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Risk-managed time-series momentum: an emerging economy experience

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Abstract

Purpose – This research study aims to design a novel risk-managed time-series momentum approach. The present study also examines the time-series momentum effect in the Indian equity market. Apart from this, the study also proposes a novel risk-managed time-series momentum approach.

Design/methodology/approach – The study considers the adjusted monthly closing prices of the stocks listed on the Bombay Stock Exchange from January 1996 to December 2020 to formulate long-short portfolios. Newey–West t statistics were used to test the significance of momentum returns. The present research has considered standard risk factors, i.e. market, size and value, to evaluate the risk-adjusted performance of time-series momentum portfolios.

Findings – The present research reports a substantial absolute momentum effect in the Indian equity market. However, absolute momentum strategies are exposed to occasional severe losses. The proposed time-series momentum approach not only yields 2.5 times higher return than the standard time-series momentum approach but also causes substantial enhancement in downside risks and higher-order moments.

Practical implications – The study's outcomes offer valuable insights for professional investors, capital market regulators and asset management companies.

Originality/value – This study is one of the pioneers attempting to test the time-series momentum effect in emerging economies. Besides, current research contributes to the escalating literature on risk-managed momentum by suggesting a novel revised time-series momentum approach.

Keywords Time-series momentum, Risk-managed time-series momentum, Indian stock market

Paper type Research paper

**JEL Classification — ** G12, G13

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Originality: This is an original work and it has not published earlier.

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1. Introduction

Return predictability has remained a core theme in investment literature over the last four decades (Huang *et al.*, 2020). Financial researchers have proposed several factors to forecast future returns, including size, value, momentum and quality (Basu, 1983; Fama and French, 1992; Jegadeesh and Titman, 1993; Sloan, 1996). Of these factors, momentum has proven to be the most pervasive and persistent (Blitz *et al.*, 2020). It is simply defined as "the continuation of the trend" (Singh and Walia, 2022). According to Georgopoulou and Wang (2017), momentum anomaly has two dimensions: "cross-sectional momentum" (relative momentum) and "time-series momentum" (absolute momentum). Most momentum anomaly researchers have concentrated on classical cross-sectional momentum. Jegadeesh and Titman's (1993) seminal work on cross-sectional momentum stated that "financial instruments that have outperformed (underperformed) their peers in the past will continue to outperform (underperform) in the immediate future". Time-series momentum is a relatively new version of the momentum anomaly that focusses on a financial asset's absolute (own) performance. Moskowitz *et al.* (2012) proposed the concept of absolute momentum and concluded that a financial instrument's own performance in the previous year predicts its future performance. They argued that investors could earn substantial abnormal profits by going long (short) in financial instruments with positive (negative) cumulative returns in the preceding year.

Financial studies have demonstrated the importance of the absolute momentum effect in many geographic regions and time periods (Hurst *et al.*, 2017; Georogopoulo and Wang, 2017; Lim *et al.*, 2018; Eldomiaty *et al.*, 2019; Guo and Ryan, 2021). Nevertheless, most of these studies were undertaken to this effect in mature markets. However, it will be fascinating to examine how absolute momentum techniques function in emerging and frontier markets. Moreover, most research publications on time-series momentum strategies have focussed on the return aspect; there has been minimal research on the risk aspect. Guo and Ryan (2021) have recently highlighted the potential risks associated with absolute momentum portfolios. Numerous financial academicians claim that absolute momentum techniques produce the best outcomes under severe market situations (Moskowitz *et al.*, 2012). It will be intriguing to test this fact in emerging markets where information distribution is sluggish (Qin and Bai, 2013). Apart from that, the majority of research on risk-managed momentum techniques has been on relative momentum. Furthermore, executing these risk-managed momentum techniques necessitates the computation of intricate parameters and the provision of additional cash (Singh *et al.*, 2021). All these considerations make existing risk-managed momentum techniques unattractive amongst practitioners. As a result, there is a need for a novel risk-managed time-series momentum approach that is simple to deploy and requires minimal funds (Salcedo, 2021).

The present study narrows down these gaps in time-series momentum literature by testing the absolute momentum strategies in an emerging economy research setting. The study focusses on time-series momentum payoffs amid severe market conditions. Recognising the significance of risk concerns, this study suggests a novel time-series risk-managed momentum approach based on market conditions. In a nutshell, the current study addresses the following research objectives (RO):

- *RO1.* Testing the profitability of time-series momentum strategies in the Indian Stock Market.
- *RO2.* Investigating the performance of time-series momentum strategies during extreme market conditions.
- *RO3.* Introducing a novel risk-managed time-series momentum approach for limiting massive absolute momentum losses.

The present study followed the methodological approach of Moskowitz *et al.* (2012) proposed to formulate time-series momentum portfolios. The study reports a significant time-series return continuation effect in the Indian equity segment. It remains substantial even after incorporating standard risk factors. Nevertheless, time-series momentum portfolios, like relative momentum portfolios, are prone to significant losses from time to time. These catastrophic absolute momentum failures frequently occur during the crisis and recovery phases. These findings contrast with outcomes in mature markets (Lim *et al.*, 2018), where time-series momentum strategies perform best amid severe market conditions. The gradual diffusion of information in emerging markets might explain these disparities (Zhang *et al.*, 2020). Trading signals are delayed because of the sluggish diffusion of information, resulting in time-series momentum losses. Furthermore, the proposed time-series momentum approach proved to be a preferable alternative since it generates about 2.5 times higher returns than traditional time-series momentum and results in significant improvements in downside risks and higher-order moments. Though financial researchers propose a plethora of risk-managed momentum approaches, however, most of them are difficult to execute due to extensive computations. The proposed time-series momentum framework is a simple, easy-to-implement approach that promises to generate almost the same returns as existing risk-managed momentum approaches.

The study makes three key contributions to the momentum literature considering the above. First, the current study is one of the first to look at the usefulness of time-series momentum strategies in the context of a developing economy. The research reveals similar effects to those reported in industrialised markets. Second, the study sheds insight into the negative aspects of time-series momentum. The author has carefully researched the return on time-series momentum portfolios in crisis and recovery stages. The findings of this investigation differ from those of the developed market. Finally, the study adds to the burgeoning literature on alternative momentum investment by providing a new risk-managed absolute momentum approach. The proposed time-momentum strategy predicts bullish (recovery) and bearish (crisis) periods and suggests which positions to take during these periods.

2. Literature review

2.1 Time-series momentum

The time-series momentum phenomenon was initially studied by Moskowitz *et al.* (2012). The authors demonstrated, using 58 financial assets, that investors may generate statistically and economically significant returns by investing in assets that have provided positive returns over the previous 12 months and selling those that have produced negative returns. They also discovered that conventional asset pricing models could not explain time-series momentum returns. Later, Hurst *et al.* (2017) corroborated the findings of Moskowitz *et al.* (2012) by examining the time-series momentum impact on a larger class of financial assets. Financial researchers also explore the various explanations of the time-series momentum effect. He and Li (2015) suggest a behavioural model based on three kinds of traders, i.e. contrarian, fundamental and momentum traders. Absolute momentum strategies generate significant payoffs only when momentum traders are active in the market. Kim *et al.* (2016) showed that volatility scaling drives absolute momentum profits. Koijen *et al.* (2018) used absolute momentum returns as a rational factor to examine carry trades. Lim *et al.* (2019) inoculated machine learning-based neural networks into the traditional time-series momentum approach and demonstrated that their hybrid approach outperforms plain time-series momentum. Yang *et al.* (2022) established a link between information diffusion and time-series momentum. They prove that stocks with faster information diffusion speed exhibit higher time-series momentum returns. More recently, Huang *et al.* (2020) found no strong evidence of an absolute momentum effect.

Even though most of the literature on absolute momentum has focussed on futures and other liquid instruments, a handful of research papers also test the time-series momentum effect in equities. For instance, Bird *et al.* (2017) tested absolute momentum strategies in 24 developed countries and reported an impact of time-series momentum on these equity markets that were both statistically and economically significant. The authors also claimed that time-series return continuation strategies outperform conventional relative momentum strategies in terms of payoffs. Lim *et al.* (2018) demonstrated the efficacy of time-series momentum strategies in the US market over a 100-year period (1927–2017). Cheema *et al.* (2018) divulged that absolute momentum provides superior returns than relative momentum only when the market continues in the same state. Traditional relative momentum tactics outperform market changes. Goyal and Jegadeesh (2018) went one step ahead and identified the causes of the time-series momentum effect's superiority over the cross-sectional momentum effect. The authors illustrate that leverage is the primary source of variation in the performance of these two momentum approaches. They also found that traditional cross-sectional momentum performs better when leverage is fully integrated than time-series momentum. Schmid and Wirth (2021) recently revealed that trend strengths and correlations between various investment instruments determine which momentum strategy, i.e. time-series or cross-sectional, yields superior results. If most of the investment instruments have similar trends and low correlations, the absolute momentum approach takes precedence; otherwise, the cross-sectional momentum approach takes precedence.

2.2 Risk-adjusted momentum

In recent years, most of the literature on momentum anomaly has concentrated on the risk aspects of the traditional cross-sectional momentum strategies (Grobys and Kolari, 2020). Several financial academicians have reported the fatter left tails of traditional cross-sectional momentum portfolios' return distribution (Moreira and Muir, 2017; Rickenberg, 2019). In Layman's terms, "cross-sectional momentum strategies are exposed to occasional severe losses". Anticipating the relevance of this concern, numerous financial studies have proposed different risk-managed momentum frameworks by modifying the classical momentum approach. Broadly these risk-managed momentum approaches can be categorised into three categories.

2.2.1 Residual momentum. Blitz *et al.* (2011) found that traditional return continuation strategies are sensitive to Fama–French factors. The author suggests that by ranking the financial securities based on the residual returns, this exposure can be minimised. These residual momentum strategies generate almost double the risk-adjusted returns of standard relative momentum strategies. Later, Chang *et al.* (2018) validated the efficacy of residual momentum strategies in Japan. These outcomes are intriguing as academic studies have reported a weak cross-sectional momentum effect in the Japanese market. In addition, numerous financial academicians test the residual momentum strategies in different markets and disclose strong residual momentum effects in these markets and time frames (Chiao *et al.*, 2018; Lin, 2019; Blitz *et al.*, 2020).

2.2.2 Volatility-managed momentum. Barroso and Santa-Clara (2015) first used the volatility scaling approach to reduce the significant momentum losses. The authors highlighted that momentum portfolios based on constant volatility scaling exclude the possibility of momentum crashes and double the risk-reward ratio compared to the standard momentum framework. Later, to prevent momentum crashes, Daniel and Moskowitz (2016) proposed dynamic volatility-scaled momentum portfolios. Fan *et al.* (2018) took it a step further and demonstrated the superiority of the dynamic volatility scaling approach by contrasting it with the constant volatility scaling approach. Incorporating the dynamic volatility scaling approach with industrial momentum, Grobys *et al.* (2018) showed that the risk-managed industrial momentum strategy outperforms the plain industrial momentum approach in terms of performance. Gao (2020) has recently emphasised the need for volatility-managed momentum portfolios to evade momentum losses.

2.2.3 Other risk-managed momentum approaches. Several financial academics have also proposed risk-managed momentum models. For example, Asness *et al.* (2013) integrated value and momentum approaches and discovered that the combined approach outperforms the standalone approaches. Han *et al.* (2016) proposed a stop-loss method in typical momentum portfolios to reduce downside risk. Jacobs *et al.* (2016) provided a novel skewness-based risk-managed momentum framework. This framework emphasises taking long (or short) positions in financial securities with low (or high) skewness. Dobrynskaya (2019) suggested a "dynamic trading rule". This trading rule follows the traditional momentum framework in normal times; nevertheless, in the crisis period, the rule follows a contrarian strategy. Singh *et al.* (2022) suggested a triple momentum framework and demonstrated the efficacy of their approach over standard momentum approaches. In addition to these research studies, several researchers focussed on volatility, liquidity and skewness as potential sources of risk (Frazzini and Pedersen, 2014; Szymanowska *et al.*, 2014).

In summary, cross-sectional momentum has been the focus of the academic literature on risk-managed momentum approaches, and there has been little academic research on the risk component of the absolute momentum approach. Therefore, it is necessary to investigate the risk involved in time-series momentum portfolios and propose a risk-managed time-series momentum approach. Also, the available literature on the time-series momentum approach has been more focussed on developed markets. Thus, the present study tries to fill these gaps by proposing a novel risk-managed time-series momentum approach in an emerging economic scenario.

3. Method

The current research considers the Indian equity market as a research setting. The rationale behind selecting the Indian equity market is that the Indian market is the second-most attractive emerging economy after China (Bhattacharya and Shahidi, 2021). Due to economic liberalisation and globalisation, the country has witnessed exponential growth in the past years, and it is expected that the Indian economy will be the only one to register double-digit growth (12.5%) in the year 2021–2022. Furthermore, the present study has focussed on monthly adjusted closing prices of stocks listed on the Bombay Stock Exchange (BSE). The reason behind this selection is two-fold: (1) BSE is the oldest stock exchange in India with a market capitalisation of $3 billion (Times of India, 2021); (2) the exchange has more than 4,700 listings. The sample period of the present study covers the time frame from January 1996 to December 2020, as the period incorporates both the bullish and bearish phases of the Indian equity market.

The study has mainly relied on the ProwessIQ database for data retrieval. ProwessIQ is one of the largest financial databases in the Indian context, as the database contains the financial data of more than 38,000 Indian companies. The study considers only those stocks that remained listed on the BSE during the above-mentioned sample period. This research also excludes penny stocks as these stocks are mostly illiquid and have low market capitalisation. These two filtration criteria result in 441 stocks. The study has used S & P BSE100 index as the market index. In addition to this, the authors have used 3-month treasury bill yields as a proxy for risk-free return, and the study has collected this data from the "Database on Indian Economy" maintained by the Reserve Bank of India (RBI). Following the retrieval of monthly closing prices of the BSE-listed securities, we compute the logarithmic returns.

3.1 Research design and procedure

3.1.1 Formulation of absolute momentum portfolios. The study employs the methodological approach suggested by Moskowitz *et al.* (2012) and Lim *et al.* (2018) to formulate absolute momentum portfolios. This procedure starts with the computation of the last 12 months' cumulative return for all the securities. After computing the cumulative returns, the study formulates the long-short absolute momentum portfolios based on the signs of the cumulative returns (Hausner and van Vuuren, 2021). The present research takes a long position in the stocks having positive cumulative and vice-versa (as shown in Figure 1).

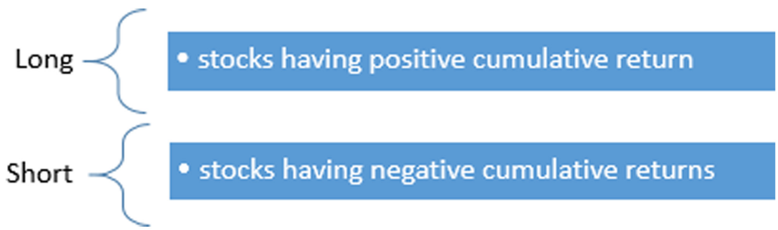
To avoid micro-structure biases, the study follows the advice of Lehmann (1990) and incorporates a one-period gap between the look-back and holding period. The present study holds these portfolios for five different periods (1, 3, 6, 9 and 12 months). The study follows the equal weighting approach for portfolio weighting, as Bird *et al.* (2017) suggest that the time-series momentum approach generates the best results when stocks are equally weighted. Portfolios are rebalanced at the end of each holding period. Finally, absolute momentum payoffs are computed by subtracting the short portfolios' returns from the returns of long portfolios. For significance testing, the study relies on Newey–West *t* statics as it considers autocorrelation and heteroscedasticity.

3.1.2 Formulation of risk-managed time-series momentum portfolios. Detailed analysis of long-short portfolios in time-series momentum reveals that absolute momentum losses occur due to short positions in a strong bullish period and long positions in a strong bearish period. Consequently, the study suggests a signal which will guide investors on whether they should take long, short or both long-short positions in a particular month. This signal is based on the concept of market states proposed by Cooper *et al.* (2004). For every period, the study will compare the lagged one-period return with the lagged two years market return to decide whether a particular month is a normal or abnormal month. A month will be considered normal if an increase or fall in the longer time frame (two years) is greater than an increase or fall in the shorter time frame (one month); otherwise, it will be considered an abnormal month. The abnormal period is further classified into two categories, i.e. bullish, and bearish abnormal periods. In a normal month, the proposed strategy will invest in both long and short portfolios as the standard time-series momentum approach does. On the other hand, the strategy will only take long (short) during bullish (bearish) periods. Therefore, one can say that risk-managed time-series momentum inserts an additional screener in the absolute momentum strategy. For portfolio weighting, rebalancing and significant testing, the study follows similar practices as described in the plain time-series momentum part. The entire risk-managed framework is described in Figure 2.

4. Results

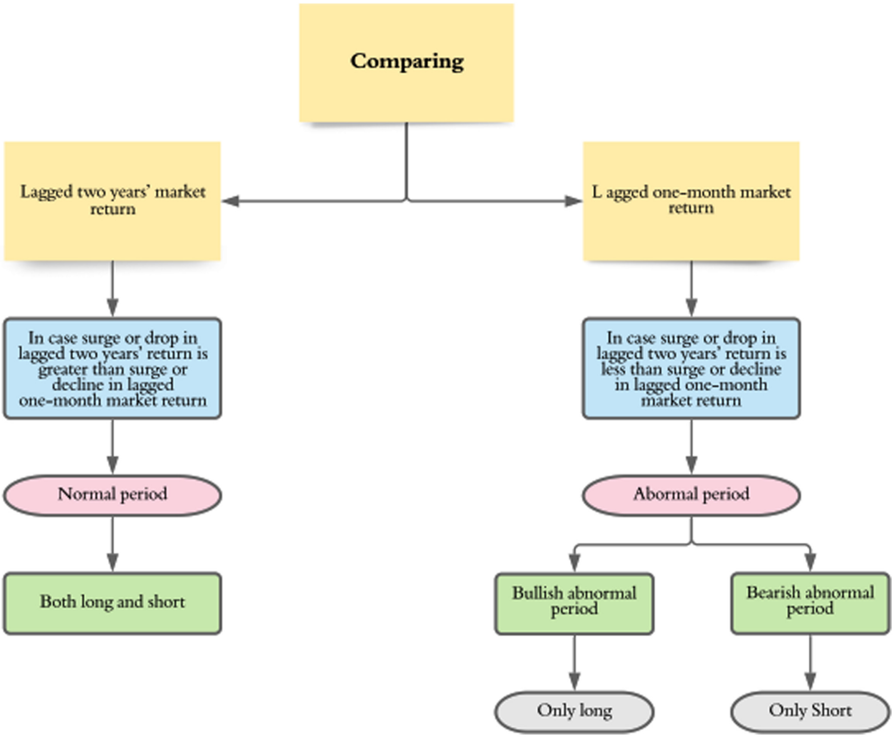
4.1 Profitability of time-series momentum strategies

The empirical analysis of the present study commences with investigating the performance of the absolute momentum strategies. Table 1 presents the excess returns (raw returns – risk free return) and risk-adjusted returns for different absolute momentum strategies. This table also reports higher- order moments and downside risks involved in time-series momentum strategies. One can observe from this table that all the tested time-series momentum strategies produce positive returns; four out of the total five absolute momentum strategies generate significant returns. The absolute momentum framework produces the highest return when portfolios are held for three months. Excess return at this combination of



Source(s): Own elaboration

Figure 1. Formulating long-short portfolios in absolute momentum strategy



Source(s): Own elaboration

Figure 2.
Risk-managed time-series momentum framework

Table 1.
Profitability of time-series momentum strategies

H =	1	3	6	9	12
RET-RF	1.267%	1.357%	0.984%	0.710%	0.878%
	(2.371**)	(2.650**)	(2.112**)	(1.632*)	(2.052**)
CAPM α	1.300%	1.397%	1.014%	0.727%	0.901%
	(2.450**)	(2.666**)	(2.012**)	(1.673*)	(1.819*)
FF3 α	1.531%	1.572%	1.197%	0.905%	1.056%
	(3.238**)	(3.342***)	(2.702**)	(2.227**)	(2.466**)
Skewness	−0.796	−0.558	−0.377	−0.463	−0.536
Kurtosis	2.081	1.989	1.901	1.682	2.084
VaR (5%)	−14.085%	−13.182%	−12.539%	−12.797%	−12.530%
CVaR (95%)	−22.610%	−21.346%	−19.815%	−19.801%	−20.248%
Adjusted Sharpe ratio	0.338	0.393	0.270	0.160	0.238
Calmer ratio	0.252	0.280	0.278	0.156	0.266

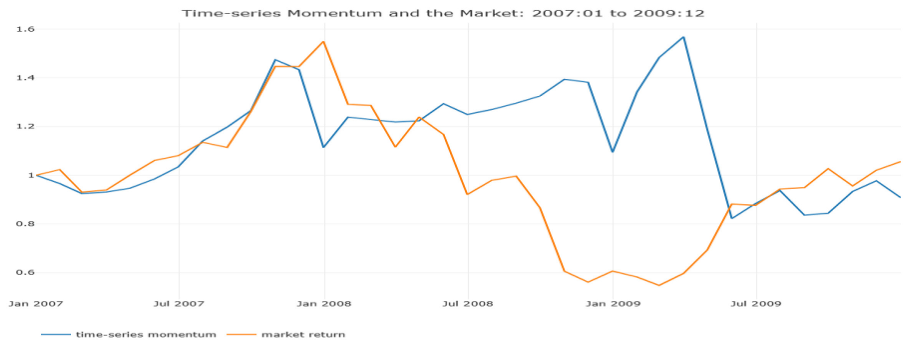
Note(s): Table 1 reports the average monthly returns of absolute momentum strategies along with higher-order moments and downside risk measures. Rf stands for riskless rate, and H denotes various holding periods. CAPM and FF3 (Fama–French three-factor model) alphas are computed by regressing relative momentum payoffs (minus riskless rate) against the payoffs of market, size and value factors. The study takes the help of the asterisk symbol to represent the significant relative momentum returns. ***, ** and * represents significance at 1%, 5% and 10% levels
Source(s): Own elaboration

formation and holding period (12 months' formation and 3 months holding) is 1.357% per month. In contrast to cross-sectional momentum strategies, Absolute momentum payoffs remain significant even for longer holding periods. These findings are consistent with the results of Lim *et al.* (2018), which report the profitability of time-series momentum strategies in the US market. In addition to this, the study also tests the risk-adjusted performances of absolute momentum strategies. For this purpose, the authors have employed standard asset pricing models, i.e. the capital asset pricing model (CAPM) and the Fama–French three-factor model (FF3). Corroborating the findings of Goyal and Jegadeesh (2018), time-series momentum payoffs remain positive and significant even after incorporating risk factors.

However, time-series momentum strategies are not free from risk. Negatively skewed absolute momentum returns indicate that these strategies can lead to occasional severe losses. Downside risk measures, i.e. value at risk (VaR) and conditional value at risk (CVaR), also signal in this direction.

4.2 Absolute momentum crashes

Extreme downside risks associated with momentum strategies make these strategies unattractive for risk-averters (Han *et al.*, 2016). Financial economists have reported that standard momentum strategies (cross-sectional momentum strategies) are prone to crash occasionally (Dobrynskaya, 2019). In this section of the study, the authors test whether absolute momentum strategies also yield occasional severe losses. If yes, do these absolute momentum losses are predictable? Daniel and Moskowitz (2016) suggest that relative momentum strategies poorly perform during the recovery phase (after the crisis period). Following their approach, the present study purposely selects the period from January 2007 to December 2009 and compares the absolute momentum and market returns during this period. The rationale behind selecting this particular time frame is that this period covers the financial crisis and recovery phases. Figure 2 shows the cumulative time-series momentum and market returns from January 2007 to December 2009. For comparability reasons, the wealth index has been set to one. It is evident from the figure in just two months (April 2009–May 2009) the time-series momentum portfolios produce a cumulative return of −56%. These results are in harmony with the findings of academic literature on cross-sectional momentum crashes (Barroso and Santa-Clara, 2015). It is also clear from Figure 3; severe time-series momentum crashes occur when the overall equity market is recovering. Further analysis of the long-short positions in the time-series momentum portfolio reveals that short positions cause more losses during the crisis and recovery phases. Table 2 also corroborates these



Source(s): Own elaboration

Figure 3.
Time-series momentum and market

findings as one can observe that three out of five worst absolute momentum payoffs occur during the market recovery phase.

4.3 Risk-managed time-series momentum

From the above section, it is evident that absolute momentum results in occasional severe losses. Now the question arises, can we control these absolute momentum losses? Through investigation of long-short portfolios reveals that these losses mainly arise due to short positions in strong bullish periods and long positions in the strong bearish period. Accordingly, the author has proposed a signal which will guide the investors in whether they should take long, short or both long-short positions in a particular month. In every month, the study will compare the lagged one-period return with the lagged two years market return to decide whether a particular month is a normal or abnormal month. A month will be considered normal if an increase or fall in the longer time frame (two years) is greater than an increase or fall in the shorter time frame (one month); otherwise, it will be considered an abnormal month. The abnormal period is further classified into two categories, i.e. bullish and bearish abnormal periods. In a normal month, the proposed strategy will invest in long and short portfolios as the standard time-series momentum approach does. On the other hand, the strategy will only take long (short) during bullish (bearish) periods. The author has named this momentum approach "the risk-managed time-series momentum approach". The proposed time-series momentum approach is motivated by the iconic work of Cooper *et al.* (2004), which demonstrates that momentum profits are conditioned on market states. To define market states, they use lagged three years' market return. If a lagged three-year market return is positive (negative) for a particular period, they define that period as bullish (bearish). Furthermore, they prove that momentum strategies generate significant payoffs only during bullish market states and behavioural models, particularly under-reaction, are the foremost cause behind it.

In this section, the authors investigate the performances of risk-managed time-series momentum strategies. Table 3 reports the excess and risk-adjusted returns of risk-managed time-series momentum strategies along with higher-order moments and downside risk measures. It is apparent from the table that risk-managed time-series momentum strategies produce positive and statistically significant returns. Comparing excess returns of the proposed time-series momentum approach with excess returns of the standard time-series momentum approach (as reported in Table 1) reveals that returns generated by risk-managed momentum strategies are approximately 2.5 times higher than standard time-series momentum strategies. For instance, when portfolios are formed based on twelve months' past returns and a one-month holding period, the time-series momentum strategy yields an average monthly return of 1.26%, whereas, at the same combination of formation and holding period, the proposed time-series momentum strategy produces 3.214% per month. In terms of risk-adjusted returns and risk-reward ratios, the proposed momentum approach also dominates the time-series momentum

Table 2. Worst absolute momentum payoffs

Rank	Month	Absolute momentum	MKT	MKT-2Y
1	2020:06	−37.49%	7.09%	−5.39%
2	2009:05	−30.73%	27.72%	−19.20%
3	2009:04	−24.27%	16.06%	−28.72%
4	2004:09	−23.36%	7.22%	82.60%
5	2001:11	−22.91%	11.40%	21.63%

Note(s): Table 2 outlines the five worst monthly payoffs of relative momentum. This table also reports concurrent month market return (MKT) and lagged 24 months market return (MKT-2Y)
Source(s): Own elaboration

H =	1	3	6	9	12
RET-RF	3.214%	3.238%	2.914%	2.584%	2.749%
	(6.001***)	(5.785***)	(5.156***)	(5.070***)	(5.233***)
CAPM α	3.219%	3.252%	2.929%	2.581%	2.754%
	(5.937***)	(5.521***)	(5.145***)	(5.090***)	(5.087***)
FF3 α	3.401%	3.379%	3.075%	2.718%	2.870%
	(7.222***)	(6.913***)	(6.161***)	(6.028***)	(5.714***)
Skewness	0.118	0.282	0.336	0.129	0.357
Kurtosis	2.369	2.294	1.449	2.748	1.920
VaR(5%)	−9.289%	−8.970%	−8.940%	−10.079%	−8.625%
CVaR (5%)	−14.505%	−13.068%	−12.348%	−15.490%	−11.971%
Adjusted Sharpe ratio	1.170	1.232	1.236	0.925	1.164
Calmer ratio	0.978	0.885	0.994	0.724	1.119

Note(s): Table 3 reports the average monthly returns of risk-managed time-series momentum strategies along with downside risk measures and higher-order moments. Rf stands for riskless rate, and H denotes various holding periods. CAPM and FF3 (Fama–French three-factor model) alphas are computed by regressing relative momentum payoffs (minus riskless rate) against the payoffs of market, size, and value factors. In parenthesis, Newey–West t statistics are reported. The study takes the help of the asterisk symbol to represent the significant relative momentum returns. ***, ** and * represents significance at 1%, 5% and 10% levels
Source(s): Own elaboration

Table 3. Performance of risk-managed time-series momentum strategies

approach. Adjusted Sharpe ratios of risk-managed momentum strategies are approximately three times higher than simple time-series momentum strategies. Apart from returns and risk-reward ratios, the revised time-series momentum approach also results in substantial improvement in downside risk measures and higher-order moments. For instance, CVaR in case 12*1 improves significantly from −22.610% (in the case of standard time-series momentum) to −14.505% in the case of the proposed time-series momentum approach. Analysis of the risk-managed time-series momentum portfolios reveals that a significant portion of risk-managed time-series momentum profits come from long positions.

Due to the gradual diffusion of information, there is a delay in the trading signal, which results in huge time-series momentum losses because of short (long) positions when the overall market is bullish (bearish). The proposed time-series momentum framework tries to overcome this delay by incorporating the concept of market states in the standard time-series momentum framework. Investors' overreaction during the crisis period results in a drop in stock prices. During this phase, long positions in absolute momentum portfolios cause substantial losses. This decline in stock prices pushes the stock prices below their intrinsic values. Eventually, these stock prices return to their intrinsic values. At this time (recovery phase), short positions in time-series momentum portfolios cause huge losses.

4.4 Comparing risk-managed time-series and time-series momentum strategies

The present research also conducts a cross-alpha comparison to validate the superiority of the proposed time-series momentum approach over the time-series momentum approach. To perform a cross-alpha comparison, the authors regresses the risk-managed momentum profits against time-series momentum profits and vice-versa. The results of the cross-alpha comparison have been reported in Table 4. In this table, the study has reported that the alphas derive from regressing the risk-managed momentum payoffs against time-series momentum payoffs and vice-versa. From this table, one can draw a conclusion that time-series momentum cannot capture risk-managed momentum as alphas are positive and significant while regressing risk-managed time-series momentum payoffs against time-series momentum payoffs. However,

Independent variable → TS momentum Dependent variable → Risk-managed TS momentum Holding period		Risk-managed TS momentum TS momentum
1	2.106% (4.275***)	−0.883% (−3.214***)
3	1.809% (3.960***)	−0.801% (−3.318***)
6	1.715% (3.986***)	−0.790% (−3.737***)
9	1.678% (4.054***)	−0.777% (−3.584***)
12	1.685% (4.188***)	−0.759% (−3.482***)

Note(s): Table 4 presents intercepts (alphas) of various risk-managed time-series momentum payoffs regressed against standard time-series momentum payoffs and intercepts of time-series momentum payoffs regressed against risk-managed time-series momentum returns
Source(s): Own elaboration

Table 4.
Cross-alpha comparison

alphas are negative when time-series momentum payoffs are regressed against risk-managed time-series momentum payoffs.

4.5 Robustness checks

Finally, the study uses a range of robustness tests to validate the findings reported in the above sections.

4.5.1 Alternative signal period. To investigate whether the findings of the study are sensitive to the length of lagged market returns used for determining whether a particular period is normal or abnormal, the author also uses lagged 36 months market returns (instead of 24 months lagged market returns). Table 5 reports the findings of the revised time-series momentum strategies using alternative signal periods. All strategies produce positive and statistically significant returns. These returns are substantially higher than the original time-series momentum returns.

4.5.2 Sub-period analysis. To perform sub-period analysis, the study splits the entire sample period into three subsample timeframes: January 1996–December 2003, January 2004–December 2011 and January 2012–December 2020. The second and third sub-sample

H =	1	3	6	9	12
RET-RF	2.912% (4.840***)	2.804% (4.615***)	2.440% (4.116***)	2.152% (3.879***)	2.311% (4.132***)
CAPM α	2.946% (4.845***)	2.831% (4.681***)	2.461% (4.197***)	2.168% (4.110***)	2.327% (4.143***)
FF3 α	3.120% (5.480***)	2.968% (5.262***)	2.607% (4.678***)	2.304% (4.506***)	2.445% (4.610***)
Skewness	−0.257	−0.091	−0.011	−0.113	−0.119
Kurtosis	2.160	2.417	2.310	2.062	2.619
Adjusted Sharpe ratio	0.980	0.965	0.868	0.760	0.819
Calmer ratio	0.868	0.737	0.809	0.583	0.835

Source(s): Own elaboration

Table 5.
Performance of alternative risk-managed time-series momentum strategies

period includes the crisis periods as the second sub-sample covers the sub-prime crisis period, and the third sub-sample period incorporates the COVID-19 period. The performance of various risk-managed time-series momentum strategies is reported in Table 6. It is evident from the table that risk-managed momentum strategies yield substantial returns in different sub-periods.

4.5.3 Out-of-sample evidence. To validate the robustness of the proposed time-series momentum approach, the strategy also considers adjusted closing prices of stocks listed on the National Stock Exchange (NSE) for the different time periods, i.e. 2005–2020. The authors form risk-managed time-series momentum portfolios using NSE-listed stocks and compare their performance with the original sample. Table 7 reports the returns, risk-reward ratios, downside risk measures and higher-order moments of risk-managed time-series momentum strategies (using NSE-listed stocks). As it is clear from the table, the results are similar to the findings reported in Table 3. All strategies generate positive and significant returns.

Table 6. Sub-period analysis

	Risk-managed TS momentum		
H	1996–2003	2004–2011	2012–2020
1	3.410%	2.976%	3.252%
	(3.122**)	(3.178**)	(4.171***)
3	3.780%	2.709%	3.226%
	(3.490***)	(2.868**)	(3.782***)
6	3.522%	2.342%	2.881%
	(3.456***)	(2.479**)	(3.203**)
9	2.591%	2.465%	2.683%
	(2.713**)	(2.629**)	(3.269**)
12	2.820%	2.460%	2.944%
	(2.936**)	(2.594**)	(3.304**)

Source(s): Own elaboration

Table 7. Out-of-sample evidence

H =	1	3	6	9	12
RET-RF	3.099%	3.173%	2.890%	2.171%	2.717%
	(5.120***)	(4.993***)	(3.968***)	(3.439***)	(3.945***)
CAPM α	3.205%	3.267%	2.970%	2.263%	2.793%
	(5.224***)	(5.388***)	(4.535***)	(3.471***)	(4.300***)
FF3 α	3.177%	3.243%	2.948%	2.248%	2.772%
	(5.532***)	(5.594***)	(4.785***)	(3.521***)	(4.504***)
Skewness	1.270	1.393	0.734	1.361	0.584
Kurtosis	4.290	4.113	3.791	4.235	3.811
VaR (5%)	−6.484%	−6.781%	−7.497%	−8.328%	−8.441%
CVaR (95%)	−10.548%	−10.181%	−11.843%	−11.099%	−13.237%
Adjusted Sharpe ratio	1.125	1.084	1.163	0.930	1.064
Calmer ratio	1.541	1.272	0.979	0.664	0.727

Note(s): Table 7 reports the average monthly returns of absolute risk-managed momentum strategies along with higher-order moments and downside risk measures (using NSE-listed stocks as a sample). Rf stands for riskless rate, and *H* denotes various holding periods. CAPM and FF3 (Fama–French three-factor model) alphas are computed by regressing relative momentum payoffs (minus riskless rate) against the payoffs of market, size and value factors. In parenthesis, Newey–West *t* statistics are reported. The study takes the help of the asterisk symbol to represent the significant relative momentum returns. ***, ** * represents significance at 1%, 5% and 10% levels
Source(s): Own elaboration

These returns are comparatively higher than standard time-series momentum strategies. Risk-reward ratios are almost 3.5 times greater than conventional absolute momentum strategies. In addition, findings for downside risk measures and higher-order moments are also in parallel with outcomes reported in Table 3.

5. Discussion

5.1 Theoretical implications

The outcomes of the present research offer novel insights and have some significant implications for professional investors, capital market regulators and asset management companies (AMC). The presence of the time-series momentum effect has some substantial consequences for the market regulators as the significant absolute momentum effect challenges the weak-form efficiency. Absolute momentum crashes during extreme market conditions corroborate the behavioural theories exceptionally gradual diffusion of information theory as these crashes mainly happen due to delays in trading signals. The outcomes of the proposed time-series momentum strategy open avenues for future studies as the proposed strategy needs to be tested in other financial markets and asset classes. Apart from this, financial researchers can also focus on potential explanations for the proposed momentum strategy in future.

5.2 Managerial implications

Apart from theoretical implications, the study offers several useful managerial insights. First, the significant absolute momentum effect in the Indian market offers investment opportunities for active fund managers who often look for stock selection rules to perform better than the market index. Second, the proposed time-series momentum approach can be used as a benchmark to measure the performance of fund managers. The proposed time-series momentum approach also provides a better option for trend-following investors who tend to avoid risk. Nevertheless, time-series and risk-managed time-series momentum strategies may not be the ideal investment strategy for private investors as these strategies involve a high frequency of transactions resulting in higher transaction costs. Third, AMC can exploit trend-following strategies by introducing exchange-traded funds and mutual funds based on these strategies. In the end, global fund managers who continuously look for diversification opportunities can add equities from emerging markets like India to their portfolios.

6. Conclusions

The present study documents persistent and significant absolute momentum profits in the Indian market. By taking into consideration a sample of BSE-listed companies, the study evaluates the profitability of time-series momentum strategies as well as the timing of the absolute momentum crashes. Similar to the outcomes from the advanced markets, time-series momentum strategies also generate substantial returns in the Indian market. Even after incorporating risk factors, these returns continue to remain substantial. The study also observes that a major portion of trend-following strategies comes from long positions. This evidence straightway challenges the random walk hypothesis and makes the concept of market efficiency more puzzling. Nevertheless, in contrast to US evidence, where absolute momentum strategies yield the best results during extreme market conditions, in the emerging economic scenario, absolute momentum strategies perform worst during the crisis and recovery phases. The gradual diffusion of information may be the potential reason for it. In addition to this, the present study also suggests a novel risk-managed time-series momentum framework based on the idea of market states proposed by Cooper *et al.* (2004). The author demonstrates that the proposed strategy is persistent and robust across different time periods. Compared to popular risk-managed momentum approaches, the proposed risk-managed time-series momentum approach is easy to implement as it involves a lesser number of computations. Furthermore, the authors have employed several robustness tests to prove the efficacy of the revised time-series momentum strategy.

The study contributes to the finance literature in multiple manners. The present research is one of the pioneer studies in investigating the performance of time-series momentum strategies in the context of an emerging market. The study is also amongst the early attempts that report the gloomy side of the absolute momentum approach. The most significant contribution of the study is the novel risk-managed time-series momentum approach. However, there are certain loopholes in the present research. First, the proposed momentum approach is tested only in the Indian market. Future studies can broaden the scope and consider multiple market settings. Second, the present study does not consider transaction costs. Since trend-following strategies involve frequent transactions that may impact the profitability of these strategies.

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