# “Does an increase in portfolio volatility create more returns? Evidence from India”


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# DOES AN INCREASE IN PORTFOLIO VOLATILITY CREATE MORE RETURNS? EVIDENCE FROM INDIA

## Abstract

The classical view of experts associates greater risks with greater rewards. The present study explores whether increased volatility in portfolios can create more returns for investors by using technical indicators or the buy-and-hold (BH) strategy. The study used closing prices of National Stock Exchange (NSE) 500 index firms for a period of 16 years (2007–2022). Five portfolios ranging from low to high volatility were created using standard deviation as a key measure. Findings indicate that as the volatility of the portfolios increases, the moving average (MA) returns seem to be higher. Across the various MA time frames, the 20-day MA seems to have generated the highest return annually (36.53% before transaction costs and 31.05% after transaction costs) due to reasonable trading opportunities with adjustable transaction costs. The CAPM also generated positive alpha (after bearing transaction costs) in the case of 20, 50, and 100 days MA, with the values being 16.66%, 13.29%, and 12.09%, respectively, in the case of highly volatile portfolios. On the other hand, while the BH strategy created substantial returns in all scenarios, the risk factor was extremely high due to the high standard deviation. Hence, it is suggested that investors/traders consider the BH strategy more cautiously while choosing between technical analysis returns and BH returns. Investors with high-risk preferences may have BH as their choice, while day traders with managed risk appetites may prefer technical tools over BH returns.

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**JEL Classification** G11, G12, G14

## INTRODUCTION

Modern portfolio theory provides insights for optimally balancing risk and rewards for investment decision-making. The theory states how the financial markets should work in ideal situations and how a rational investor should construct a diversified portfolio to maximize expected return for a given level of risk preferences. The major points of this theory were captured in the Efficient Market Hypothesis (EMH) that stock prices reflect all available information. Accordingly, markets are efficient and cannot be beaten. Contrary to this, technical analysts do not pay much attention to the efficient market hypothesis. These practitioners believe that certain price patterns repeat themselves and provide profit opportunities. Consequently, they pore over historical data and draw charts using technical analysis tools. They assume investors are rational and tend to have invariant preferences while making investment decisions. Active traders generally find it difficult to outperform passive strategies such as buy-and-hold (BH) of portfolio indices. To do so, this requires a differential insight, and they focus on active trading strategies of technical analysis, such as moving average techniques, to create returns for their risky portfolios.

Finance academia firmly believes that the higher the volatility, the riskier the portfolio and the classical view associates greater risk with



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greater rewards. Therefore, conceptualizing the above observations, the study specifically explores whether volatility decile portfolios could create more returns by using technical indicators such as moving averages. Since the studies are limited in the Indian context on portfolio riskiness and returns, the present study comprehends the effect of transaction costs and the capital asset pricing model (CAPM) on moving average returns and BH returns for volatility decile portfolios.

# 1. LITERATURE REVIEW AND HYPOTHESES

Research related to stock market volatility and returns has long been of interest to finance researchers. The prime focus of these studies is to either understand the technical analysis of various market-based indices (Mitra, 2011) or analyze portfolio returns based on time-varying beta (Agarwal et al., 2023; Chakrabarti & Das, 2021). Few other studies attempt to understand the factors behind crashes and volatility in the markets. For instance, Wang et al. (2009) examined how the market crashes affected stocks with varying financial characteristics. Arshanapalli and Doukas (1993) focused on the stock market crashes and the international co-movements of stock price indices, whereas Pan et al. (2021) examined the rationale behind variations in stock downfall in the stock market through the lens of investor structure. The foremost assumption behind any event or crisis is investors' sentiments that move markets (De Long et al., 1990). Thus, the information asymmetrical aspect of an inefficient market is a contributory factor to its excessive volatility and return (Haritha & Rishad, 2020). As a result, investor sentiments play a vital role in determining the stock market's volatility (Kumari & Mahakud, 2016).

According to Fama and Blume (1966), investors cannot beat market performance in the long run due to the random walk hypothesis, which suggests that past movements of stocks are independent random variables, and this historical data of return changes cannot be used to forecast future movements. In contrast, Brock et al. (1992) found their results inconsistent with the random walk theory and other GARCH models and provided strong evidence for technical tools, especially the moving average. Thus, technical analysis has predictive power in measuring stock returns (Han et al., 2021). It is a frequently used approach to predict market trends using historical trading data of stock returns (Hung & Lai, 2022), and technical trading rules usually outperform in terms of returns (Zhu & Zhou, 2009). The findings of Alanazi and Alanazi (2020) were also consistent with the linkage between market efficiency and profitability of technical analysis.

Technical charts are used frequently for short-term forecasting, and short-term technical trading rules have a better explanatory power as compared to long-term trading (Han et al., 2021). From among the various techniques of technical analysis, including moving average, relative strength index, moving average convergence divergence, etc., simple moving average turns out to be highly used among investors. This technique gives early indications that help to create meaningful returns (Marshall et al., 2017). Fifield et al. (2008) found the moving average trends to be more persistent for longer moving averages. Likewise, Avramov et al. (2021) and Gencay (1998) also found robust results of moving averages for the long side as compared to the short side. They also noted that nonparametric models of technical trading rules provided substantial profits as compared to simple BH strategy; this resulted in buy signal rules creating higher returns as against sell signals (Brock et al., 1992). Han et al. (2013) documented the application of the moving average strategy on portfolios which outperformed the BH strategy. Contradicting the above findings, Kwon and Kish (2002) are of the view that while technical trading created more value to profit opportunities as compared to BH strategy, the profit potential weakened over time across different periods. This indicated the efficiency of the market in distributing information to more investors over time. Further, examining the reasons behind the weakening of the predictive ability of the moving average rules, Urquhart et al. (2015) noted that the market reacted to the prior day's buy/sell signals as against the days for which the actual signals were generated. Thus, moving averages do have the potential to generate returns, however, few studies found their predictive ability to be low.



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Exploring the investors' motivation to use technical analysis, Wang and Sun (2015) found that many technical strategies provided substantial returns to the investors. Stocks with greater asymmetrical aspects and low liquidity generated large returns for the investors. Besides, technical analysis has also been considered to be important among trade dealers and fund managers in terms of generating returns (Gehrig & MenKhoff, 2006). Technical analysis supports them in fundamental analysis by selecting the most dynamic firms in the market (De Souza et al., 2018).

In the context of emerging and developing nations, a few studies indicated their results for technical analysis. For instance, Fifield et al. (2008) noticed that the return pattern in emerging markets was different from that in developed markets. Metghalchi et al. (2018) and Bessembinder and Chan (1995) noticed that technical analysis revealed a robust predictive power for emerging market indexes, while their results seemed to be weak in the developed markets. Thus, technical trading rules can predict better in the emerging stock markets as compared to developed stock markets (Yu et al., 2013).

Contracting the above views, Jensen and Benington (1970) indicated no relevance or power of technical analysis on the market performance. Alhashel and Almudhaf (2020) also failed to provide predicted profitability of technical trading – the Gulf market showed a weak form of efficiency, and this created implications for investors' choice in selecting different investment tools. Garg et al. (2020) also noted that, due to an increase in the breakage of trends over a while, the performance of several assets and asset classes was impacted negatively due to these trend-following strategies. Thus, this evidence provided mixed results on the relevance and use of technical tools.

Another major aspect that is significant to explore is the impact of transactions' cost on trading. The majority of the technical trading rules can capture the direction of market movements and provide significant positive returns (Mitra, 2011). However, the full exploitation of these returns is not possible due to the presence of real-world transaction costs. Some aspects of transaction costs, like bid-ask spread and brokerage fees, can never be zero. The short-term moving average rule generates more trades, thus creating higher transaction costs. According to Avramov et al. (2021), moving average returns reasonably bear the trading costs. Similarly, Han et al. (2013) noticed that portfolios with higher volatility had higher abnormal returns as compared to the famous CAPM and Fama and French (1993) three-factor models. These returns were found to be higher even after adjusting transaction costs (Jiang et al., 2017). In contrast to the above findings, Yu et al. (2013) noticed that transaction costs could erode trading profitability thus conveying a weak form efficiency. Park and Irwin (2007) were of the view that despite having positive results from technical analysis, studies in the literature were subject to problems such as the selection of trading rules, data snooping, problems in estimating risk, and transaction costs.

The various aspects of technical analysis have been explored in previous research. However, the literature did not shed light on the risk (standard deviation) based portfolio volatility and returns using technical analysis tools such as simple moving average aspect in the context of the Indian market. Therefore, the present work aims to examine whether increased volatility in risk-based portfolios can create more returns for investors using technical indicators rather than merely following a BH strategy. Using this rationale, the hypotheses framed for the study are:

H1: *Highly volatile portfolios create more returns than low volatile portfolios.*

H2: *The moving average technical tool creates more profits than the buy-and-hold strategy.*

# 2. METHODS

## 2.1. Data

The sample comprises National Stock Exchange (NSE) 500 index firms spanning over 16 years from 2007–2022. Firms were subject to filtration each year based on the lack of data availability. As the study was based on portfolios, each year, a new set of firms with varying numbers was created using volatility (standard deviation) as a key variable. Daily closing prices of firms were collected from the Refinitive EIKON database.

## 2.2. Methodology framework

Closing prices of stocks were used to calculate the daily returns. Standard deviation was taken as a key measure for segregating firms into different portfolios each year. Firms with low standard deviation were considered as low volatile firms, while those with high standard deviation were categorized as high volatile firms. Five portfolios were created each year which ranged from low to high volatility. These portfolios were used to create index values every day. Simple moving average (SMA), a technical analysis tool, was used to calculate returns on these index values. This method has been widely used by researchers (Avramov et al., 2021; Marshall et al., 2017; Han et al., 2013; Gencay, 1998); it calculates the arithmetic means of a given set of prices over a specific number of days in the past.

$$SMA = \frac{A_1 + A_2 + \ldots + A_n}{N}, \tag{1}$$

where $A$ is the average in period, and $n$ is the number of periods.

The study used moving averages (MA) of 5 days, 10 days, 20 days, 50 days, and 100 days to understand the implications of short-term to long-term trading strategies in terms of the creation of returns in a one-year time frame. The strategies were then used to create buy and sell signals each year. The short-term strategies created trading signals (buy and sell) more frequently as compared to long-term strategies. The results were also tested during the US recession and COVID-19 phases. This is to understand whether extreme volatility during these specific phases has provided more opportunities to create returns. The study further compared the buy-and-hold (BH) returns with the moving average technical analysis to understand whether the technical analysis is supportive in the creation of better returns as against normal BH strategy across various portfolios.

The study also considered transaction costs (on 30 basis points in the Indian context) an important variable in trading strategies. Since there were many signals during the year, especially in short-term trades, transaction costs played a significant role in creating returns. Other studies, such as Balduzzi and Lynch (1999), used one point to 50 basis points as lower and upper bounds. Lynch and Balduzzi (2000) considered a transaction cost of 25 basis points.

## 2.3. CAPM model

The study used capital asset pricing model (CAPM) regression of the with- and without-cost portfolio returns on the market portfolio.

$$E\left(R_p\right) - R_f = \alpha_{ip} + \beta_{mkt}\left(r - rf\right) + e_{it}, \tag{2}$$

where $E\left(R_p\right)$ is the expected return on a portfolio, $R_f$ is the risk-free rate, $mkt\left(r - rf\right)$ is the market premium.

The CAPM model has been used to understand the creation of alphas in portfolios using technical analysis strategies.

# 3. RESULTS

The results in Table 1 show the average returns (without adjusting transaction costs) of 5 portfolios from short to long trading periods. The mean values are highest across highly volatile portfolios, revealing the fact that high volatility or risk creates more returns. 20-day MA seems to generate the highest return (36.53%) annually vis-à-vis other windows. MA of 50 days and 100 days have relatively lower returns due to the occurrence of less frequent trading signals. This is due to the limitation of a one-year portfolio. Comparing the buy-and-hold returns with moving average returns, it

**Table 1.** Portfolio returns (without transaction costs)

| Volatility Rank | BH | | 5 Days | | 10 Days | | 20 Days | | 50 Days | | 100 Days | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Avg Ret | SD | Avg Ret | SD | Avg Ret | SD | Avg Ret | SD | Avg Ret | SD | Avg Ret | SD |
| Low | 16.36 | 32.21 | 13.19 | 16.13 | 10.80 | 17.38 | 13.47 | 19.22 | 14.88 | 26.78 | 9.70 | 14.84 |
| 2 | 19.44 | 39.36 | 15.52 | 23.09 | 12.47 | 22.25 | 18.48 | 22.58 | 19.04 | 28.43 | 12.03 | 19.21 |
| 3 | 24.82 | 46.78 | 16.00 | 24.91 | 14.43 | 25.93 | 20.87 | 26.78 | 20.27 | 31.17 | 13.33 | 18.52 |
| 4 | 30.51 | 55.28 | 18.64 | 29.61 | 20.07 | 33.11 | 29.18 | 37.54 | 27.82 | 43.07 | 19.21 | 27.21 |
| High | 44.60 | 74.71 | 25.95 | 35.74 | 29.27 | 38.72 | 36.53 | 43.35 | 32.18 | 46.09 | 26.18 | 30.75 |


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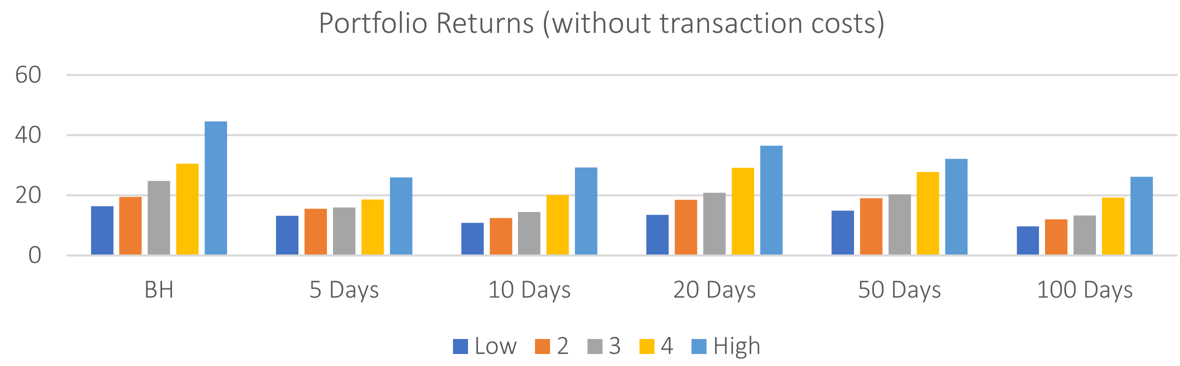


**Figure 1.** Portfolio average returns without adjusting transaction costs

can be observed that the BH strategy has created the highest returns across all portfolios, with the maximum being at 44.60%. Equally interesting to note is that the risk factor is extremely high in the case of BH strategy (ranging from 32.21% to 74.71%). Figure 1 portrays similar findings.

Table 2 presents similar results to those presented in Table 1. There is, however, a reduction in profitability across all portfolios due to the effect of transaction costs. The major impact can be seen in the case of 5-day MA due to frequent trading signals. The returns seem to be negative (–1.28%) in the case of a low volatile portfolio scenario. In fact, in this case, the returns of a highly volatile portfolio reduced from 26% (Table 1) to 11.51% (Table 2) due to the impact of transaction costs. It can be seen that as the tenure of the window increases, the magnitude of transaction costs decreases. Figure 2 portrays a similar impact graphically.

The study also tests the results during the 2007–2008 recession, as can be seen in Table 3. This has been done to understand whether or not technical analysis moves to provide an edge over the normal BH strategy during a crisis period. From the results, it can be inferred that during a downfall scenario like a recession, 20, 50, and 100-day MA seems to provide better returns than the BH strategy. These findings are consistent even after

**Table 2.** Portfolio returns (after transaction costs)

| Volatility Rank | BH | | 5 Days | | 10 Days | | 20 Days | | 50 Days | | 100 Days | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Avg Ret | SD | Avg Ret | SD | Avg Ret | SD | Avg Ret | SD | Avg Ret | SD | Avg Ret | SD |
| Low | 15.71 | 32.11 | –1.28 | 16.41 | 1.26 | 18.08 | 7.41 | 19.70 | 11.76 | 27.70 | 7.83 | 15.65 |
| 2 | 18.79 | 39.25 | 0.71 | 23.19 | 2.67 | 22.71 | 12.69 | 23.13 | 16.17 | 29.16 | 10.24 | 20.05 |
| 3 | 24.15 | 46.64 | 0.94 | 25.16 | 4.91 | 26.00 | 14.86 | 27.18 | 17.36 | 31.65 | 11.60 | 19.07 |
| 4 | 29.82 | 55.11 | 4.11 | 29.83 | 10.68 | 33.72 | 23.35 | 38.16 | 24.87 | 43.83 | 17.59 | 27.71 |
| High | 43.82 | 74.49 | 11.51 | 35.97 | 20.02 | 38.50 | 31.05 | 43.58 | 29.23 | 46.41 | 24.71 | 30.95 |

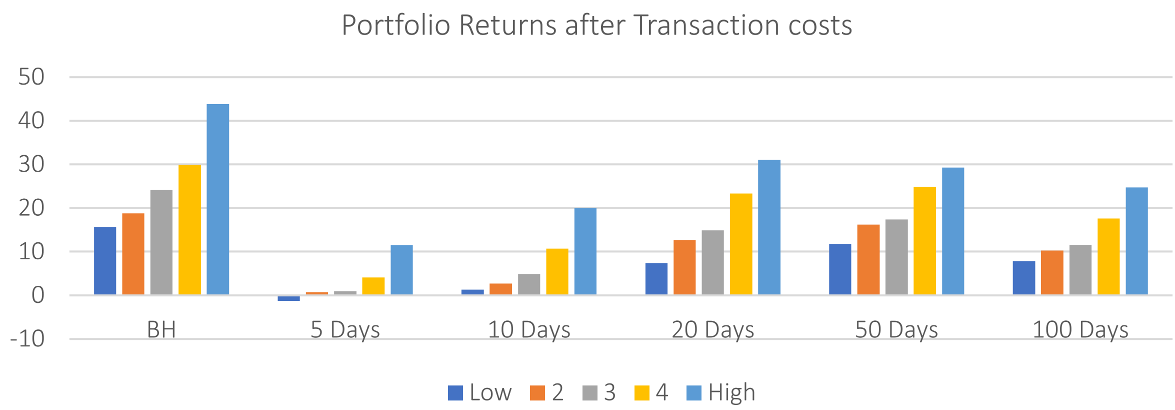


**Figure 2.** Portfolio average returns after adjusting transaction costs

**Table 3.** Portfolio returns during the 2007–2008 recession

| Rank | Without Transaction costs | | | | | | After Transaction costs | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | BH | 5 Days | 10 Days | 20 Days | 50 Days | 100 Days | BH | 5 Days | 10 Days | 20 Days | 50 Days | 100 Days |
| Low | –17.63 | 3.87 | –0.34 | 7.46 | 3.01 | 4.36 | –18.17 | –10.23 | –9.64 | 2.19 | –0.15 | 1.94 |
| 2 | –12.57 | –0.44 | –3.38 | 11.91 | 10.95 | 12.10 | –13.13 | –14.83 | –13.27 | 6.47 | 8.52 | 10.27 |
| 3 | –20.04 | 1.76 | –4.75 | 6.12 | 4.53 | 25.09 | –20.58 | –12.04 | –12.68 | 0.85 | 2.27 | 22.91 |
| 4 | 6.85 | –0.40 | 4.76 | 30.10 | 34.45 | 73.72 | 6.23 | –15.70 | –4.10 | 25.21 | 32.99 | 72.30 |
| High | 26.73 | 6.16 | 15.92 | 30.97 | 32.97 | 52.09 | 26.05 | –9.75 | 6.57 | 25.93 | 30.03 | 50.83 |

**Table 4.** Portfolio returns during COVID-19 (2020–2021)

| Rank | Without Transaction costs | | | | | | After Transaction costs | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | BH | 5 Days | 10 Days | 20 Days | 50 Days | 100 Days | BH | 5 Days | 10 Days | 20 Days | 50 Days | 100 Days |
| Low | 15.42 | 10.40 | 11.31 | 11.02 | 12.70 | 10.01 | 14.77 | –5.53 | 1.53 | 4.24 | 9.51 | 7.43 |
| 2 | 30.36 | 22.06 | 18.44 | 23.42 | 28.64 | 24.86 | 29.67 | 7.00 | 7.89 | 17.35 | 25.70 | 23.74 |
| 3 | 48.36 | 28.70 | 31.27 | 31.38 | 34.73 | 28.33 | 47.62 | 14.97 | 21.12 | 25.59 | 32.53 | 27.05 |
| 4 | 56.58 | 33.77 | 33.59 | 42.33 | 58.66 | 40.70 | 55.80 | 19.26 | 23.43 | 35.60 | 56.38 | 39.08 |
| High | 86.34 | 51.62 | 60.62 | 62.83 | 65.85 | 45.64 | 85.48 | 37.81 | 51.29 | 56.63 | 63.10 | 45.12 |

adjusting transaction costs. Table 4 discusses the results during the COVID-19 scenario. Here, the results are more supportive of the BH strategy (nearly 86% returns after adjusting transaction costs), but the results are also substantial in the case of MA (37% to 63%). These results indicate that technical analysis is a useful indicator during a crisis period since the volatility is pretty much higher in the case of the BH strategy. Lento and Gradojevic (2022) examined the technical trading potential to generate profits in the COVID-19 pandemic situation. Their results concluded that technical trading had significant potential to create more profits than the BH strategy.

Table 5 indicates the CAPM model's alpha and beta values of 5, 10, 20, 50, and 100-day MA strategy without adjusting transaction costs. The alpha values are positive in all the cases in Panel A. This is aligned with the first hypothesis of the study that highly volatile portfolios create more returns than low volatile portfolios. The values are highest in the case of 20-day MA (ranging from 3.96% to 22.10%). The values are significant at 1, 5, and 10% levels. Thus, MA strategies do provide substantial returns, especially in the case of highly volatile portfolios. The returns decline in the case of 50 and 100-day MA due to fewer trading opportunities in a one-year time frame.

Table 6 presents results after the adjustment of transaction costs. The moment transaction costs are adjusted, the alpha values reduce significantly in all the cases. It can be inferred that transaction costs have a greater impact on returns due to frequent trading signals, which is quite visible in terms of negative alphas in the case of 5 and 10-day MA. 20, 50, and 100 days have positive returns

**Table 5.** CAPM-based alpha and beta values (without TC adjustment)

| Rank | 5 Days | | | 10 Days | | | 20 Days | | | 50 Days | | | 100 Days | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | α | β | Adj $R^2$ | α | β | Adj $R^2$ | α | β | Adj $R^2$ | α | β | Adj $R^2$ | α | β | Adj $R^2$ |
| Low | 0.72* (1.298) | 0.44*** (4.730) | 0.6 | 1.115 (0.577) | 0.47*** (4.821) | 0.57 | 3.96 (0.969) | 0.45*** (3.435) | 0.41 | 4.02 (0.784) | 0.64*** (3.524) | 0.43 | 0.44 (0.169) | 0.35*** (3.571) | 0.43 |
| 2 | 2.11 (1.175) | 0.68*** (5.881) | 0.68 | 1.125 (0.962) | 0.59*** (4.341) | 0.53 | 5.54* (1.317) | 0.53*** (3.546) | 0.42 | 7.62 (1.429) | 0.72*** (4.001) | 0.5 | 2.80 (0.623) | 0.37*** (2.553) | 0.27 |
| 3 | 4.21 (1.500) | 0.77*** (7.551) | 0.785 | 2.83 (0.811) | 0.76*** (5.715) | 0.675 | 9.68* (1.947) | 0.70*** (4.139) | 0.52 | 7.64* (1.764) | 0.90*** (5.659) | 0.67 | 2.75 (0.812) | 0.46*** (3.821) | 0.46 |
| 4 | 6.01* (1.471) | 0.90*** (6.465) | 0.73 | 6.915 (1.427) | 0.97*** (5.968) | 0.69 | 15.45** (2.595) | 1.05*** (5.258) | 0.64 | 13.58* (1.762) | 1.13*** (4.329) | 0.54 | 7.47* (1.307) | 0.60*** (3.112) | 0.36 |
| High | 12.47** (2.322) | 1.02*** (5.837) | 0.655 | 15.141*** (2.523) | 1.12*** (5.601) | 0.665 | 22.10*** (2.880) | 1.16*** (4.533) | 0.56 | 16.29** (2.445) | 1.36*** (6.009) | 0.7 | 13.60** (2.274) | 0.77*** (3.976) | 0.49 |

*Note*: t-statistics values are significant at 1, 5, and 10%, indicating ***, **, and *, respectively.



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**Table 6.** CAPM-based alpha and beta values (after TC adjustment)

| Rank | 5 Days | | | 10 Days | | | 20 Days | | | 50 Days | | | 100 Days | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | α | β | Adj $R^2$ | α | β | Adj $R^2$ | α | β | Adj $R^2$ | α | β | Adj $R^2$ | α | β | Adj $R^2$ |
| Low | –10.72* (–3.814) | 0.44*** (4.462) | 0.55 | –8.39** (–2.663) | 0.47*** (4.371) | 0.52 | –1.98 (–0.553) | 0.43*** (3.092) | 0.36 | 0.82 (0.146) | 0.66*** (3.425) | 0.41 | –1.52 (–0.433) | 0.36*** (3.393) | 0.41 |
| 2 | –10.29** (–3.085) | 0.66*** (5.531) | 0.65 | –7.76* (1.556) | 0.58*** (4.168) | 0.51 | 2.72 (0.492) | 0.52*** (3.313) | 0.39 | 4.73 (0.842) | 0.72*** (3.830) | 0.47 | 0.96 (0.214) | 0.37*** (2.437) | 0.24 |
| 3 | –10.80*** (–5.265) | 0.77 (6.972) | 0.75 | –6.71* (–1.723) | 0.76*** (5.715) | 0.67 | 3.66 (0.682) | 0.70*** (4.041) | 0.50 | 4.68 (1.072) | 0.90*** (5.513) | 0.66 | 0.90 (0.333) | 0.46*** (3.653) | 0.44 |
| 4 | –8.42* (–1.951) | 0.88 (5.957) | 0.70 | –2.55 (–0.546) | 0.98*** (5.815) | 0.68 | 9.59 (1.520) | 1.06*** (5.096) | 0.61 | 10.58 (1.325) | 1.14*** (4.216) | 0.53 | 5.77 (1.009) | 0.59*** (3.035) | 0.35 |
| High | –1.91 (–0.425) | 1.01 (5.568) | 0.63 | 6.05 (0.931) | 1.09*** (5.383) | 0.64 | 16.66* (2.106) | 1.15*** (4.430) | 0.55 | 13.29* (1.969) | 1.36* (5.972) | 0.7 | 12.09* (1.997) | 0.77*** (3.937) | 0.49 |

*Note*: t-statistics values are significant at 1, 5, and 10%, indicating ***, **, and *, respectively.

after bearing transaction costs; this is due to less frequency of trading. The highest alphas can be again observed in the case of the 20-day MA timing strategy. The alpha increases with an increase in the portfolio volatility.

## 4. DISCUSSION

There are several studies in the past documenting the irrelevance of technical analysis (Fama & Blume, 1996; Jensen & Benington, 1970; Garg et al., 2020; Alhashel & Almudhaf, 2020) and indicating negative results in the case of various assets and classes. Contrary to this, other studies have found technical analysis to be a supportive tool to the fundamental analysis for value creation (Fifield et al., 2008; Yu et al., 2013; Metghalchi et al., 2018; Han et al., 2021). The present study finds technical analysis as a useful indicator for profit opportunities. Upon using the SMA technique, it can be seen that the results are consistent with the observations made by Avramov et al. (2021), Marshall et al. (2017), and Gencay (1998), which indicate that moving averages give early indications to create meaningful returns. As the portfolios become highly volatile and risky, the returns increase significantly. Comparing the MA performance with the BH strategy, the returns seem to be more in the BH strategy across all portfolios. However, the risk factor is extremely high, as evidenced by high standard deviation. This is in line with the second hypothesis of the study that moving average technical tools create more profits than the BH strategy. Thus, the BH strategy should be considered more cautiously before choosing between technical analysis returns and BH returns. Investors with high-risk preferences may have BH as their choice, while investors with relatively low-risk choices may prefer the SMA tool.

Further discussing the impact of transaction costs, Yu et al. (2013) and Mitra (2011) are of the view that full exploitation of technical analysis returns is not possible due to the presence of real-world transaction costs. In this paper, it can be seen that short-term moving averages such as 5- and 10-day MA generated a greater number of trades, creating higher transaction costs which seemed to cause a reduction in profitability. As the tenure of the window becomes longer, the magnitude of transaction costs reduces due to fewer trading signals. The CAPM model also depicts positive alpha values, which increase with the increase in portfolio volatility. These results are in tune with the findings of Jiang et al. (2017) and Han et al. (2013). 20-day SMA would be recommended for reasonable trade opportunities and lower transaction costs in one year. Once transaction costs are adjusted, the alpha values reduce significantly in all cases. Further, the testing of results during the US recession and COVID-19 shows that technical analysis is a useful indicator during the crisis period since the volatility is much higher in the case of the BH strategy. According to Lento and Gradojevic (2022), technical trading has significant potential to create more profits than the BH strategy.

Based on the above points of discussion, future researchers could extend their scope of work to more portfolios to find the changes in their pieces of evidence. Further, more tools of technical analysis could be used to examine the relevance of technical trading opportunities.

# CONCLUSION

The present study uses volatility-based portfolios to examine whether increased volatility in the portfolios could create more returns for the investors using technical indicators. The study also compares the buy-and-hold returns with the SMA technical analysis tool in the Indian market. The results indicate that highly volatile portfolios create more returns. MA strategies do provide substantial returns, especially in the case of highly volatile portfolios. Across various MA windows, a 20-day MA seems to generate the highest return annually due to reasonable trading opportunities with adjustable transaction costs. It can also be seen that 5 and 10-day MA witnessed a higher transaction costing impact due to frequent trading signals. The returns seem to be negative in low-volatile portfolios. As the tenure of the window becomes long, the magnitude of transaction costs reduces. While the BH strategy also creates substantial returns across all portfolios, the risk factor is extremely high.

The CAPM model also indicates positive alpha values; however, the alpha returns decline due to the impact of transaction costs. Thus, MA strategies do provide substantial returns, especially in the case of highly volatile portfolios. The moment transaction costs are adjusted, the alpha values reduce significantly in all cases.

The study contributes to the existing literature on technical analysis in two ways. First, it is the first study to create various portfolios using standard deviation as a base in the Indian context. Second, it tests the results using the CAPM method. The research is helpful to traders and investors in designing their buy-and-sell strategy. For risk takers, BH could be beneficial, while for risk-neutral to high-risk takers MA would prove to be useful for creating more benefits.

# AUTHOR CONTRIBUTIONS

Conceptualization: Vandana Bhama.
Data curation: Vandana Bhama.
Formal analysis: Vandana Bhama.
Methodology: Vandana Bhama.
Software: Vandana Bhama.
Validation: Vandana Bhama.
Visualization: Vandana Bhama.
Writing – original draft: Vandana Bhama.
Writing – review & editing: Vandana Bhama.

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