Analyzing the Existence of Momentum and Reversal Effects in Colombo Stock Exchange

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Abstract

This study reexamines the existence of momentum and reversal effects in the Colombo Stock Exchange over the period from January 2015 to March 2024. The sample consists of 261 voting stocks listed on the main board, with firms having less than 12 months of data excluded. The analysis is motivated by recent structural changes in the CSE, including increased retail participation, post-crisis volatility and evolving market microstructure, which may affect the persistence of return anomalies. After cleaning the data, zero cost long short portfolios were constructed using various formations and holding periods. From 2015 to 2019, momentum and contrarian strategies produced negative and statistically insignificant returns. Even extreme (1% and 5%) and broader splits (25% and 30%) failed to deliver reliable performance. Shorter term strategies (3 and 6 months) produced smaller losses, while 12-month strategies incurred larger declines, highlighting the market's inability to sustain momentum. Findings from 2020 to 2024 reconfirm the earlier pattern. Of 96 portfolios tested, only 19 showed statistical significance, most with negative returns. Winner portfolios often underperformed relative to loser portfolios. While a few strategies revealed stronger momentum, their returns remained mostly negative. Overall, the lack of consistent performance across all strategies suggests that traditional momentum and reversal approaches are ineffective in the Sri Lankan context. The results highlight the need for alternative models incorporating fundamental factors, machine learning approaches to better understand and potentially exploit the market inefficiencies.

Keywords: Market inefficiency, Momentum effect, Reversal effect, Sri Lankan stock market, Zero cost portfolios

1. Introduction

In an efficient market, stock prices are expected to reflect all available information. In this context, investors should not be able to earn extra returns by analysing past prices. However, behavioural finance researchers have identified strategies that appear to consistently generate excess returns. These strategies, known as financial anomalies, include effects such as momentum and contrarian patterns (Huang et al., 2023). Momentum is one of the few patterns in returns that still challenges popular asset pricing models like the Fama and French (2015) five factor model. So far, no clear risk factor has been found to explain why stocks with recent performance tend to earn higher returns. This makes momentum a key topic in debates about whether markets are truly efficient (Kelly et al., 2021).

The momentum effect suggests that stocks with strong past performance tend to continue performing well, while underperforming stocks continue to underperform for a short time (Jegadeesh & Titman, 1993). Hence, the momentum effect implies that

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past price trends can exist for a period, creating opportunities for investors to capitalize on the continuation of these trends. The momentum effect has been widely observed in global equity markets, showing that stock returns can be significantly influenced by investor behavior and market inefficiencies, rather than just by fundamental factors. Jegadeesh and Titman’s (1993) pioneering study showed that buying stocks with strong past performance and selling those with weak performance could lead to substantial risk adjusted returns. These findings challenged traditional views on market anomalies. Later research has supported the persistence of this effect, suggesting that momentum strategies may result from many reasons, such as investor overreaction or the delayed information diffusion.

However, the momentum effect is often contrasted with the reversal effect, another anomaly identified in financial markets. De Bondt and Thaler (1985) highlighted the reversal effect, where stocks that performed poorly in the past (for three to five years) tend to outperform in the future (for the next three to five years), and stocks that have outperformed tend to experience negative returns. This reversal is believed to occur due to overreaction, where investors excessively react to the new information, pushing stock prices too high or too low, only for prices to correct themselves over time. De Bondt and Thaler (1985) study proved that stocks that were the worst performers over the period tend to experience significant rebounds, while the best performing stocks see corrections, a pattern that challenges the continuation suggested by the momentum effect.

The coexistence of both momentum and reversal effects raises questions regarding the nature of stock price movements. Studies have shown that these effects may not be mutually exclusive but could operate on different time horizons or market conditions. While momentum might dominate in the short to medium term (up to 12 months), reversals could become more evident in the long term (Fama & French, 1996). Moreover, the reversal effect could be more prominent in value stocks, while momentum tends to favour growth stocks (De Bondt, 1998). This creates a more detailed perspective, where investors may observe both effects in different market conditions or with different types of stocks.

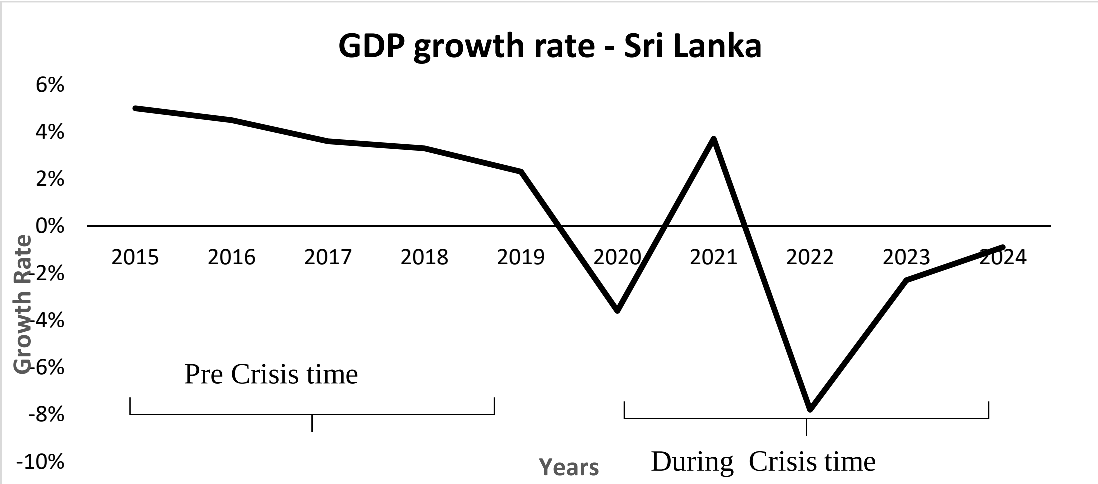
Most studies produced contradicting results. Ehsani and Linnainmaa (2022) show that time series factor momentum delivers average monthly return of 0.10% across fifty-one countries, with significance in 23 markets. The effect is held under both time series and cross-sectional approaches, but is not consistent among all regions. The time series strategy shows significant results in only 16 while cross sectional approaches show significant results in only twelve countries. This fails to hold in major countries like France, Germany, and Japan. This suggests that factor momentum is promising but not universally reliable.

Although extensively studied in developed markets (Fama & French, 1996; Carhart, 1997), research on momentum in emerging markets like Sri Lanka remains scarce, with most studies conducted many years ago (Anuradha & Nimal, 2017; Weerakoon Banda & Pathirawasam, 2008). This gap in knowledge calls for an updated investigation, particularly in the context of the Colombo Stock Exchange, where unique market inefficiencies and behavioural biases may drive stock returns differently from developed markets.

This study focuses on the period from 2015 to the first quarter of 2024, divided into two different time frames. 2015 to 2019 can be considered as pre crisis period for Sri Lanka, while from 2020 to the first quarter of 2024, a transformative year for Sri Lanka, marked by several significant events that likely influenced market behaviour. The 2019 Easer attacks caused loss of investor confidence, disrupting economic stability (Jayasinghe et al., 2023). The COVID-19 pandemic started in 2020, introducing challenges with lockdowns, reduced economic activity, and increased market volatility (Wanniarachchige, 2023). Further, adding to these disruptions, Sri Lanka faced a historic economic crisis in 2022, marked by hyperinflation, currency depreciation, and a debt default, all of which significantly impacted market performances (Nimal & Namboodiripad, 2022).

Figure 1

GDP growth rate of Sri Lanka (2015 – 2024)



Source. Central Bank of Sri Lanka

This research aims to fill the existing gap by revisiting the momentum effect and reversal effect in the CSE during the higher volatile market conditions. By analysing the cross-sectional stock returns and forming momentum portfolios based on past performance, the study seeks to provide updated insights into the impact of momentum strategies in Sri Lanka and to guide whether investors can earn excess returns by using only zero cost portfolio strategy.

This research offers significant contributions to theory, practice and policy. Theoretically, it extends the literature on momentum effect in frontier markets by analysing its presence in the Sri Lankan equity market during periods of heightened volatility, crisis, and digital transformation. Unlike prior studies that tested limited portfolios in stable conditions, the study adopts a broader and more recent time frame (2015-2024) and evaluated 96 strategy combinations to reflect real world trading dynamics. Practically, the findings inform investors, fund managers and analysts that momentum-based strategies alone may not be effective in the Sri Lankan market. From a policy perspective, the results highlight the need for improved market infrastructure, investor awareness and regulatory safeguards price discovery and reduce volatility.

2. Literature Review

Momentum and reversal effects are two widely studied phenomena in financial markets that have been the subject of extensive research. Momentum strategies involve buying assets that have performed well in the recent past and selling those that have underperformed, with the expectation that this performance will continue in the short term. This concept was first introduced by Jegadeesh and Titman in 1993, who found that stocks with high returns tend to continue outperforming in the subsequent 3-to-12-month period and expressed that behavioral biases, namely investors under reaction to new information or herding behaviour may drive the persistence of momentum. They mentioned that these abnormal returns were not explained by the market risks alone.

Reversal strategies, on the other hand, involve buying underperforming assets and selling outperforming ones, anticipating that their performance will revert to the mean overtime. This idea is supported by studies such as De Bondt and Thaler (1985), who found that stocks with poor past performance tend to outperform in the long run. According to them, stocks that didn’t do so well over the past three to five years often end up doing better in the next three to five years. This idea comes from the overreaction hypothesis in behavioral finance, which says that stock prices sometimes move too much because people overreact to past news and performance. Hence, when prices decline significantly below their intrinsic value, there is a strong likelihood of a subsequent rebound. That’s why buying underperforming stocks can sometimes turn out to be a good strategy.

Momentum is generally measured in two main ways, which are time series momentum and cross-sectional momentum. Time series momentum, often called trend following, looks at whether an individual asset or factor has performed well compared to its own past performance. If recent returns have been positive, the strategy assumes they might continue to be positive for some time, and the same idea applies if returns have been negative. This approach focuses on a single asset over a period. On the other hand, cross-sectional momentum compares the performance of several assets at the same point in time. This ranks them based on recent returns and builds a portfolio by buying the top performers (winners) and selling the underperformers (losers). While time series momentum is based on an asset’s absolute performance, cross-sectional momentum focuses on how assets perform relative to one another. Both methods have been widely researched and are known to produce profitable signals across different asset classes and markets, although their success can vary depending on the market environment and region (Ehsani & Linnainmaa, 2022; Pirie & Chan, 2018).

Several theoretical explanations have been proposed to explain the existence of momentum and reversal effects in financial markets. These explanations can be broadly divided into risk based and behavioural based theories.

2.1 Risk based theories

These suggest that momentum and reversal effects are due to the presence of systematic risks that are not captured by traditional asset pricing models. Momentum could be a result of exposure to specific risk factors that are associated with the continuation of past returns. Similarly, reversal could be due to the correction of mispricing that arises from the market's inability to fully incorporate the information into prices (Huang et al, 2023; Luo et al., 2018).

To account for momentum effects, researchers integrated them into risk-based asset pricing models, notably in Carhart's (1997) four factor model. However, many of the other models such as the Capital Asset Pricing Model (CAPM) (Sharpe, 1964) and the Fama and French three and five factor model failed to capture this (Fama & French, 2015; Fama & French, 1993; Fama & French, 2015) .

2.2 Behavioural based theories

The theory of bounded rationality explains how cognitive limitations and the inherent complexity of decision-making processes prevent individuals from achieving complete rationality (Simon, 1955). This is further elaborated by Barberis and Thaler (2003) where the researchers emphasized that investors are influenced by many psychological biases which challenge the concept of rational decision making. Instead of achieving optimisation in investment decisions, investors rely on mental shortcuts or heuristics bias which introduce systematic biases such as overconfidence, representativeness, conservatism, self-attribution biases, loss aversion (Anuradha & Nimal, 2017).

These biases influence the financial market activities, particularly in explaining concept like the momentum effect. Investors' conservative behavior, a psychological tendency where individuals are slow to update their beliefs in response to new information, is rooted in anchoring and adjustment (Barberis et al., 1998). This bias leads to underreaction, where stock prices do not fully reflect new information, causing prices to gradually adjust to their intrinsic values. Investors tend to anchor expectations to historical trends and incrementally adjust their beliefs, discounting significant news as temporary. This underreaction created momentum where stocks that perform well or poorly continue their trends in the short to medium term, offering opportunities for momentum strategies. By buying underreacting winners (with positive news not fully priced) and selling under reacting losers (with negative news), investors can profit as prices eventually correct.

However, according to Daniel et al. (1998), momentum effects are created through two psychological biases, namely overconfidence and self-attribution bias. Overconfidence causes investors to overestimate the accuracy of their private information and interpret it better than others, leading to overreactions to signals or news and driving the stock prices beyond their intrinsic values, resulting in short term momentum. Self-attribution bias occurs when investors attribute successes to their skill and failures to external factors, reinforcing overconfidence through a feedback loop. These biases collectively cause prices to excessively drift in the direction of trend in the short to medium term (momentum), but overreaction ultimately leads to price corrections, resulting in reversals over the long term.

Empirical studies have provided contradicting evidence of the existence of momentum and reversal effects in various financial markets (Cakici et al., 2025). According to Chui et al. (2023), there was a strong intermediate and long term momentum in Bombay Stock Exchange listed stocks, with the momentum effect amplified by high liquidity, while illiquidity stocks show short term reversals without persistence. Further, Boussaidi and Dridi (2020) found momentum profits remain after adjusting for risk, and that prices slowly adjust to earnings surprises, supporting the underreaction hypothesis. Another study on China's A share market from 2010 to 2020 found a strong short term contrarian effect (Zhang & Zhu, 2024).

According to Huang et al. (2023), short term momentum prevailed in China's growth enterprise market, however, it disappeared over time. After the registration-based system was introduced, the effect shifted from momentum to contrarian. Further, small companies with low market cap, low price to book ratio, and high turnover are more likely to show contrarian effects. In contrast, Chen et al. (2024) show that short term momentum is more common among stocks with high turnover and high price to 52 week high ratios, while stocks with low turnover and low price to 52 week high ratio show stronger short term reversals. They attribute these patterns to two competing mechanisms which are underreaction (leading to momentum) and liquidity provision (leading to reversals). Also, the additional variation is explained by analyst forecast differences and overall market sentiment.

Empirical evidence shows that there is a momentum effect in the Colombo Stock exchange. Weerakoon Banda and Pathirawasam (2008) analyzed momentum and contrarian strategies from October 1991 to June 2005, using the seminal work of Jegadeesh and Titman (1993). Momentum strategies are found to be highly profitable, particularly in the post automation period, emphasising that role of automation in enhancing market efficiencies. This momentum effect was further supported by Anuradha and Nimal (2017) where researchers considered all the stocks listed between the period of October 1991 to December 2012 using same c method and confirmed that there is a momentum effect in Colombo Stock Exchange and concluded that taking long position on the winner portfolio while short in the loser portfolio will give a zero cost profits to investors.

Optional implementation of momentum and reversal strategies involve careful consideration of various factors, including the choice of assets, the formation and holding periods, and the use of risk management techniques. Studies have shown that momentum strategy can be enhanced by incorporating information about the market states and investor sentiment. Similarly, reversal strategies can be improved by more sophisticated models that account for time varying market conditions (Koijen et al., 2009 ; He et al., 2014).

3 Methodology

3.1 Data

This study employs data from the Colombo Stock Exchange spanning from 01 January 2015 to March 2024. It includes all voting stocks on the main board, excluding those companies that have less than 12 months of available data. Further, data is cleaned by addressing missing values, removing inactive stocks and ensuring a consistent time series for analysis. The final list consists of 261 companies.

Daily stock price data is then transformed into daily returns using the following formula.

$$R_{n,t} = \frac{P_{n,t}}{P_{n,t-1}} - 1$$

where $R_{n,t}$ is the daily return, $P_{n,t}$ is the closing price of the stock on that day and $P_{n,t-1}$ is the closing price on the previous trading day, which is not adjusted for any other factors. These daily returns are compounded to compute monthly cumulative returns for each stock using,

$$D_{n,T} = \prod_{i=1}^{T}(R_{n,i} + 1) - 1$$

where Rn,t represents daily returns within the month.

The analysis focuses on multiple formation and holding periods, including 3 months, 6 months, 9 months, and 12 months. For each formation period, cumulative returns are calculated by rolling the monthly cumulative returns over the specified window. These cumulative returns serve as the foundation for portfolio formation. The portfolios are constructed based on the ranked cumulative returns during the formation period. Stocks are sorted into percentiles, with specific splits defined at 1%, 5%, 10%, 20%, 25% and 30%. From this sorting process, winner and loser portfolios are created. The winner portfolio comprises the top performing stocks based on the cumulative returns and the loser portfolio consists of bottom performing stocks.

For each holding period (3, 6, 9, 12 months), cumulative holding period returns are calculated. This study examines two different time frames, pre crisis period from 2015 to 2019, and the crisis period from 2020 to first quarter of 2024. The average returns for the Winner (ARw) and the Loser (AR_l) portfolios are computed for each holding period.

$$AR_w = \frac{1}{N}\sum_{i=1}^{N} R_{i,k}, \quad AR_l = \frac{1}{N}\sum_{i=1}^{N} R_{i,k}$$

From these, the zero cost portfolio return is derived by calculating the difference between the returns of the winner and loser portfolios.

$$AR_{w-l} = AR_w - AR_l$$

A one sample t test is conducted to determine whether the average long short portfolio returns are significantly different from zero. The null hypothesis assumes no significant difference. Significance is assessed at a 5% level, with results indicating whether the long short strategy yields statistically significant returns. (μ_{RLS} – population mean return).

$$H_0 = \mu_{RLS} = 0$$

4. Analysis

The following table 1, 2, 3 and 4 show the characteristics of portfolios, including momentum and contrarian strategies, and assesses the viability of zero cost portfolios in the Sri Lankan market using data from 2015 to 2019. The analysis consists of different formation and holding periods (3, 6, 9, 12 months), split percentages and portfolio returns, emphasizing statistical significance at the 5% level.

In the selection process involving 261 shortlisted companies, for example, in the split of 25%, the top 25% were classified as winners, while the bottom 25% were categorized as losers. This means that 65 companies, representing the top performing quarter, were designated as winners, whereas the bottom 65 companies, representing the lowest performing, were labelled as losers. So, this division helps to highlight the highest and lowest performers within the group. This approach aligns with methodologies widely adopted in momentum and reversal literature ((Jegadeesh & Titman, 1993 ; Asness et al., 2013), where extreme quantiles are used to construct long short portfolios to examine predictive return patterns. Such sorting allows for clearer contrasts between outperformers and underperformers, facilitating tests of return predictability.

These combinations of different formations, holding and split percentage allow to create 96 strategies under this 2015–2019-time frame. Only 22 sets of zero cost portfolios show significant results while the other 74 set of zero cost portfolios were indicating insignificant result.

Table 1

Performance of zero cost portfolios (2015 to 2019) – Statistically significant results

Time Period	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	T-Statistic	P-Value
2015-2019	6m	12m	1%	-21%	-11%	-11%	-2.2889	0.0272*
2015-2019	6m	6m	20%	-2%	1%	-4%	-2.0642	0.0444*
2015-2019	6m	9m	20%	-4%	0%	-4%	-2.4521	0.0181*
2015-2019	9m	12m	1%	-17%	-7%	-10%	-2.2540	0.0299*
2015-2019	9m	6m	10%	-2%	2%	-4%	-2.4623	0.0177*
2015-2019	9m	9m	10%	-5%	0%	-5%	-2.0569	0.0459*
2015-2019	9m	6m	20%	-3%	3%	-5%	-3.0586	0.0037*

Table 1 continued

Time Period	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	T-Statistic	P-Value
2015-2019	9m	9m	20%	-4%	0%	-5%	-2.3099	0.0259*
2015-2019	9m	12m	20%	-7%	-3%	-4%	-2.0884	0.0433*
2015-2019	9m	6m	25%	-2%	2%	-4%	-2.6285	0.0117*
2015-2019	9m	6m	30%	-2%	1%	-3%	-2.2004	0.0330*
2015-2019	12m	6m	1%	-9%	0%	-9%	-2.2867	0.0273*
2015-2019	12m	9m	1%	-13%	-1%	-12%	-2.4386	0.0194*
2015-2019	12m	12m	1%	-16%	-7%	-9%	-2.1880	0.0352*
2015-2019	12m	6m	10%	-2%	3%	-5%	-2.2065	0.0329*
2015-2019	12m	12m	10%	-9%	-3%	-5%	-2.4736	0.0182*
2015-2019	12m	3m	20%	-1%	2%	-3%	-2.7935	0.0076*
2015-2019	12m	6m	20%	-2%	3%	-5%	-2.6673	0.0108*
2015-2019	12m	9m	20%	-4%	1%	-5%	-2.5646	0.0143*
2015-2019	12m	12m	20%	-6%	0%	-6%	-2.3746	0.0230*
2015-2019	12m	3m	25%	0%	2%	-2%	-2.2591	0.0288*
2015-2019	12m	3m	30%	0%	2%	-2%	-2.1478	0.0372*

* Significant at 5%

The above table 1 shows the significant result for the period 2015 – 2019 under varying split percentages, formation periods, and holding periods. In the context of split percentages, the impact of portfolio size is evident. For instance, with a 1% split, the long – short portfolio experiences some of the most negative returns, such as -11% (6m formation, 12m holding) and -9% (12m formation, 6m holding) with t statistics of -2.2889 and -2.2867 respectively. These extreme splits suggest that portfolios concentrated on extreme performers yield strong divergence in returns between winners and losers, yet this divergence does not favour the momentum based long – short zero cost portfolios and produced opposite results. These findings are consistent with a reversal effect, where the extreme past performers tend to revert in the subsequent period, leading to underperformance of past winners and outperformance of past losers. This undermines the profitability of momentum-based strategies and suggests the presence of mean reversion in asset returns, particularly for portfolios based on narrow split thresholds.

When observing larger splits, such as 20%, the trend persists with negative long-short returns. Notably, a 9m formation and 6m holding period yield a return of -5% with a *t* statistic of 3.0586, the most statistically significant result (p = 0.0037). Similarly, a 12m formation and 6m holding period with a 20% split also yield significant results (-5% return, -2.6673 *t* statistic, *p* = 0.0108). These results suggest that moderate splits capture the difference between the extremes of performance but still result in unfavorable outcomes for long short portfolios and support the reversal effect.

At larger splits like 25% and 30%, the long- short returns are less extreme but remain negative. For example, with a 25% and a 9m formation/6m holding period, the return is -4% (*t*-statistic of -2.6285, *p*= 0.0117). Similarly, with a 30% split, the returns remain negative (-3% for 9m formation/6m holding, *t* statistic of -2.2004, *p*= 0.0330), indicating that even broader portfolio compositions cannot reverse the negative performance of the long-short strategy.

The influence of formation and holding period is also significant. Shorter holding periods, such as 3m or 6m, often result in smaller negative returns (-2% for a 12M formation/ 3M holding period with 25% and 30% splits). However, longer holding periods like 12M shows increased losses, especially at narrower splits (-12% for a 12m formation/ 9m holding period with a 1% split, t statistic of -2.4386, p = 0.0194).

The table 2 below shows insignificant results for the period of 2015-2019. Around 72 portfolios revealed insignificant results. Long short portfolio returns (winner minus loser) are mostly close to zero or negative, with random positive returns that lack statistical significance. Other than the portfolios mentioned in Table 1, when varying split percentages, the results remain inconsistent, with higher split percentages typically yielding negligible long short portfolio returns. These show an absence of notable momentum or reversal effects in the Sri Lankan market during this study period, indicating inefficiency in using past returns to predict future performance. However, Weerakoon Banda and Pathirawasam (2008) and Anuradha and Nimal (2017) provided evidence of momentum profitability in the Sri Lankan market between the periods of 1991 to 2013.

Table 2

Performance of zero cost portfolios (2015 to 2019) – Statistically insignificant results

Time Period	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2015-2019	3m	3m	1%	-2%	-3%	1%	0.2365	0.8140
2015-2019	3m	6m	1%	-8%	-4%	-4%	-1.0362	0.3050
2015-2019	3m	9m	1%	-12%	-8%	-5%	-0.9716	0.3361
2015-2019	3m	12m	1%	-16%	-11%	-5%	-0.8835	0.3816
2015-2019	3m	3m	5%	1%	-1%	2%	0.9090	0.3674
2015-2019	3m	6m	5%	-1%	1%	-1%	-0.5986	0.5521
2015-2019	3m	9m	5%	-3%	1%	-3%	-0.9293	0.3574
2015-2019	3m	12m	5%	-4%	-4%	-1%	-0.1404	0.8890
2015-2019	3m	3m	10%	0%	0%	0%	0.3265	0.7453
2015-2019	3m	6m	10%	-1%	0%	-1%	-0.3617	0.7191
2015-2019	3m	9m	10%	-3%	-1%	-2%	-0.8133	0.4201
2015-2019	3m	12m	10%	-4%	-4%	0%	0.1097	0.9131
2015-2019	3m	3m	20%	1%	0%	1%	0.4721	0.6387
2015-2019	3m	6m	20%	0%	1%	-1%	-0.4525	0.6529
2015-2019	3m	9m	20%	-2%	-1%	-1%	-0.5568	0.5802
2015-2019	3m	12m	20%	-3%	-3%	0%	0.2558	0.7992

Table 2 continued

Time Period	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2015-2019	3m	3m	25%	1%	0%	1%	0.5134	0.6098
2015-2019	3m	6m	25%	0%	1%	-1%	-0.5684	0.5723
2015-2019	3m	9m	25%	-2%	-1%	-1%	-0.6545	0.5159
2015-2019	3m	12m	25%	-3%	-2%	0%	-0.2419	0.8100
2015-2019	3m	3m	30%	1%	0%	1%	0.5671	0.5730
2015-2019	3m	6m	30%	0%	0%	-1%	-0.4618	0.6462
2015-2019	3m	9m	30%	-2%	-1%	-1%	-0.4140	0.6808
2015-2019	3m	12m	30%	-3%	-3%	0%	0.1611	0.8727
2015-2019	6m	3m	1%	-7%	-3%	-4%	-1.4374	0.1567
2015-2019	6m	6m	1%	-12%	-5%	-7%	-1.8674	0.0680
2015-2019	6m	9m	1%	-16%	-7%	-8%	-1.7173	0.0928
2015-2019	6m	3m	5%	-1%	1%	-2%	-1.3582	0.1804
2015-2019	6m	6m	5%	-4%	1%	-5%	-1.9919	0.0521
2015-2019	6m	9m	5%	-5%	0%	-5%	-1.5371	0.1313
2015-2019	6m	12m	5%	-8%	-5%	-3%	-0.7318	0.4683
2015-2019	6m	3m	10%	0%	0%	0%	-0.1670	0.8680
2015-2019	6m	6m	10%	-3%	0%	-3%	-1.2222	0.2276

Table 2 continued

Time Period	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2015-2019	6m	9m	10%	-5%	-1%	-3%	-1.3660	0.1787
2015-2019	6m	12m	10%	-7%	-5%	-2%	-0.8589	0.3953
2015-2019	6m	3m	20%	0%	1%	-1%	-0.6967	0.4892
2015-2019	6m	12m	20%	-5%	-3%	-2%	-1.1710	0.2482
2015-2019	6m	3m	25%	0%	0%	-1%	-0.4313	0.6681
2015-2019	6m	6m	25%	-2%	1%	-3%	-1.7836	0.0808
2015-2019	6m	9m	25%	-3%	0%	-3%	-1.9340	0.0594
2015-2019	6m	12m	25%	-4%	-3%	-1%	-0.7160	0.4780
2015-2019	6m	3m	30%	0%	0%	0%	-0.0536	0.9574
2015-2019	6m	6m	30%	-1%	1%	-2%	-1.0437	0.3019
2015-2019	6m	9m	30%	-3%	-1%	-2%	-0.9543	0.3450
2015-2019	6m	12m	30%	-3%	-3%	0%	0.0779	0.9383
2015-2019	9m	3m	1%	-3%	-4%	1%	0.2522	0.8020
2015-2019	9m	6m	1%	-9%	-4%	-5%	-1.3553	0.1821
2015-2019	9m	9m	1%	-13%	-5%	-8%	-1.9084	0.0632
2015-2019	9m	3m	5%	-1%	1%	-1%	-0.9207	0.3618
2015-2019	9m	6m	5%	-2%	1%	-3%	-1.3059	0.1982
2015-2019	9m	9m	5%	-5%	-3%	-2%	-0.6514	0.5183

Table 2 continued

Time Period	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2015-2019	9m	12m	5%	-8%	-8%	0%	0.0517	0.9590
2015-2019	9m	3m	10%	-1%	1%	-2%	-1.9014	0.0633
2015-2019	9m	12m	10%	-8%	-4%	-3%	-1.4115	0.1660
2015-2019	9m	3m	20%	-1%	1%	-2%	-1.8916	0.0646
2015-2019	9m	3m	25%	-1%	1%	-2%	-1.5981	0.1166
2015-2019	9m	9m	25%	-3%	0%	-3%	-1.7069	0.0952
2015-2019	9m	12m	25%	-5%	-3%	-2%	-0.9497	0.3481
2015-2019	9m	3m	30%	-1%	0%	-1%	-1.1013	0.2763
2015-2019	9m	9m	30%	-3%	-1%	-2%	-1.2283	0.2262
2015-2019	9m	12m	30%	-4%	-3%	-1%	-0.6789	0.5012
2015-2019	12m	3m	1%	-3%	-1%	-2%	-0.6284	0.5329
2015-2019	12m	3m	5%	0%	1%	-1%	-0.4098	0.6839
2015-2019	12m	6m	5%	-2%	1%	-3%	-0.9027	0.3718
2015-2019	12m	9m	5%	-5%	-4%	-1%	-0.2974	0.7677
2015-2019	12m	12m	5%	-9%	-8%	0%	-0.1258	0.9006
2015-2019	12m	3m	10%	-1%	2%	-2%	-1.9970	0.0519
2015-2019	12m	9m	10%	-5%	-1%	-4%	-1.6712	0.1027
2015-2019	12m	6m	25%	-1%	2%	-4%	-1.9538	0.0574

Table 2 continued

Time Period	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2015-2019	12m	9m	25%	-3%	0%	-3%	-1.6326	0.1106
2015-2019	12m	12m	25%	-4%	-1%	-4%	-1.6128	0.1155
2015-2019	12m	6m	30%	-1%	2%	-2%	-1.3438	0.1862
2015-2019	12m	9m	30%	-2%	1%	-3%	-1.3018	0.2006
2015-2019	12m	12m	30%	-3%	-1%	-3%	-1.2967	0.2030

The following table 03 shows the significant results for the time period of 2020-2024. The findings from the 2020 to 2024 period highlight only 19 portfolios revealed significant results. Winner portfolios generally underperform compared to loser portfolios, resulting in negative long-short portfolios returns across various formation and holding periods. For instance, during a 3m formation and 6m holding period with a 10% split, the long, short return is -17% with a statistically significant t statistic of -2.5674 (p= 0.0153). Similar trends persist for higher split percentages, with all t statistics indicating significant at the 5% level.

For 6m formation periods, short term and long-term holding strategies exhibit stronger momentum effects. Long short returns range from -7% to -20%, with highly significant p –values (Example, -16% return for a 10% split, t = -3.055, p = 0.0046). A 12m formation and holding period at a 1% split yielded an exceptionally high 78% return (t = 2.0702, p = 0.0489).

Table 3

Performance of zero cost portfolios (2020 to 2024) – Statistically significant results

Timeframe	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2020-2024	3m	6m	10%	8%	25%	-17%	-2.5674	0.0153*
2020-2024	3m	6m	20%	9%	22%	-13%	-2.4529	0.0200*
2020-2024	3m	6m	25%	10%	21%	-11%	-2.2010	0.0353*
2020-2024	3m	6m	30%	11%	22%	-12%	-2.3750	0.0239*
2020-2024	6m	3m	1%	7%	25%	-19%	-2.0357	0.0496*
2020-2024	6m	3m	5%	3%	13%	-10%	-2.1454	0.0391*
2020-2024	6m	6m	5%	9%	28%	-20%	-2.7131	0.0108*
2020-2024	6m	3m	10%	5%	12%	-7%	-2.0700	0.0461*
2020-2024	6m	6m	10%	8%	25%	-16%	-3.0550	0.0046*
2020-2024	6m	3m	20%	4%	11%	-7%	-2.5586	0.0151*
2020-2024	6m	6m	20%	8%	22%	-13%	-3.6704	0.0009*
2020-2024	6m	3m	25%	4%	11%	-7%	-2.7848	0.0087*
2020-2024	6m	6m	25%	9%	22%	-13%	-3.7622	0.0007*
2020-2024	6m	3m	30%	5%	11%	-7%	-2.8210	0.0079*
2020-2024	6m	6m	30%	10%	21%	-11%	-3.9048	0.0005*

Table 3 Continued

Timeframe	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2020-2024	9m	3m	5%	3%	15%	-11%	-2.6383	0.0125*
2020-2024	9m	3m	20%	6%	11%	-5%	-2.2354	0.0321*
2020-2024	9m	3m	25%	6%	10%	-5%	-2.0431	0.0489*
2020-2024	12m	12m	1%	89%	11%	78%	2.0702	0.0489*

* Significant at 5%

Other than the above mentioned 19 portfolios, all other 77 portfolios reveal insignificant results for this 2020 to 2024 time periods. Overall, these findings imply that the strategies tested in the analysis did not achieve strong performance.

Table 4

Performance of zero cost portfolios (2020 to 2024) – Statistically insignificant results

Timeframe	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2020-2024	3m	3m	1%	25%	6%	19%	1.5073	0.1410
2020-2024	3m	6m	1%	25%	54%	-28%	-1.1805	0.2468
2020-2024	3m	9m	1%	44%	108%	-64%	-1.1048	0.2787
2020-2024	3m	12m	1%	151%	95%	56%	0.6041	0.5512
2020-2024	3m	3m	5%	10%	7%	2%	0.4114	0.6833
2020-2024	3m	6m	5%	9%	24%	-16%	-1.9341	0.0623

Table 4 continued

Timeframe	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2020-2024	3m	9m	5%	17%	38%	-21%	-1.2584	0.2187
2020-2024	3m	12m	5%	34%	32%	2%	0.1069	0.9157
2020-2024	3m	3m	10%	9%	9%	0%	-0.0212	0.9832
2020-2024	3m	9m	10%	12%	34%	-23%	-2.0074	0.0544
2020-2024	3m	12m	10%	24%	27%	-4%	-0.3147	0.7556
2020-2024	3m	3m	20%	8%	9%	-1%	-0.4187	0.6781
2020-2024	3m	9m	20%	13%	29%	-17%	-1.9721	0.0586
2020-2024	3m	12m	20%	21%	22%	-1%	-0.1118	0.9118
2020-2024	3m	3m	25%	7%	9%	-1%	-0.4553	0.6518
2020-2024	3m	9m	25%	14%	27%	-13%	-1.6861	0.1029
2020-2024	3m	12m	25%	21%	20%	1%	0.1933	0.8483
2020-2024	3m	3m	30%	8%	9%	-2%	-0.6077	0.5474
2020-2024	3m	9m	30%	16%	27%	-11%	-1.6008	0.1206
2020-2024	3m	12m	30%	21%	20%	1%	0.1460	0.8851
2020-2024	6m	6m	1%	17%	53%	-36%	-1.7266	0.0942
2020-2024	6m	9m	1%	46%	77%	-31%	-0.5666	0.5755

Table 04 continued

Timeframe	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2020-2024	6m	12m	1%	102%	68%	34%	0.4980	0.6228
2020-2024	6m	9m	5%	16%	39%	-23%	-1.4936	0.1465
2020-2024	6m	12m	5%	19%	37%	-18%	-1.0729	0.2936
2020-2024	6m	9m	10%	18%	29%	-12%	-1.0727	0.2926
2020-2024	6m	12m	10%	17%	29%	-12%	-1.1235	0.2719
2020-2024	6m	9m	20%	17%	24%	-7%	-1.0367	0.3088
2020-2024	6m	12m	20%	17%	21%	-4%	-0.5147	0.6113
2020-2024	6m	9m	25%	18%	23%	-5%	-0.8614	0.3963
2020-2024	6m	12m	25%	21%	21%	0%	0.0245	0.9807
2020-2024	6m	9m	30%	19%	23%	-4%	-0.7953	0.4331
2020-2024	6m	12m	30%	20%	19%	1%	0.1471	0.8843
2020-2024	9m	3m	1%	16%	18%	-2%	-0.2029	0.8404
2020-2024	9m	6m	1%	33%	49%	-16%	-0.5370	0.5951
2020-2024	9m	9m	1%	61%	102%	-40%	-0.6226	0.5386
2020-2024	9m	12m	1%	86%	90%	-5%	-0.0626	0.9506
2020-2024	9m	6m	5%	12%	25%	-13%	-1.8660	0.0715

Table 4 continued

Timeframe	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2020-2024	9m	9m	5%	18%	37%	-19%	-1.5155	0.1408
2020-2024	9m	12m	5%	21%	40%	-18%	-1.3136	0.2009
2020-2024	9m	3m	10%	6%	13%	-6%	-1.8264	0.0766
2020-2024	9m	6m	10%	14%	20%	-7%	-1.3792	0.1777
2020-2024	9m	9m	10%	21%	29%	-7%	-0.9436	0.3535
2020-2024	9m	12m	10%	20%	28%	-8%	-0.9683	0.3422
2020-2024	9m	6m	20%	15%	18%	-4%	-0.9388	0.3551
2020-2024	9m	9m	20%	22%	22%	0%	-0.0564	0.9554
2020-2024	9m	12m	20%	20%	24%	-4%	-0.6826	0.5011
2020-2024	9m	6m	25%	14%	18%	-4%	-1.0150	0.3180
2020-2024	9m	9m	25%	21%	22%	-1%	-0.1287	0.8985
2020-2024	9m	12m	25%	19%	23%	-3%	-0.6380	0.5292
2020-2024	9m	3m	30%	7%	10%	-3%	-1.2848	0.2075
2020-2024	9m	6m	30%	16%	17%	-2%	-0.4898	0.6277
2020-2024	9m	9m	30%	23%	22%	1%	0.1728	0.8640
2020-2024	9m	12m	30%	21%	22%	-1%	-0.1117	0.9120

Table 4 continued

Timeframe	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2020-2024	12m	3m	1%	19%	4%	15%	1.5006	0.1427
2020-2024	12m	6m	1%	29%	19%	10%	0.4631	0.6465
2020-2024	12m	9m	1%	61%	24%	37%	1.3159	0.1989
2020-2024	12m	3m	5%	6%	11%	-6%	-1.3054	0.2005
2020-2024	12m	6m	5%	11%	26%	-14%	-1.9823	0.0564
2020-2024	12m	9m	5%	17%	36%	-19%	-1.5517	0.1320
2020-2024	12m	12m	5%	23%	36%	-13%	-0.9632	0.3447
2020-2024	12m	3m	10%	8%	9%	-1%	-0.4241	0.6741
2020-2024	12m	6m	10%	16%	20%	-4%	-0.7158	0.4794
2020-2024	12m	9m	10%	21%	27%	-6%	-0.8345	0.4111
2020-2024	12m	12m	10%	21%	25%	-4%	-0.5293	0.6013
2020-2024	12m	3m	20%	8%	8%	0%	0.0316	0.9749
2020-2024	12m	6m	20%	17%	16%	1%	0.2830	0.7791
2020-2024	12m	9m	20%	24%	22%	2%	0.3893	0.7000
2020-2024	12m	12m	20%	22%	22%	1%	0.1650	0.8702
2020-2024	12m	3m	25%	8%	8%	1%	0.2927	0.7715

Table 4 continued

Timeframe	Formation Period	Holding Period	Split Percentage	Winner Portfolio Return	Loser Portfolio Return	Long-Short Portfolio Return	t-Statistic	p-Value
2020-2024	12m	6m	25%	18%	15%	2%	0.4937	0.6250
2020-2024	12m	9m	25%	23%	21%	2%	0.3354	0.7399
2020-2024	12m	12m	25%	22%	20%	2%	0.4098	0.6855
2020-2024	12m	3m	30%	9%	8%	1%	0.4087	0.6853
2020-2024	12m	6m	30%	17%	16%	1%	0.3880	0.7007
2020-2024	12m	9m	30%	22%	22%	0%	0.0650	0.9486
2020-2024	12m	12m	30%	21%	22%	-1%	-0.1749	0.8625

5. Discussion

Market inefficiency and lack of predictive power (2015-2019) show a significant inefficiency in using momentum or contrarian strategies. The zero cost portfolios, particularly those employing momentum based long short strategies, show negative returns across the many sets of formation and holding periods. Despite different split percentages, the results were largely insignificant, suggesting that past stock performance could not reliably predict the future returns. Specifically, the lack of statistical significance in most of the portfolios implies that momentum and reversal effects were not present in the market during this period. This inefficiency is reflected in the failure of extreme splits (1% or 5%) to generate positive returns, despite their clear divergence between winners and losers. Even broader split strategies such as 25% and 30%, failed to reverse the negative performance, supporting the argument that predictive models based on past returns were ineffective.

Further, the results show that shorter formation and holding periods (3m and 6m) led to smaller negative returns, while longer holding periods (12m) given larger losses. This trend suggests that the market does not sustain momentum over longer durations, and the performance of winners and losers fluctuates inconsistently, adding further to the lack of reliability in using such strategies. The fact that even moderately significant returns did not exceed negative performance for most portfolios confirms that the Sri Lankan stock market during this period was not conducive to profitable momentum or contrarian approaches.

When examining the period from 2020 to 2024, the findings suggest a similar lack of effectiveness in using momentum or contrarian strategies. Even though a few portfolios (19 out of 96) showed statistically significant results, the returns were primarily negative. This period also showed that the winning portfolios underperformed in comparison to loser portfolios. Notably, some short term and long term holding strategies exhibited stronger momentum effects, yet they remained negative, with significant t-strategies confirming the negative nature of returns. However, there is an instance where an exceptionally high return (78% in a 12m formation/holding period at a 1% split) provides a rare anomaly, but this does not change the overall trend of market in efficiency during the period.

Therefore, results for both 2015-2019 and 2020- 2024 periods confirm that neither momentum nor contrarian strategies can predict market performance in the Sri Lankan stock market. Most of the zero-cost portfolios had no strategically significant returns, and there is no consistent evidence of momentum or reversal in the markets. The negative returns of different strategies, regardless of split percentages, formation periods, and holding periods, indicate a high level of inefficiency in the Sri Lankan market, which contradicts the results produced already (Anuradha & Nimal, 2017; Weerakoon Banda & Pathirawasam, 2008). The divergence can be reasonably attributed to several structural and macroeconomic shifts that occurred in Sri Lanka between 2015 and 2024. First, despite improvements in trading infrastructure (eg-ATS 7), the CSE remains a thin and illiquid market, dominated by retail investors who are often driven by short term speculation, herd behaviour and rumor-based trading. This highlights the persistence of rational pricing trends needed for momentum strategies to work. Second, the period from 2020 onward has been marked by a series of systematic shocks, including the COVID 19 pandemic, political instability and 2022 sovereign debt default. This distorted return distributions and overwhelmed any predictive power on past prices.

This shows that traditional asset pricing models, which rely only on the past stock alone, are not viable in the Sri Lankan market. Researchers can test some alternative models or incorporate other variables, such as sentiment analysis, adding fundamental factors or machine learning models to find the potential inefficiencies and profitable strategies.

6. Conclusion

This study reinvestigates momentum and reversal effects within the Colombo Stock Exchange over the period January 2015 to March 2024, analysing 261 voting stocks listed on the main board. The evidence consistently suggests that neither momentum nor contrarian trading strategies produce persistent excess returns. Across a wide range of formation and holding periods, including both extreme and broader quantile splits, most strategies generated negative and statistically insignificant outcomes. Shorter term strategies produced relatively smaller losses, while longer horizon portfolios suffered deeper declines, highlighting the market’s limited capacity to sustain price trends. These findings held consistently across the two sub periods examined (2015 to 2019 and 2020 to 2024), with only a small fraction (19 out of 96) of the tested portfolios showing statistical significance and most of which exhibited negative returns. Moreover, the frequent underperformance of winner portfolios relative to loser portfolios further weakens the case for traditional momentum-based investing. The persistent lack of profitability in both momentum and reversal strategies points to inefficiencies that are not easily captured by price-based signals alone. Hence, these outcomes contribute to the broader academic disclosure by highlighting the inadequacy of traditional momentum and reversal frameworks in emerging markets such as Sri Lanka. From a practical point of view, the findings offer less support for implementing momentum or contrarian trading strategies in the Sri Lankan equity market. The frequent underperformance of winner portfolios relative to loser portfolios, combined with statistically insignificant outcomes in many cases, suggests that such strategies are unlikely to deliver consistent alpha. Short-term strategies led to smaller losses, while longer term portfolios experienced larger declines, suggesting that relying only on past price trends may lead to poor risk return outcomes. These insights are relevant for asset managers, retail investors and portfolio managers operating in frontier or less efficient markets. Hence, this outcome invites further exploration into alternative frameworks. In particular, the incorporation of firm specific fundamental factors, investor sentiment and behavioral anomalies may offer deeper insights.

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