


# “Can technical analysis create returns for beta-based portfolios in the Indian market?”

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## ARTICLE INFO

Vandana Bhama (2025). Can technical analysis create returns for beta-based portfolios in the Indian market?. *Investment Management and Financial Innovations*, 22(4), 260-275. doi:[10.21511/imfi.22\(4\).2025.21](https://doi.org/10.21511/imfi.22(4).2025.21)

## DOI

[http://dx.doi.org/10.21511/imfi.22\(4\).2025.21](http://dx.doi.org/10.21511/imfi.22(4).2025.21)

## RELEASED ON

Wednesday, 26 November 2025

## RECEIVED ON

Monday, 14 July 2025

## ACCEPTED ON

Thursday, 06 November 2025

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## JOURNAL

"Investment Management and Financial Innovations"

## ISSN PRINT

1810-4967

## ISSN ONLINE

1812-9358

## PUBLISHER

LLC “Consulting Publishing Company “Business Perspectives”

## FOUNDER

LLC “Consulting Publishing Company “Business Perspectives”



NUMBER OF REFERENCES

**50**



NUMBER OF FIGURES

**2**



NUMBER OF TABLES

**10**

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## BUSINESS PERSPECTIVES



LLC "CPC "Business Perspectives"  
Hryhorii Skovoroda lane, 10,  
Sumy, 40022, Ukraine  
[www.businessperspectives.org](http://www.businessperspectives.org)

**Type of the article:** Research Article

**Received on:** 14<sup>th</sup> of July, 2025

**Accepted on:** 6<sup>th</sup> of November, 2025

**Published on:** 26<sup>th</sup> of November, 2025

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# CAN TECHNICAL ANALYSIS CREATE RETURNS FOR BETA-BASED PORTFOLIOS IN THE INDIAN MARKET?

## Abstract

Beta serves as a critical measure in portfolio optimization, capturing systematic risk and underpinning numerous asset-pricing frameworks. The present study examines the performance of beta-based portfolios of NSE 500 firms over 27 years using technical trading strategies – Simple Moving Average (SMA) and Exponential Moving Average (EMA) – across short-to-long-time horizon windows. Portfolios are constructed based on beta deciles to examine the relationship between systematic risk exposure and trading-rule effectiveness. The study incorporates transaction costs, emphasizing how trading frequency across five window lengths (5, 10, 20, 50, and 100 days) affects net returns and multiple risk-adjusted performance metrics. The findings indicate that technical trading strategies are more effective than the buy-and-hold (BH) strategy for beta portfolios. The SMA and EMA strategies demonstrate substantial positive alphas before transaction-cost adjustments. Mid-beta portfolios consistently show high returns and statistically significant alphas (ranging from 7% to 14% for SMA and EMA), confirming that technical strategies are most effective in beta portfolios with moderate systematic risk exposure. Further, transaction costs erode much of the excess returns generated by shorter-lag strategies. Despite this, selected mid-beta portfolios continue to generate net positive alpha (ranging between 6% to 11% for 20 and 50-day SMA/EMA) at longer windows, highlighting their resilience and practicality in real-world scenarios. These findings are further validated using various risk-adjusted performance metrics.

## Keywords

portfolio choice, investment decisions, technical analysis, risk analysis, asset returns

## JEL Classification

G11, G12

## INTRODUCTION

Professional analysts and technical traders believe that markets exhibit identifiable trends and patterns that, if interpreted correctly, can be exploited for profit. While price movements in speculative markets often follow a random walk, technical analysis provides a mechanism for information discovery, particularly when markets deviate from market efficiency.

In practice, portfolio managers adopt various strategies to construct profitable portfolios. Among these, beta-based portfolios have gained significance in literature. Beta, a key measure of systematic risk, remains fundamental to portfolio optimization and asset pricing. Academic finance generally holds that high-beta portfolios are inherently riskier but offer greater return potential. As risk increases, the predictive power of fundamental indicators weakens, prompting investors to rely more heavily on technical indicators. Therefore, if these technical tools are genuinely effective, their profitability should be evident in high-beta portfolios. Building on these observations, the present study explores whether technical indicators, particularly SMA and EMA, can generate higher returns and significant alpha for high-beta portfolios.



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## Conflict of interest statement:

Author(s) reported no conflict of interest

The practitioners further believe that a technical strategy is truly efficient if its returns exceed the costs of execution. Including transaction costs in these technical strategies can significantly deteriorate portfolio performance. Therefore, the study tests the impact of these real-world transaction costs on the net returns of beta portfolios. This dimension, which remains underexplored in the Indian context, offers a practical framework for identifying the most profitable trading windows.

## 1. LITERATURE REVIEW AND HYPOTHESES

The random walk theory implies that historical prices cannot be used to predict future price movements and that it is impossible for investors to consistently outperform the market (Fama & Blume, 1966). In contrast, some investors apply technical analysis to identify recurring patterns and exploit profitable trading opportunities (Treynor & Ferguson, 1985). However, these forecasting patterns tend to be transient and unstable over time (Timmermann & Granger, 2004).

Several studies have shown that technical indicators outperform the traditional buy-and-hold strategy, especially when adjusted for risk and transaction costs (Metghalchi et al., 2018; Neely et al., 2014; Park & Irwin, 2007; Kwon & Kish, 2002). Wang and Sun (2015) found that certain technical trading rules generate significant excess returns and enhance portfolio value (Zhu & Zhou, 2009). Examining return patterns across global markets, Hafsal and Durai (2020) and Fifield et al. (2008) observed that emerging markets exhibit distinct return behaviors compared to developed markets. Trading rules tend to demonstrate stronger predictive power in emerging economies, as evidenced by Ghanem et al. (2024), Metghalchi et al. (2018), and Yu et al. (2013).

Examining the tools of technical analysis, Gencay (1998) reported robust results for the moving average method. Marshall et al. (2017) found that the moving-average technique provided earlier signals conducive to generating meaningful returns. Foltice and Dolvin (2021) employed a 200-day simple moving average and observed excess returns of 0.58%, even after accounting for marginal transaction costs. They also noted that the 200-day strategy achieved a higher Sharpe ratio. Ghanem et al. (2024) and Zakamulin and Giner (2023) affirmed that the simple moving average remains one of the most effective and widely adopt-

ed technical indicators in practice. Han et al. (2013, 2021) reported that such strategies outperform the traditional buy-and-hold approach. Additionally, their findings suggest that portfolios exhibiting higher volatility tend to generate greater abnormal returns. Svogun and Rudys (2023) also observed superior returns associated with long-period moving-average strategies, further reinforcing their relevance. Han et al. (2016) also found that moving average trends tend to be more persistent and profitable when longer time windows are used. In contrast, Yu et al. (2013) noted that technical trading rules applied to shorter time frames possess greater predictive power.

Exploring the evidence on portfolio volatility, beta remains a fundamental consideration in both traditional asset pricing models and advanced portfolio optimization frameworks (Silva et al., 2024). Numerous empirical studies have documented a flat or even inverse risk–return relationship for beta-based portfolios. For instance, Friend and Blume (1970) and Black et al. (1972) demonstrated that high-beta portfolios often generate lower returns, resulting in negative alphas, whereas low-beta portfolios tend to produce positive alphas. By contrast, more recent evidence suggests a positive outlook for beta-based strategies. Hafsal and Durai (2020) reported that beta-sorted portfolios outperform the traditional Markowitz (1952) model, yielding higher Sharpe ratios under both static and dynamic conditions. Terregrossa and Eraslan (2016) identified a robust and systematic relationship between beta and portfolio returns. Fernández et al. (2023) indicated that technical indicators tend to perform well during periods of low financial uncertainty. However, when market risk intensifies, investor preferences often shift away from technical signals toward more fundamental or conservative strategies.

Based on the above discussion, technical trading rules generally can capture market direction and generate significant positive returns. However,

the full realization of these returns is often constrained by real-world frictions, particularly transaction costs (Mitra, 2011). Key components of transaction costs, such as bid-ask spreads and brokerage fees, are inherent to financial markets and can never be entirely eliminated. Rink (2023) noted that once these transaction costs are considered, the performance of many strategies deteriorates significantly. These findings suggest that even marginal trading costs can substantially erode profitability (Bajgrowicz & Scaillet, 2012), thereby reinforcing the notion of weak-form market efficiency (Yu et al., 2013).

In the context of technical trading, short-term moving-average strategies tend to generate more frequent trades, which in turn increases exposure to transaction costs. Barber et al. (2014) highlighted the limitations of short-term trading, noting that fewer than 1% of day traders consistently earn abnormal returns once transaction costs are accounted for. By contrast, Metghalchi et al. (2018) observed that moving average-based technical trading rules retain their predictive power and can outperform the buy-and-hold strategy even after accounting for such costs. Similarly, Avramov et al. (2021) reported that returns from moving average strategies remain viable after incorporating trading costs. Han et al. (2013) also found that these strategies continue to yield superior returns, suggesting their resilience in cost-adjusted environments. Jiang et al. (2017) also documented that technical trading strategies can still generate significant profits in the presence of transaction costs. These findings collectively underscore the importance of incorporating transaction costs into performance evaluations of technical strategies.

Although significant progress has been made in the literature on technical trading strategies and their returns, gaps related to the relevance and effectiveness of technical analysis specifically for beta portfolios still need to be identified. Most existing research focuses on applying technical analysis to broad indices, sectors, and individual stocks (Agarwal et al., 2023; Chakrabarti & Das, 2021; Challa et al., 2018; Agarwalla et al., 2020; Mitra, 2011). However, the varying time frames of beta portfolios—along with the implications of transaction costs and risk-return analysis in an emerging economy like India, remain underexplored.

By addressing these issues, the present study examines the performance of beta-based portfolios using technical trading strategies across short-to-long-horizon windows. Specifically, it examines the effect of transaction costs, emphasizing how trading frequency across different window lengths influences net returns and multiple risk-adjusted performance metrics. Based on this rationale, the study frames the following hypotheses:

*H1: High beta portfolios create more returns due to increased risk.*

*H2: High beta portfolios can absorb transaction costs and generate positive alpha values.*

## 2. METHODS

The study used daily stock price data for NSE 500 firms over 27 years, spanning January 1, 1996, to December 31, 2023. The number of firms included each year varied due to data availability. The dataset was obtained from the Refinitiv Eikon database. For the analysis, the stocks were sorted annually into ten decile portfolios by beta, ranging from low to high.

Following the approach of Block and French (2002), who argue that equal weighting is a more equitable and consistent method across diverse fund sizes and investment styles, this study employs an equal-weighting scheme for portfolio construction. Once stocks are assigned to their respective decile portfolios, portfolio index levels are generated based on equal-weighted returns, consistent with the methodology used by Han et al. (2013). Each portfolio is held for a one-year period and rebalanced at year-end.

To evaluate portfolio performance, the study compares returns from the traditional buy-and-hold strategy with those derived from technical trading strategies. Specifically, it applies two commonly used moving-average techniques: the Simple Moving Average (SMA) and the Exponential Moving Average (EMA). The calculation of the SMA is represented in Equation (1), where the moving average at time  $t$  with lag  $L$  is defined as the arithmetic average of stock prices over the preceding  $L$  days.

$$A_{jt,L} = \frac{P_{jt-L-1} + P_{jt-L-2} + \dots + P_{jt-1} + P_{jt}}{L}, \quad (1)$$

where  $A_{jt}$  is the average return of the index,  $P_{jt}$  is the corresponding portfolio prices (index levels).

An exponential moving average places greater weight on the most recent data points. Therefore, to assess the importance of recent information for returns and investment decisions, the EMA was also used in this study. Equation (2) shows the EMA calculation of portfolio index values for each day.

$$\begin{aligned} &EMA \\ &= (Today's\ closing\ price - Previous\ EMA) \quad (2) \\ &\times Multiplier + Previous\ EMA. \end{aligned}$$

$$Multiplier = \frac{Smoothing}{1 + Length}. \quad (3)$$

Following Han et al. (2016), the present study extends the time frames to 5-, 10-, 20-, 50-, and 100-day moving averages to address limited trading opportunities in a year. This captures the very short-term to long-term impact of trading on returns. On each trading day, if the last closing price  $P_{jt-1}$  is above the MA price,  $A_{jt-1,L}$ , a long position is created in portfolio  $j$  for the next trading day  $t$ . Once the MA price is above the last closing price, a sell signal is generated on the next day. One round-trip trade is defined as a complete trade consisting of a buy and sell signal. The SMA and EMA results are compared with the buy-and-hold strategy.

The study further applies the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), which highlights that the beta exposure must be compensated by the market risk premium. Therefore, to test the statistical significance of moving-average returns across portfolios, CAPM and other risk-adjusted measures are employed. Equation (4) presents the calculation of CAPM alpha.

$$E(R_{pt}) = \alpha_j + \beta_{j,mkt} r_{mkt,t} + e_{jt}, \quad (4)$$

where  $r_{mkt,t}$  is the daily excess return on market portfolios.

To capture the real-world implications of trading strategies, this study incorporates transaction

costs into return calculations. Transaction costs generally consist of three primary components: the bid-ask spread, brokerage fees, and market impact costs (Zakamulin & Giner, 2023). In addition, other costs such as taxes, opportunity costs, and short-term borrowing expenses may also affect net returns. Previous studies have employed a wide range of assumptions regarding transaction costs, typically between 1 and 50 basis points. For example, Condon (1981) estimated one-way transaction costs at 1%, while Lynch and Balduzzi (2000) used 0.25%. Bessembinder (2003) reported average costs of 0.48% for NYSE stocks and 0.74% for NASDAQ stocks. Similarly, Lesmond et al. (1999) suggested a cost of 0.6%, and Berkowitz et al. (1988), Chan and Lakonishok (1993), and Knez and Ready (1996) estimated costs in the range of 0.23% to 0.25%.

Based on a synthesis of the literature and consultations with industry professionals, the present study applies a conservative transaction-cost estimate of 0.30%. This assumption enables a more realistic evaluation of trading strategy performance by accounting for costs that would materially affect net returns under actual market conditions.

### 3. RESULTS AND DISCUSSION

Table 1 reports the buy-and-hold strategy returns (before and after transaction costs) for different beta portfolios. Given the negligible trading frequency, the returns appear almost similar in both scenarios. Alpha returns are significant for portfolios 2, 4, 5, 6, 7, and 9 with values of 12.34, 11.28, 8.26, 9.70, 6.32, and 8.47. These results indicate that the buy-and-hold (BH) strategy generates higher returns in the mid-beta portfolios that outperform the market. In contrast, very-low- and very-high-beta portfolios exhibit negative and insignificant returns, suggesting less effective long-term passive investing.

Table 2 presents SMA alpha returns across various time lags before adjusting for transaction costs. The results show substantial returns and statistically significant positive alphas, particularly for mid-beta portfolios (Portfolios 2

**Table 1.** BH returns (before and after TC)

Portfolio (Low to high Beta)	Alpha	Market Premium	Adjusted R2	Before TC			After TC		
				Alpha	Market Premium	Adjusted R2	Alpha	Market Premium	Adjusted R2
Low	0.24	0.84***	0.74	-0.36	0.85**	0.74			
2	12.90***	1.05***	0.79	12.34***	1.05***	0.79			
3	7.69**	1.13***	0.76	3.31	0.13	0.76			
4	11.84***	0.93***	0.62	11.28***	0.94***	0.63			
5	8.83***	1.04***	0.89	8.26***	1.04***	0.89			
6	10.26***	1.02***	0.85	9.70***	1.03***	0.85			
7	6.89**	0.92***	0.75	6.32**	0.92***	0.75			
8	0.93	1.04***	0.89	0.34	1.05***	0.89			
9	9.03***	0.77***	0.81	8.47***	0.76***	0.81			
High	-3.13	0.96**	0.68	-0.36	0.85**	0.74			

to 6). For instance, Portfolio 2 stands out with alphas consistently above 10% across all time frames and above 15% in 10- and 20-day windows, indicating strong market outperformance. Portfolios 4, 5, and 6 also demonstrate high alphas (18.27% for Portfolio 4, 13.07% for Portfolio 5, and 12.67% for Portfolio 6 at 20 days), with robust returns across short to medium lags (10-20 days). These results suggest that SMA strategies are effective in moderate-risk portfolios with balanced exposure to market factors. They also reject the first hypothesis that high-beta portfolios generate high returns (except for the 7th portfolios). Overall, the findings are more favorable for mid-beta portfolios.

However, when transaction costs are accounted for (Table 3), performance deteriorates significantly (Rink, 2023; Bajgrowicz & Scaillet, 2012), especially for low and high-beta portfolios, rejecting the second hypothesis that high-beta portfolios can absorb transaction costs. The lowest beta portfolio's alpha is negative in all 5-day and 10-day lags; indeed, all alpha values are negative except for portfolios 2 and 4. This trend highlights that frequent trading with shorter lags incurs high costs, eroding excess returns. These findings are consistent with Rink (2023), which shows that the performance of technical strategies deteriorates significantly after incorporating transaction costs. Some mid-beta portfolios, such as 2, 4, 5, and 6, still generate positive net alphas above 7% and 5%, especially at the 20- and 50-day lags, making them the most resilient to cost impact. Figure

1 presents the alpha values of various portfolios before and after transaction costs.

Table 4 highlights the average returns and alpha values before transaction-cost adjustment of the EMA strategy across low- to high-beta portfolios. The results indicate higher alphas at longer EMA lags, particularly for mid-beta portfolios (Portfolios 2-7), rejecting the first hypothesis that high-risk portfolios generate higher returns; the results show strong and statistically significant alphas (nearly 6% or more) for MAPs of 10, 20, and 50 days. This indicates potential mispricing that could generate profitable trading strategies. The highest return is observed for the 20-day MAP with 16.62% in Portfolio 2; on average, alpha values exceed 11% for mid-level beta portfolios.

After adjusting transaction costs, the results of the EMA strategy (Table 5) reveal that portfolio alphas drop significantly. This is seen particularly at the shorter lags of 5- and 10-days; by and large, alphas are negative for most portfolios. For mid-beta portfolios, returns remain sustainable for Portfolios 2, 4, 5, and 6 at the 20- and 50-day lags. These findings indicate that transaction costs erode profitability, especially with short and frequent trading. However, the 20- and 50-day MAPs are short enough to capture trends and long enough to avoid excessive trading costs. This is consistent with the findings of Avramov et al. (2021), Jiang et al. (2017), and Han et al. (2013). Figure 2 presents EMA-based alpha returns for all beta decile portfolios before and after transaction costs.

**Table 2.** SMA – Alternative Moving Average lag length before adjusting TC

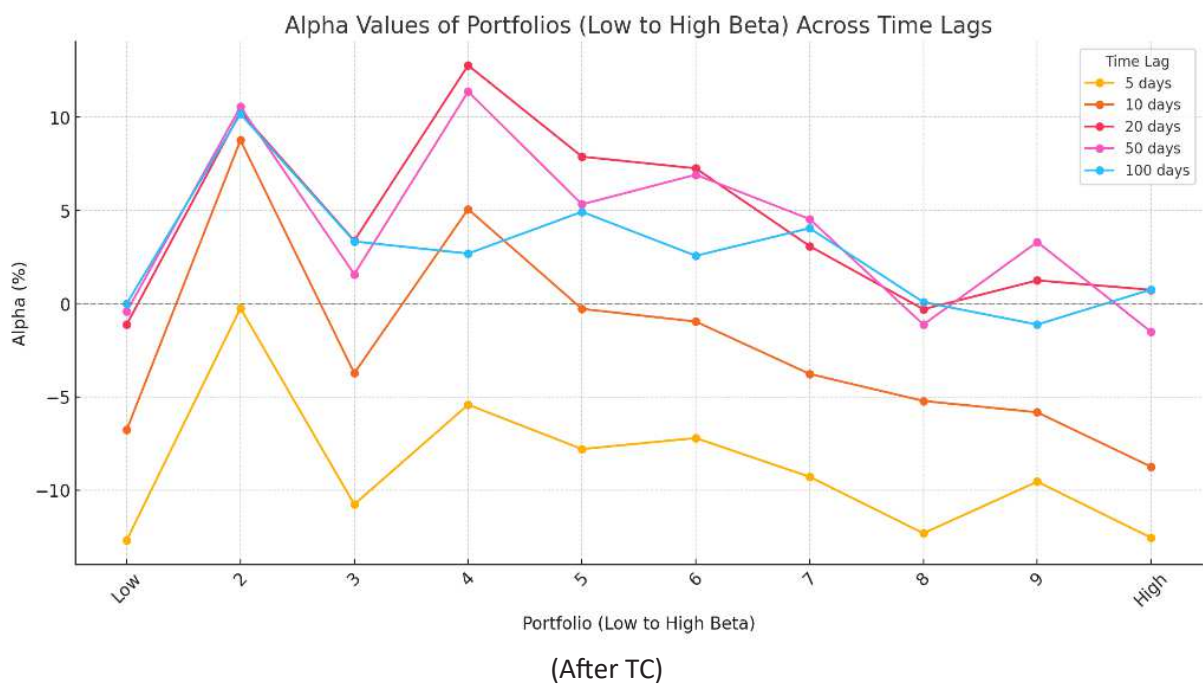
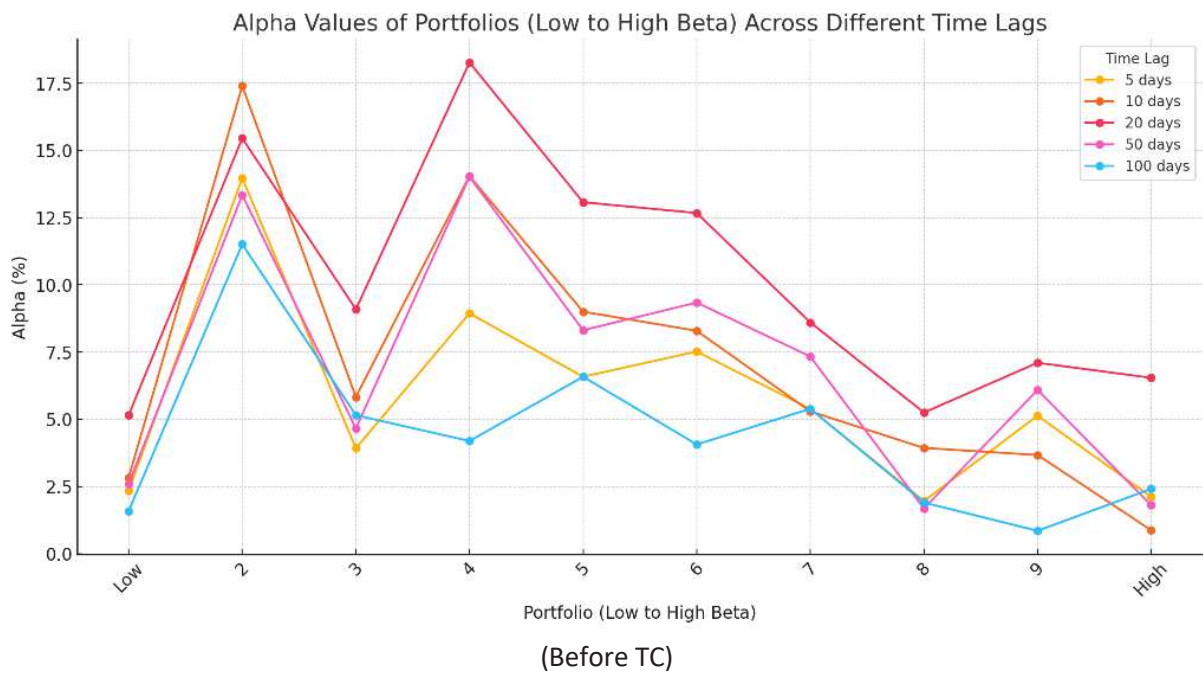
Portfolio (Low to high Beta)	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>
	MAP 5 days			MAP 10 days			MAP 20 days			MAP 50 days			MAP 100 days		
Low	2.35	0.51***	0.46	2.82	0.44***	0.41	5.15**	0.54***	0.41	2.60	0.27***	0.34	1.58	0.29***	0.29
2	13.97***	0.45***	0.47	17.40***	0.46***	0.55	15.45***	0.36***	0.39	13.34***	0.61***	0.66	11.51***	0.48***	0.56
3	3.92	0.30***	0.33	5.83*	0.35***	0.33	9.09***	0.30***	0.29	4.66	0.42***	0.40	5.15	0.10	0.01
4	8.94***	0.54***	0.51	14.04***	0.54***	0.51	18.27***	0.52***	0.48	14.02***	0.69***	0.66	4.19***	0.44***	0.19
5	6.58***	0.46***	0.68	9.00***	0.38***	0.48	13.07***	0.34***	0.36	8.31	0.54	0.58	6.58	0.39	0.47
6	7.52***	0.28***	0.24	8.29***	0.31***	0.30	12.67***	0.22**	0.15	9.34***	0.43***	0.38	4.06	0.45***	0.46
7	5.38	0.53***	0.45	5.29*	0.45***	0.51	8.60**	0.46***	0.41	7.33**	0.30***	0.18	5.39*	0.25**	0.12
8	1.96	0.64***	0.58	3.93	0.44***	0.54	5.25**	0.36***	0.47	1.68	0.41***	0.50	1.90	0.27**	0.15
9	5.13***	0.52***	0.67	3.67	0.36***	0.37	7.10***	0.34***	0.41	6.09***	0.49***	0.63	0.85	0.51***	0.56
High	2.11	0.49***	0.61	0.87	0.36***	0.35	6.54**	0.30***	0.29	1.80	0.46***	0.39	2.41	0.26**	0.13

Note(s): This table describes the alpha and market premium beta values of the SMA strategy of beta decile portfolios for various time lags. The results have been shown before adjusting transaction costs. MAP is the moving average portfolio for various 5, 10, 20, 50, and 100 lags. \*\*\*, \*\*, and \* indicate significance level at 1, 5, and 10 percent levels.

**Table 3.** SMA – Alternative Moving Average lag length after adjusting TC

Portfolio (Low to high Beta)	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>
	MAP 5 days			MAP 10 days			MAP 20 days			MAP 50 days			MAP 100 days		
Low	-12.70***	0.48***	0.46	-6.78**	0.41***	0.41	-1.13	0.53***	0.43	-0.43	0.25	0.35	-0.01	0.29***	0.30
2	-0.24	0.45***	0.42	8.77***	0.45***	0.48	10.29***	0.45***	0.48	10.56***	0.45***	0.48	10.18***	0.45***	0.48
3	-10.77***	0.29***	0.27	-3.73	0.33***	0.25	3.38	0.28***	0.21	1.58	0.42***	0.35	3.34	0.12	-0.02
4	-5.42*	0.53***	0.47	5.07*	0.53***	0.46	12.79*	0.53***	0.47	11.38*	0.69***	0.64	2.69*	0.46***	0.20
5	-7.80***	0.46***	0.66	-0.28	0.36***	0.43	7.89***	0.33***	0.31	5.33*	0.55***	0.56	4.93*	0.41***	0.48
6	-7.21**	0.28***	0.23	-0.96	0.31***	0.28	7.26***	0.20**	0.12	6.92**	0.43***	0.36	2.57	0.46***	0.46
7	-9.29**	0.51***	0.40	-3.77	0.44***	0.46	3.09	0.46***	0.39	4.54	0.29**	0.15	4.05	0.25*	0.11
8	-12.32***	0.65***	0.56	-5.22**	0.43***	0.51	-0.30	0.36***	0.44	-1.12	0.42***	0.47	0.08	0.28**	0.15
9	-9.55***	0.54***	0.68	-5.83*	0.37***	0.36	1.25	0.34***	0.36	3.31	0.51***	0.62	-1.12	0.54***	0.57
High	-12.56***	0.48***	0.56	-8.75***	-0.36***	0.31	0.74	0.30***	0.25	-1.51	0.48***	0.37	0.76	0.26**	0.12

Note(s): This table describes the alpha and market premium beta values of the SMA strategy of beta decile portfolios for various time lags. The results have been shown before adjusting transaction costs. MAP is the moving average portfolio for various 5, 10, 20, 50, and 100 lags. \*\*\*, \*\*, and \* indicate significance level at 1, 5, and 10 percent levels.



**Figure 1.** SMA alpha of various portfolios before and after TC

**Table 4.** EMA – Alternative Moving Average lag length before adjusting TC

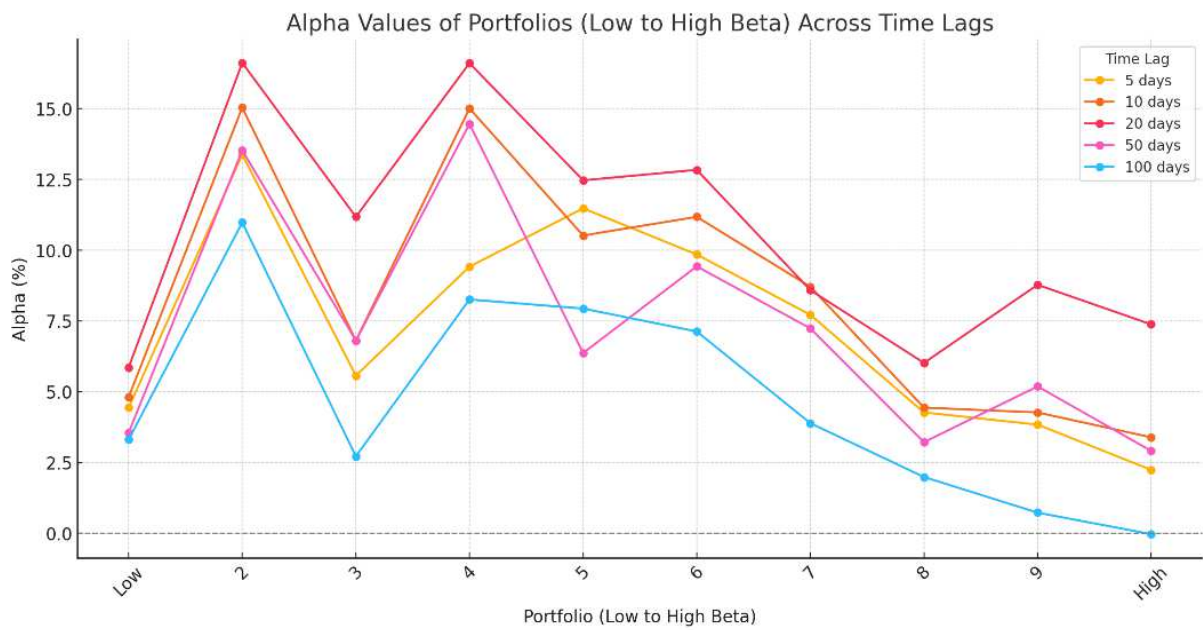
Portfolio (Low to high Beta)	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>
	MAP 5 days			MAP 10 days			MAP 20 days			MAP 50 days			MAP 100 days		
Low	4.44	0.41***	0.44	4.81*	0.34***	0.45	5.86**	0.40***	0.49	3.55	0.26**	0.15	3.31	0.28***	0.33
2	13.38***	0.53***	0.58	15.04***	0.47***	0.51	16.62***	0.48***	0.51	13.53***	0.53***	0.61	10.98***	0.38***	0.47
3	5.57*	0.26**	0.21	6.81*	0.31***	0.27	11.18***	0.40***	0.38	6.81**	0.45***	0.44	2.72	0.52***	0.44
4	9.42***	0.51***	0.48	15.01***	0.53***	0.50	16.61***	0.45***	0.38	14.46***	0.62***	0.64	8.26***	0.51***	0.58
5	11.48***	0.34***	0.42	10.52***	0.39***	0.49	12.47***	0.35***	0.41	6.37**	0.31***	0.30	7.94***	0.38***	0.53
6	9.85***	0.38***	0.42	11.18***	0.24**	0.22	12.84***	0.22**	0.17	9.43***	0.40***	0.40	7.13***	0.37***	0.50
7	7.72**	0.37***	0.37	8.71***	0.43***	0.44	8.59**	0.51***	0.45	7.24**	0.28***	0.21	3.89	0.42***	0.44
8	4.27*	0.33***	0.41	4.44*	0.39***	0.52	6.02***	0.32***	0.36	3.22	0.35***	0.38	1.99	0.23*	0.11
9	3.84	0.42***	0.54	4.27	0.35***	0.38	8.78***	0.35***	0.43	5.19*	0.40***	0.44	0.73	0.47***	0.44
High	2.24	0.31***	0.45	3.39	0.33***	0.20	7.38**	0.40***	0.40	2.91	0.37***	0.30	-0.03	0.41***	0.40

Note(s): This table describes the alpha and market premium beta values of the EMA strategy of beta decile portfolios for various time lags. The results have been shown before adjusting transaction costs. MAP is the moving average portfolio for various 5, 10, 20, 50, and 100 lags. \*\*\*, \*\*, and \* indicate significance level at 1, 5, and 10 percent levels.

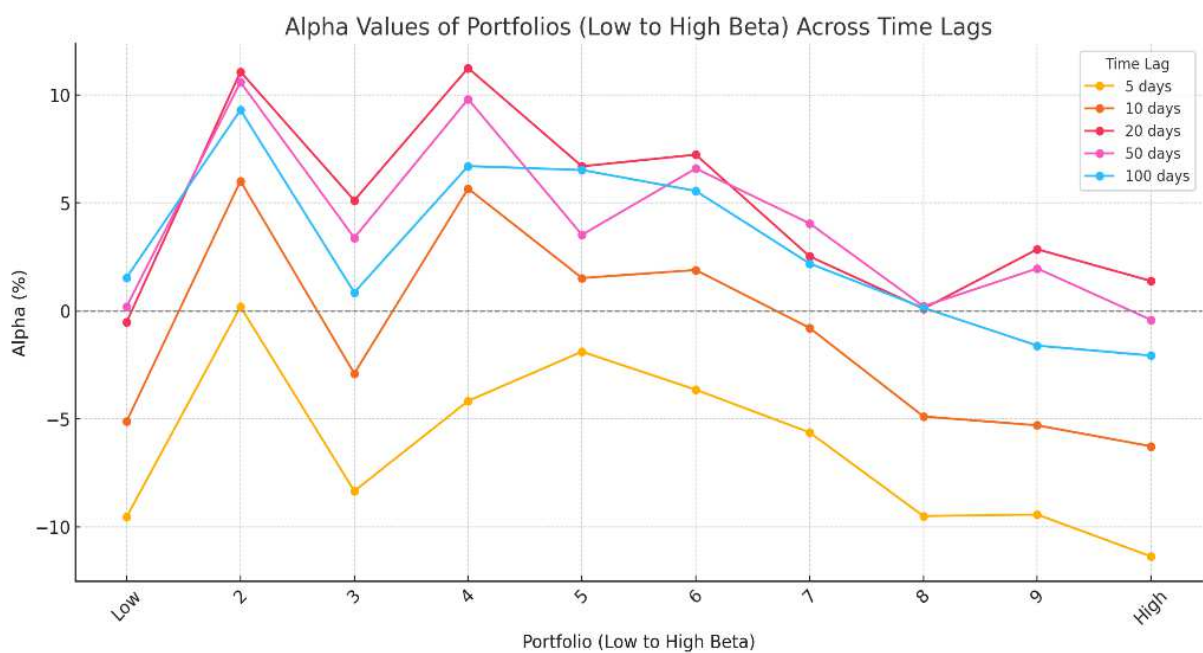
**Table 5.** EMA – Alternative Moving Average lag length after adjusting TC

Portfolio (Low to high Beta)	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>	Alpha	Market premium	Adjusted R <sup>2</sup>
	MAP 5 days			MAP 10 days			MAP 20 days			MAP 50 days			MAP 100 days		
Low	-9.54***	0.40***	0.39	-5.12*	0.34***	0.41	-0.52	0.40***	0.46	0.20	0.26*	0.14	1.54	0.28***	0.32
2	0.19	0.52***	0.54	6.01*	0.46***	0.47	11.07***	0.48***	0.47	10.59***	0.55***	0.60	9.30***	0.40***	0.46
3	-8.34***	0.23**	0.16	-2.90	0.28***	0.22	5.11	0.40***	0.35	3.38	0.46***	0.42	0.85	0.54***	0.44
4	-4.17	0.50***	0.44	5.66	0.53***	0.47	11.24***	0.48***	0.40	9.80***	0.52***	0.47	6.70**	0.53***	0.58
5	-1.89	0.34***	0.38	1.52	0.39***	0.46	6.69**	0.35***	0.36	3.52	0.33***	0.31	6.52***	0.39***	0.54
6	-3.65	0.39***	0.40	1.89	0.23**	0.19	7.23**	0.21*	0.14	6.59**	0.41***	0.38	5.55**	0.38***	0.49
7	-5.63	0.36***	0.33	-0.79	0.43***	0.41	2.52	0.50***	0.42	4.05	0.29***	0.19	2.19	0.44***	0.42
8	-9.50***	0.32***	0.35	-4.89**	0.39***	0.47	0.10	0.32***	0.34	0.21	0.35***	0.34	0.14	0.22*	0.09
9	-9.43***	0.43***	0.51	-5.30*	0.36***	0.35	2.85	0.36***	0.39	1.96	0.42***	0.42	-1.61	0.50***	0.44
High	-11.37***	0.29***	0.36	-6.27*	0.33**	0.15	1.38	0.40***	0.36	-0.42	0.37***	0.27	-2.07	0.42***	0.37

Note(s): This table describes the alpha and market premium beta values of the EMA strategy of beta decile portfolios for various time lags. The results have been shown before adjusting transaction costs. MAP is the moving average portfolio for various 5, 10, 20, 50, and 100 lags. \*\*\*, \*\*, and \* indicate significance level at 1, 5, and 10 percent levels.



(Before TC)



(After TC)

Figure 2. EMA alpha of various portfolios before and after TC

**Table 6.** Break-even TC

Portfolio (Low to high Beta)	BH Returns	5 days SMA	10 days	20 days	50 days	100 days	5 days EMA	10 days	20 days	50 days	100 days
Low	0.74	17.13	17.64	21.48	16.71	14.86	20.34	20.60	22.59	17.82	17.69
2	0.79	34.65	42.55	35.64	37.73	33.69	33.78	36.41	38.96	33.28	29.27
3	0.76	18.02	21.23	25.66	18.14	20.02	20.68	22.77	30.13	21.63	19.91
4	0.62	31.79	36.89	43.69	39.89	23.44	27.12	38.39	44.09	37.55	26.79
5	0.89	25.82	24.91	31.72	25.54	22.88	33.76	27.40	30.68	25.84	24.70
6	0.85	24.24	24.83	31.30	25.18	17.99	30.10	28.78	31.57	25.42	23.31
7	0.75	26.91	24.52	30.10	23.53	21.64	27.72	30.05	30.61	23.38	22.03
8	0.89	14.07	18.27	20.29	14.37	16.72	18.63	18.99	21.49	16.80	16.54
9	0.81	27.01	17.70	24.05	21.75	18.03	19.05	19.44	26.91	21.04	18.58
High	0.68	20.25	13.02	23.42	16.18	16.20	16.37	19.26	25.33	17.52	15.35

Higher break-even transaction costs (TC) indicate greater robustness and profitability of a trading strategy compared to passive investing. Table 6 reports the break-even TC for BH returns, SMA, and EMA strategies. The results indicate that in low-beta portfolios, the BH return is just 0.74%, whereas SMA and EMA returns range from 14% to 22%. For medium-beta portfolios, BH ranges

from 0.76% to 0.89%; SMA is as high as 43.69% (portfolio 4, 20-day), and EMA is slightly higher than SMA in most cases. This evidence indicates that both SMA and EMA strategies significantly outperform BH, even at longer windows such as 50- and 100-day. These are suitable for active trading, despite frequent signals, given the substantial cushion for transaction costs. In mid- to high-beta

**Table 7.** Sharpe ratio of portfolios

Portfolio (Low to high Beta)	5 days	10 days	20 days	50 days	100 days	5 days	10 days	20 days	50 days	100 days
	Before TC					After TC				
Low	0.20	0.23	0.39	0.20	0.17	-0.61	-0.30	-0.02	-0.02	0.00
2	0.74	0.97	0.93	0.68	0.69	-0.01	0.49	0.55	0.53	0.61
3	0.28	0.35	0.56	0.23	0.32	-0.70	-0.20	0.13	0.00	0.22
4	0.69	0.68	0.69	0.69	0.69	-0.11	0.27	0.59	0.51	0.25
5	0.51	0.60	0.85	0.24	0.48	-0.30	-0.07	0.43	0.24	0.31
6	0.55	0.55	0.89	0.47	0.24	-0.40	-0.05	0.45	0.29	0.13
7	0.55	0.43	0.53	0.41	0.45	-0.23	-0.05	0.26	0.20	0.35
8	0.12	0.26	0.38	0.13	0.28	-0.83	-0.32	-0.04	-0.09	0.14
9	0.63	0.24	0.54	0.37	0.28	-0.32	-0.35	0.08	0.15	0.11
High	0.36	0.08	0.45	0.15	0.16	-0.55	-0.47	0.08	-0.01	0.07

**Table 8.** Sortino ratio of portfolios

Portfolio (Low to high Beta)	5 days	10 days	20 days	50 days	100 days	5 days	10 days	20 days	50 days	100 days
	Before TC					After TC				
Low	0.39	0.51	2.95	0.44	0.38	-0.90	-0.60	-0.06	-0.03	0.00
2	2.65	2.69	7.99	4.06	3.28	-0.03	1.11	3.44	2.45	3.18
3	1.18	1.29	2.04	0.58	0.99	-1.40	-0.42	0.34	0.00	0.60
4	5.92	3.60	5.93	5.93	5.93	-0.34	0.82	1.46	2.31	0.69
5	1.25	3.51	5.74	0.76	3.68	-0.56	-0.22	2.23	0.76	2.26
6	3.49	1.92	2.45	1.62	0.39	-0.86	-0.13	0.95	0.98	0.22
7	1.10	1.27	1.93	1.33	1.62	-0.46	-0.11	0.91	0.66	1.18
8	0.27	0.56	0.76	0.28	0.83	-1.18	-0.72	-0.07	-0.21	0.36
9	7.29	0.91	8.46	0.84	1.71	-0.80	-0.71	0.24	0.43	0.77
High	0.76	0.20	2.95	0.47	0.22	-1.02	-1.04	0.28	-0.03	0.11

portfolios, active strategies remain attractive, especially EMA 20-50-day windows, which consistently outperform BH; break-even TC margins are in the 20-30% range.

To validate the study’s findings for specific portfolios, multiple risk-adjusted performance measures, including the Sharpe Ratio, Sortino Ratio, Treynor Ratio, and Information Ratio, were employed. These metrics provide a comprehensive assessment of portfolio performance by accounting for different dimensions of risk.

The analysis of Sharpe ratios across beta-sorted portfolios in Table 7 reveals that technical strategies using moving averages can significantly enhance risk-adjusted returns compared with the buy-and-hold (BH) approach, particularly before accounting for transaction costs. Among various window lengths, the 20-day SMA consistently demonstrates superior performance across low- to

mid-beta portfolios, with Sharpe ratios peaking at 0.85 before costs in Portfolio 5. This indicates that mid-frequency strategies are more effective in capturing short-term momentum without excessive trading. However, after incorporating transaction costs, a notable deterioration in Sharpe ratios is observed, especially for short-window strategies such as 5-day and 10-day SMAs, which frequently turn negative due to high churn; the lowest value reaches -0.83. In contrast, longer windows like the 100-day SMA, while offering lower pre-cost performance, exhibit greater robustness post-costs, particularly in higher-beta portfolios. These findings suggest that, for sustainable outperformance, mid-frequency strategies like the 20-day SMA are best suited for low to mid-beta portfolios, whereas low-frequency strategies like the 100-day SMA are more effective for high-beta portfolios, offering a balance between signal quality and transaction cost sensitivity. This is consistent with the findings of Hafsal and Durai (2020).

**Table 9.** Treynor ratio of portfolios

Portfolio (Low to high Beta)	5 days	10 days	20 days	50 days	100 days	5 days	10 days	20 days	50 days	100 days
	Before TC					After TC				
Low	8.79	10.64	16.49	12.02	9.58	-27.88	-15.29	-0.80	-0.97	0.01
2	33.58	42.93	43.93	27.63	30.30	-0.53	23.15	27.93	21.72	27.09
3	15.11	18.92	32.52	11.40	105.67	-41.08	-12.28	8.59	-0.11	58.40
4	24.79	30.20	24.79	24.79	24.79	-4.28	12.74	27.71	21.10	14.12
5	20.35	23.79	40.17	9.86	20.70	-12.33	-3.22	22.68	9.86	13.87
6	32.64	30.24	65.53	21.81	10.73	-24.62	-3.04	38.21	14.00	6.03
7	31.22	19.65	27.02	27.97	29.05	-14.17	-2.57	13.70	15.78	23.28
8	4.77	10.51	16.65	5.45	15.61	-34.80	-13.75	-1.97	-4.18	8.12
9	19.36	11.80	25.20	13.85	9.28	-9.94	-18.03	4.14	5.95	3.63
High	11.87	3.71	26.22	7.65	13.63	-19.26	-25.54	4.99	-0.48	5.93

**Table 10.** Information ratio of portfolios

Portfolio (Low to high Beta)	5 days	10 days	20 days	50 days	100 days	5 days	10 days	20 days	50 days	100 days
	Before TC					After TC				
Low	0.03	0.04	0.14	0.02	-0.03	-0.64	-0.35	-0.13	-0.10	-0.10
2	0.60	0.69	0.72	0.58	0.39	-0.02	0.30	0.48	0.43	0.33
3	0.12	0.20	0.37	0.21	-0.06	-0.43	-0.16	0.13	0.06	-0.12
4	0.31	0.56	0.31	0.31	0.31	-0.47	0.16	0.49	0.48	-0.02
5	0.18	0.46	0.61	0.24	0.23	-0.49	0.05	0.38	0.24	0.16
6	0.21	0.30	0.52	0.45	0.16	-0.33	-0.04	0.32	0.34	0.10
7	0.11	0.06	0.19	0.24	0.06	-0.38	-0.31	-0.02	0.13	0.00
8	0.03	0.16	0.20	0.05	-0.15	-0.64	-0.27	-0.04	-0.09	-0.23
9	0.05	0.12	0.23	0.29	-0.15	-0.91	-0.27	-0.02	0.13	-0.28
High	-0.10	0.01	0.15	0.00	-0.01	-0.90	-0.36	-0.05	-0.12	-0.04

Table 8 presents the analysis of the Sortino Ratio. The findings indicate that, prior to transaction costs, the 20-day SMA strategy exhibits particularly strong performance across multiple portfolios, with notable Sortino ratios of 7.99 (Portfolio 2), 5.93 (Portfolio 4), and 8.46 (Portfolio 9), indicating superior returns with limited downside volatility. Similarly, 50-day and 100-day strategies offer consistently high ratios in mid-beta portfolios, suggesting these timeframes effectively filter noise and capture meaningful trends. Once transaction costs are incorporated, a substantial decline in Sortino ratios is observed, especially for short-window strategies like the 5-day SMA, whose ratios often turn negative due to excessive trading. Despite this, the 20-day SMA retains relatively strong performance post-cost in individual portfolios, for instance, a ratio of 3.44 in Portfolio 2 and 2.23 in Portfolio 5, reaffirming its robustness. Longer windows, such as the 100-day SMA, also show moderate resilience (3.18 in Portfolio 2 and 2.26 in Portfolio 5), making them suitable for high-beta portfolios where transaction cost sensitivity is greater. Overall, the findings suggest that the 20-day SMA offers the most effective trade-off between capturing alpha and managing downside risk, while longer-term strategies serve as viable alternatives in cost-sensitive or higher volatility environments.

Table 9 presents the performance of various portfolios using Treynor ratios. The findings suggest strong evidence of moving-average-based trading strategies, particularly in the 20-day and 50-day windows before transaction costs. Portfolios 2, 3, and 6 stand out with exceptionally high pre-cost Treynor ratios; for instance, Portfolio 2 records 43.93 (20-day), and Portfolio 6 shows 65.53 (20-day), indicating that these strategies not only yield higher returns but do so efficiently relative to market risk. The consistency across mid-beta portfolios suggests that technical strategies aligned with these windows are particularly effective in capitalizing on momentum without overexposure to market volatility. However, the Treynor ratios decline sharply across most portfolios when accounting after accounting for transaction costs, especially in short-window strategies such as the 5-day and 10-day SMAs, where several values turn negative (−27.88 for Portfolio 1, 5-day SMA).

Nevertheless, select strategies retain their efficiency – most notably the 20-day SMA in Portfolio 2 (27.93) and Portfolio 6 (38.21), and the 100-day SMA in Portfolio 3 (58.40) – highlighting their resilience and suitability for beta-sensitive trading environments. These findings underscore the importance of balancing trading frequency and market exposure, as mid-frequency strategies like the 20-day SMA offer the most favorable Treynor ratios even after trading frictions, while longer-term approaches such as the 100-day SMA serve as effective alternatives in high-beta portfolios.

Table 10 presents the validation of portfolios in the context of the information ratio (IR). The results reveal that, prior to transaction costs, the 20-day moving average stands out as the most effective across multiple beta-based portfolios, particularly in mid-beta ranges; portfolio 2 – 0.72, portfolio 5 – 0.61, and portfolio 6 – 0.52. These elevated IR values suggest that the 20-day SMA not only outperforms the benchmark on average but does so with relatively stable returns, making it a reliable strategy for active managers aiming to generate excess returns while maintaining disciplined tracking of benchmark volatility. After adjusting for transaction costs, a sharp deterioration in Information ratios is observed, particularly in shorter-window strategies such as the 5-day SMA, where values frequently turn negative (−0.64 in portfolio 1 and −0.91 in portfolio 9). Despite this decline, the 20-day SMA maintains modest yet positive IRs in select portfolios. For instance, portfolio 2: 0.48, portfolio 4: 0.49, and portfolio 6: 0.32, underscoring its robustness and viability even in cost-sensitive environments. These results reinforce the superiority of mid-frequency strategies like the 20-day SMA in balancing alpha generation and tracking error, while highlighting the diminishing value of high-frequency strategies when real-world frictions such as transaction costs are accounted for.

Technical trading strategies are widely used by fund managers, especially for short-term forecasting purposes (Gehrig & Menkhoff, 2006). Several studies have documented that technical indicators outperform the traditional buy-and-hold strategy, especially when adjusted for risk and transaction costs (Metghalchi et al., 2018;

Neely et al., 2014; Park & Irwin, 2007; Kwon & Kish, 2002). Consistent with this evidence, the findings of the present study indicate that SMA and EMA technical strategies (without the impact of transaction costs) are effective in medium-risk beta portfolios with balanced exposure to market factors (Ghanem et al., 2024; Zakamulin & Giner, 2023).

The mid-level portfolios demonstrate high alpha with robust returns across short-to-medium lags (10 & 20 days). However, when transaction costs are accounted for, performance deteriorates significantly, especially for low- and high-beta portfolios over a short time window, indicating less effective long-term passive investing. This evidence aligns with Rink (2023) and Bajgrowicz and Scaillet (2012), highlighting that frequent trading with shorter lags incurs high costs, eroding excess returns (Friend & Blume, 1970; Jensen & Benington, 1970; Black et al., 1972; Blitz et al., 2013; Alhashel & Almudhaf, 2021). Further, 20- and 50-day MAPs are short

enough to capture trends and long enough to avoid excessive trading costs. This is consistent with the findings of Avramov et al. (2021), Jiang et al. (2017), and Han et al. (2013).

Analyzing the risk-return relationship, the Sharpe ratio indicates sustainable outperformance for mid-frequency strategies (20-day), which are best suited to low- to mid-beta portfolios, whereas low-frequency strategies like the 100-day SMA are more effective for high-beta portfolios, offering a balance between signal quality and transaction cost sensitivity. This evidence is consistent with the findings of Hafsal and Durai (2020). Similarly, Sortino ratio indicates an effective trade-off between capturing alpha and managing downside risk for the 20-day window, particularly in Portfolios 2 and 4.

Based on the above points, mid-beta portfolios exhibit resilience to transaction costs and provide an effective strategy for fund managers and investors.

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## CONCLUSION

The study examines the performance of beta-decile portfolios across short and long-time horizons. It contrasts the performance of the conventional Buy-and-Hold (BH) strategy with technical trading approaches, specifically Simple Moving Averages (SMA) and Exponential Moving Averages (EMA), applied across short- to long-term lag periods.

The findings provide strong empirical evidence that technical trading strategies based on moving averages are more effective than the buy-and-hold (BH) strategy, especially for mid-beta portfolios. BH returns are relatively stable in low-transaction environments due to minimal trading activity, but their alpha-generating ability is mostly limited to mid-beta portfolios, suggesting that passive investing may not be optimal across all risk categories. In contrast, SMA and EMA strategies demonstrate substantial positive alpha values before transaction cost adjustments, particularly at the 10-, 20-, and 50-day windows. Portfolios 2 to 6 consistently show high returns and statistically significant alpha values, confirming that technical strategies are most effective in portfolios with moderate systematic risk exposure. Further, transaction costs erode much of the excess returns generated by shorter-lag strategies. Frequent trading amplifies cost impacts, neutralizing alpha gains. Despite this, selected mid-beta portfolios continue to generate net positive risk-adjusted alpha over longer windows (20-day and 50-day), highlighting their resilience and practicality in real-world scenarios.

The study has important implications for portfolio managers and academic researchers. First, mid-frequency technical strategies, especially the 20-day SMA/EMA-are empirically validated as effective tools for alpha generation in mid-beta environments. Second, the study advocates for a nuanced approach to active portfolio construction, selecting optimal timeframes based on beta exposure and balancing return potential against trading efficiency. This positions mid-frequency SMA/EMA strategies as viable alternatives for active fund managers seeking to outperform passive benchmarks in moderately volatile markets.

The scope of the study could be extended to different portfolios based on other factors, such as volatility and firm size. Further, other technical analysis tools could be used to examine the relevance of technical trading opportunities in a multi-country context.

## AUTHOR CONTRIBUTIONS

Conceptualization: Vandana Bhama.

Data curation: Vandana Bhama.

Formal analysis: Vandana Bhama.

Investigation: Vandana Bhama.

Methodology: Vandana Bhama.

Software: Vandana Bhama.

Validation: Vandana Bhama.

Visualization: Vandana Bhama.

Writing – original draft: Vandana Bhama.

Writing – review & editing: Vandana Bhama.

## REFERENCES

- Agarwal, S., Chakravarti, S., Ghosh, O., & Chakrabarti, G. (2023). Dynamic market risk and portfolio choice: Evidence from Indian stock market. *IIMB Management Review*, 35(3), 240-257. <https://doi.org/10.1016/j.iimb.2023.08.001>
- Agarwalla, S. K., Jacob, J., Varma, J. R., & Vasudevan, E. (2020). Betting against beta in the Indian market. *Springer International Publishing*, 29-44. <http://dx.doi.org/10.2139/ssrn.2464097>
- Alhashel, B. S., & Almudhaf, F. W. (2021). Even in emerging markets, technical trading is hazardous to your wealth. *Emerging Markets Finance and Trade*, 57(13), 3739-3765. <https://doi.org/10.1080/1540496X.2019.1706046>
- Avramov, D., Kaplanski, G., & Subrahmanyam, A. (2021). Moving average distance as a predictor of equity returns. *Review of Financial Economics*, 39(2), 127-145. <https://doi.org/10.1002/rfe.1118>
- Barber, B. M., Lee, Y. T., Liu, Y. J., & Odean, T. (2014). The cross-section of speculator skill: Evidence from day trading. *Journal of Financial Markets*, 22, 1-24. <http://dx.doi.org/10.1016/j.finmar.2013.05.006>
- Bajgrowicz, P., & Scaillet, O. (2012). Technical trading revisited: False discoveries, persistence tests, and transaction costs. *Journal of Financial Economics*, 106(3), 473-491. <https://doi.org/10.1016/j.jfineco.2012.06.001>
- Berkowitz, S. A., Logue, D. E., & Noser, Jr. E. A. (1988). The Total Cost of Transactions on the NYSE. *The Journal of Finance*, 43(1), 97-112. <https://doi.org/10.1111/j.1540-6261.1988.tb02591.x>
- Bessembinder, H. (2003). Trade Execution Costs and Market Quality after Decimalization. *The Journal of Financial and Quantitative Analysis*, 38(4), 747-777. <https://doi.org/10.2307/4126742>
- Black, F., Jensen, M., & Scholes, M. S. (1972). *The Capital Asset Pricing Model: Some Empirical Findings. Studies in the Theory of Capital Markets* (79-124). Retrieved from <https://www.hbs.edu/faculty/Pages/item.aspx?num=3739>
- Blitz, D., Pang, J., & Vliet, P. V. (2013). The Volatility Effect in Emerging Markets. *Emerging Markets Review*, 16, 31-45. <https://doi.org/10.1016/j.ememar.2013.02.004>
- Block, S. B., & French, D. W. (2002). The effect of portfolio weighting on investment performance evaluation: the case of actively managed mutual funds. *Journal of Economics and Finance*, 26(1), 16-30. Retrieved from [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=218971](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=218971)
- Chakrabarti, G., & Das. R. (2021). TVB, market volatility and stress: A comparison between the United States and India. *IIMB Management Review*, 33(1), 50-63. <https://doi.org/10.1016/j.iimb.2021.03.003>
- Challa, M. L., Malepati, V., & Kolusu, S. N. R. (2018). Forecasting risk using auto regressive integrated moving average approach: an evidence from S&P BSE Sensex. *Financial Innovation*, 4(1), 24. <https://doi.org/10.1186/s40854-018-0107-z>
- Chan, L. K. C., & Lakonishok, J. (1993). Institutional trades and intraday stock price behaviour. *Journal of Financial Economics*, 33(2), 173-199. [https://doi.org/10.1016/0304-405X\(93\)90003-T](https://doi.org/10.1016/0304-405X(93)90003-T)
- Condon, K. A. (1981). Measuring equity transaction costs. *Financial Analysts Journal*, 37(5), 57-60. <https://doi.org/10.2469/faj.v37.n5.57>
- Fama, E. F., & Blume, M. E. (1966). Filter rules and stock-market trading. *The Journal of Business*, 39, 226-241. Retrieved from <http://www.e-m-h.org/FaBl66.pdf>

17. Fernández, M. F., Henry, O., Pybis, S., & Stamatogiannis, M. P. (2023). Can we forecast better in periods of low uncertainty? The role of technical indicators. *Journal of Empirical Finance*, 71, 1-12. <https://doi.org/10.1016/j.jempfin.2022.12.014>
18. Fifield, S. G. M., Power, D. M., & Knipe, D. G. S. (2008). The performance of moving average rules in emerging stock markets. *Applied Financial Economics*, 18(19), 1515-1532. <http://dx.doi.org/10.1080/09603100701720302>
19. Foltice, B., & Dolvin, S. (2021). Using a Simple Technical Analysis Indicator to Guide Asset Allocation Decisions. *The Journal of Wealth Management*, 24(3), 31-41. <https://doi.org/10.3905/jwm.2021.1.148>
20. Friend, I., & Blume, M. (1970). Measurement of Portfolio Performance Under Uncertainty. *The American Economic Review*, 60(4), 561-575. Retrieved from <https://www.jstor.org/stable/1818402>
21. Gehrig, T., & Menkhoff, L. (2006). Extended evidence on the use of technical analysis in foreign exchange. *International Journal of Finance & Economics*, 11(4), 327-338. <https://doi.org/10.1002/ijfe.301>
22. Ghanem, S., Harasheh, M., Sbaih, Q., & Ajmal, T. K. (2024). The predictability of technical analysis in foreign exchange market using forward return: evidence from developed and emerging currencies. *Cogent Business & Management*, 11(1), 2428781. <https://doi.org/10.1080/23311975.2024.2428781>
23. Hafsal, K., & Durai, S. R. S. (2020). Fundamental beta and portfolio performance: evidence from an emerging market. *Macroeconomics and Finance in Emerging Market Economies*, 13(3), 264-275. <https://doi.org/10.1080/17520843.2020.1760913>
24. Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, 48, 1433-1461. Retrieved from [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1656460](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1656460)
25. Han, Y., Zhou, G., & Zhu, Y. (2016). A trend factor: Any economic gains from using information over investment horizons? *Journal of Financial Economics*, 122(2), 352-375. <https://doi.org/10.1016/j.jfineco.2016.01.029>
26. Han, Y., Liu, Y., Zhou, G., & Zhu, Y. (2021). *Technical Analysis in the Stock Market: A Review*. Retrieved from [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3850494](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3850494)
27. Jensen, M. C., & Benington, G. A. (1970). Random walks and technical theories: Some additional evidence. *Journal of Finance*, 25, 469-482. <https://doi.org/10.2307/2325495>
28. Jiang, F., Tong, G., & Song, G. (2017). Technical Analysis Profitability Without Data Snooping Bias: Evidence from Chinese Stock Market. *International Review of Finance*, 19(1), 191-206. <https://doi.org/10.1111/irfi.12161>
29. Knez, P. J., & Ready, M. J. (1996). Estimating the profits from trading strategies. *The Review of Financial Studies*, 9(4), 1121-1163. <https://doi.org/10.1093/rfs/9.4.1121>
30. Kwon, K. Y., & Kish, R. J. (2002). A comparative study of technical trading strategies and return predictability: an extension of Brock, Lakonishok, and LeBaron (1992) using NYSE and NASDAQ indices. *The Quarterly Review of Economics and Finance*, 42(3), 611-631. [https://doi.org/10.1016/S1062-9769\(01\)00089-8](https://doi.org/10.1016/S1062-9769(01)00089-8)
31. Lesmond, D. A., Ogden, J. P., & Trzcinka, C. A. (1999). A new estimate of transaction costs. *The Review of Financial Studies*, 12(5), 1113-1141. <https://doi.org/10.1093/rfs/12.5.1113>
32. Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 47(1), 13-37. <http://dx.doi.org/10.2307/1924119>
33. Lynch, A. W., & Balduzzi, P. (2000). Predictability and Transaction costs: The impact on rebalancing rules and behavior. *The Journal of Finance*, 66, 2285-2309. <https://doi.org/10.1111/0022-1082.00287>
34. Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 7(1), 77-91. <https://doi.org/10.1111/j.1540-6261.1952.tb01525.x>
35. Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2017). Time series momentum and moving average trading rules. *Quantitative Finance*, 17(3), 405-421. Retrieved from [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2225551](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2225551)
36. Metghalchi, M., Hayes, L. A., & Niroomand, F. (2018). A technical approach to equity investing in emerging markets. *Review of Financial Economics*, 37(3), 389-403. <https://doi.org/10.1002/rfe.1041>
37. Mitra, S. K. (2011). How rewarding is technical analysis in the Indian stock market? *Quantitative Finance*, 11(2), 287-297. <https://doi.org/10.1080/14697680903493581>
38. Neely, C. J., Rapach, D., Tu, J., & Zhou, G. (2014). *Forecasting the Equity Risk Premium: The Role of Technical Indicators*. Retrieved from <https://ssrn.com/abstract=1787554>
39. Park, C. H., & Irwin, S. H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic Surveys*, 21(4), 786-826. <https://doi.org/10.1111/j.1467-6419.2007.00519.x>
40. Rink, K. (2023). The predictive ability of technical trading rules: an empirical analysis of developed and emerging equity markets. *Financial Markets and Portfolio Management*, 37(4), 403-456. <https://doi.org/10.1007/s11408-023-00433-2>
41. Sharpe, W. F. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425-442. <https://doi.org/10.1111/j.1540-6261.1964.tb02865.x>
42. Silva, N. F., De Andrade, L. P., Da Silva, W. S., De Melo, M. K., & Tonelli, A. O. (2024). Portfolio optimization based on the

- pre-selection of stocks by the Support Vector Machine model. *Finance Research Letters*, 61, 105014. <https://doi.org/10.1016/j.frl.2024.105014>
43. Svogun, D., & Rudys, V. (2023). Adjustable-band moving average learning strategies for technical analysis: evidence from the Dow Jones Industrial Average. *Applied Economics*, 56(50), 1-10. <https://doi.org/10.1080/00036846.2023.2269632>
44. Terregrossa, S. J., & Eraslan, V. (2016). An analysis of the relation between return and beta for portfolios of Turkish equities. *Cogent Economics & Finance*, 4(1), 1168501. <https://doi.org/10.1080/2322039.2016.1168501>
45. Timmermann, A., & Granger, C. W. (2004). Efficient market hypothesis and forecasting. *International Journal of Forecasting*, 20(1), 15-27. Retrieved from <https://ssrn.com/abstract=353300>
46. Treynor, J. L., & Ferguson, R. (1985). In defense of technical analysis. *The Journal of Finance*, 40(3), 757-773 <https://ssrn.com/abstract=3117588>
47. Wang, T., & Sun, Q. (2015). Why investors use technical analysis? Information discovery versus herding behavior. *China Finance Review International*, 5(1), 53-68. <https://doi.org/10.1108/CFRI-08-2014-0033>
48. Yu, H., Nartea, G. V., Gan, C., & Yao, L. J. (2013). Predictive ability and profitability of simple technical trading rules: Recent evidence from Southeast Asian stock markets. *International Review of Economics & Finance*, 25, 356-371. <https://doi.org/10.1016/j.iref.2012.07.016>
49. Zakamulin, V., & Giner, J. (2023). Optimal trend-following with transaction costs. *International Review of Financial Analysis*, 90, 102928. <https://doi.org/10.1016/j.irfa.2023.102928>
50. Zhu, Y., & Zhou, G. (2009). Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics*, 92(3), 519-544. <https://doi.org/10.1016/j.jfineco.2008.07.002>