      | 3.35           | 3.54               | 2.96    |

Table 7 presents the result of the two-tailed t-test for technical trading strategies for the buy and sell spread using different indices. We can observe that all the results reject the null hypothesis for the buy-sell spread in terms of statistical significance.

**Table 8 Simulation Tests from Random Walk Bootstraps for 500 Replications of NEPSE**

| Strategy              | p-value (buy) | p-value (sell) | p-value buy-sell | p-value $\sigma$ (buy) | p-value $\sigma$ (sell) |
|-----------------------|---------------|----------------|------------------|------------------------|-------------------------|
| SMA                   | 0.53          | 0.95           | 0.00             | 0.57                   | 0.43                    |
| MACD                  | 0.51          | 0.95           | 0.00             | 0.51                   | 0.49                    |
| RSI                   | 0.46          | 0.94           | 0.00             | 0.44                   | 0.55                    |
| Stochastic Oscillator | 0.54          | 0.95           | 0.00             | 0.49                   | 0.50                    |
| BB                    | 0.53          | 0.93           | 0.00             | 0.49                   | 0.52                    |

Table 8 includes performance statistics of the five trading strategies models using the bootstrap method. Contrary to the test statistics of buy and sell signals presented in Table 5 and Table 6, none of the trading strategies reject the null hypothesis for buy and sell signals not generating greater returns than the unconditional mean, as the p-values for all the strategies were greater than 0.05. However, the buy-and-sell spread rejected the null hypothesis for all the trading techniques. Table 8 also shows that the models decrease the standard deviation for buy or sell signals.

While testing the performance through the bootstrap method, it contradicts the t-statistics results. The results of this study support the outcome from Muruganandan (2020), which concluded that RSI and MACD could not generate abnormal returns. It also supports the result of Brock et al. (1992) for GARCH-M and EGARCH models but denies its results for the Random walk model used in this study.

## Conclusion

The performance metrics show positive results towards significant results, where the Stochastic oscillator generated the highest profits. RSI performed worst among all the indicators which could not beat the market. Though the metrics were exceptional for other indicators, the number of trades was not significant enough to assure the results, indicating that more data is required. This study found that the test statistics support the performance metrics results as the Stochastic oscillator generated the highest mean returns from the buy and sell signals. It also had the highest buy-sell spread among all the other indicators. However, SMA and BB failed to generate significant returns in some indices, suggesting they were weaker in generating profits than the Stochastic oscillator and MACD. The results conflicted with Azhara (2010), where the result was similar for SMA; it contradicted the result of RSI.

Finally, the Bootstrap method contradicts previous findings as no indicators could generate returns significantly over simulated bootstrap data sets. The simulated results show that the indicators could not generate consistent returns from either buy signals or sell signals questioning the capability of the technical indicators. The results further show that the indicators cannot significantly decrease the volatility of the data during buy signals or sell signals. The results contradict the study by Radovanov, Marcikić, and Fakulta (2017) as the study concluded that the technical analysis beats the market even after including transaction costs. However, The results conflict with Brock et al. (1992), where few technical analysis rules in some regression models could not generate significant returns than the market. The results thus indicate that the technical analysis tools cannot predict the returns.

In conclusion, while backtesting the technical trading rules on the Nepalese stock market, the stochastic oscillator provides the best returns. However, it is risky with a low-profit factor and win rates. SMA and MACD also generate substantial profits with good profit factors and win rates, with MACD having the upper hand over SMA. But the bootstrap results discard the predictability power of technical indicators. The two sets of results hence contradict themselves. Nevertheless, this study demonstrates that stock returns generation is likely more complex than it is shown by the research, which employs trading rules and analyzes the returns. Technical limitations may detect hidden patterns, but “how” would remain a question for further studies.

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