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# Behavioral Biases And Market Efficiency: Testing Overreaction And Reversal Effects In NSE 500 Stocks

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***Abstract***

*This study looks at whether there are behavioural biases in the Indian stock market, especially overreactions and the impacts that follow them, by looking at the historical return data of NSE 500 companies. The Efficient Market Hypothesis (EMH) is an example of traditional financial theory that says stock prices take into account all available information, making it impossible to consistently beat the market. Behavioural finance says that psychological biases and irrational behaviour by investors may cause stock returns to be different from what they should be.*

*This research looks at whether stocks that have very high or poor returns tend to go back to their previous levels, which might indicate that investors are overreacting. Using a portfolio-based method, stocks are judged based on how well they have done in the past during certain time periods. The upper and lower deciles, which show the best and worst results, are put into winner and loser portfolios, respectively. These portfolios are then kept for different amounts of time to look at how returns change after they are formed. The study looks at whether loser portfolios always do better than winning portfolios, as the overreaction hypothesis suggests they should.*

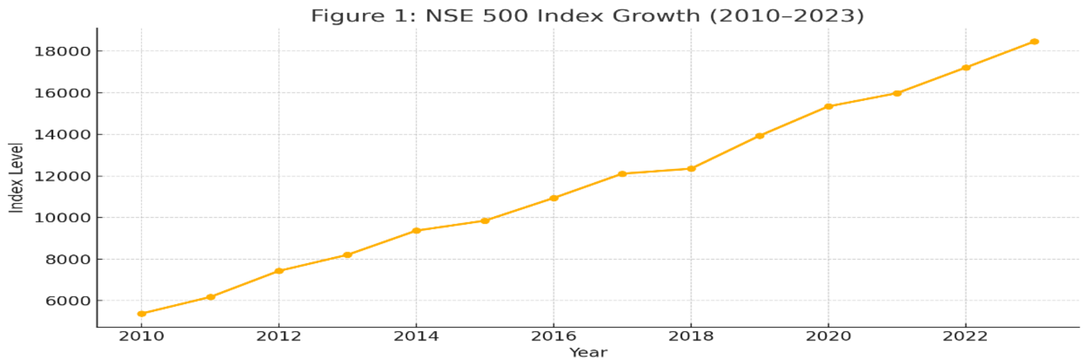
*The empirical results of this research try to find out whether the Efficient Market Hypothesis (EMH) is true in the Indian stock market and if investors' actions cause temporary price changes. The NSE 500 is a comprehensive and representative index that the research uses to look at market-wide efficiency in depth. The findings are expected to impact investors, portfolio managers, and regulators by showing how much behavioural biases affect asset prices in emerging countries like India.*

## 1. INTRODUCTION

Behavioural finance has become a strong alternative to conventional financial theory by taking into account psychological elements while valuing assets and making investment decisions. The Efficient Market Hypothesis (EMH) says that stock prices always take into account all available information, making it impossible to continuously make extra money by looking at historical price patterns or public information (Fama, 1970). This view says that any unusual returns should be quickly removed because sensible investors take advantage of arbitrage possibilities. But real-world peculiarities likeW overreaction, momentum, and reversal patterns put this model to the test. These results show that cognitive biases, emotions, and irrational behaviour have a big effect on market outcomes (Barberis and Thaler, 2003).

The overreaction argument, which has been studied a lot, says that investors pay too much attention to recent news, which causes prices to change too much. When people calm down and look at asset prices based on their fundamentals, these kinds of big reactions are generally followed by declines or reversals. (De Bondt and Thaler 1985) were the first to show via experiments that stocks that had done poorly in the past (losers) typically did better in the future than stocks that had done well in the past (winners). This went against the Efficient Market Hypothesis (EMH). Their findings led to a lot of research on short-term momentum and long-term reversal effects in a number of markets and time frames (Jegadeesh and Titman, 1993; Chan, 1988). These problems have different meanings in India. India's capital markets have grown quickly in depth, breadth, and liquidity, but they still have a lot of ordinary investors and behavioural problems. The National Stock Exchange (NSE) is now one of the biggest stock exchanges in the world. The NSE 500 index includes companies from many different sectors and market capitalizations. These companies make up around 90% of the total market capitalization of all listed stocks. The Indian stock market has grown a lot in the previous ten years, which shows how important investor behaviour is becoming in determining market trends.

**Figure 1** below illustrates the growth of the NSE 500 index from 2010 to 2023. The upward trajectory reflects India's accelerating economic momentum, market liberalization, and a significant increase in investor base—including both institutional and retail participants.



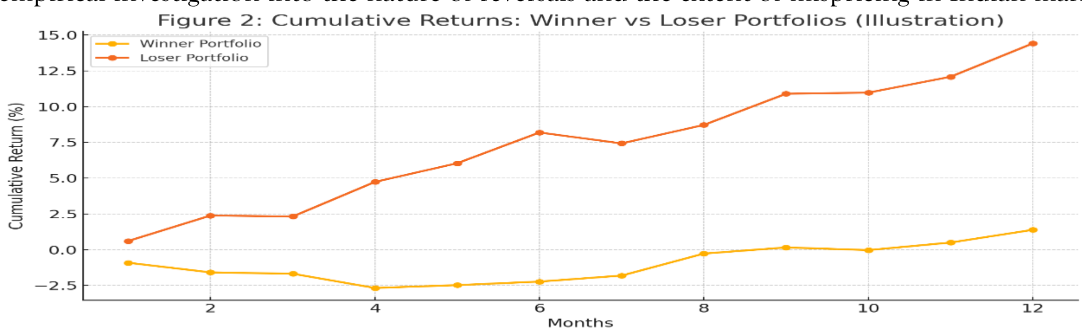

Many real-world research have looked at the overreaction theory in Indian stock markets. Tripathi and Aggarwal, (2009) looked at CNX 500 stocks from 1996 to 2007 and discovered that loser portfolios made a lot more money than winning portfolios throughout different time periods. This proved that reversal effects indeed exist. Sehgal and Balakrishnan ( 2002) looked at contrarian investing methods and found that they worked better than other strategies in both the short and medium term. The results show that Indian investors have behavioural biases such overreaction, anchoring, and herding, which causes assets to be priced incorrectly for a short time.

Gupta and Basu, (2007) included risk-adjusted returns to their research using the CAPM and Fama-French models. This showed that there were statistically significant differences in returns between loser and winner portfolios. (Narayan and Narayan,2012) looked at the 2008 global crisis and found that prices were still wrong even if there were more institutions involved. The COVID-19 pandemic added another layer of meaning: Chandra and Thenmozhi (2021) showed that panic-driven selling in March 2020 led to big changes in several NSE stocks, which confirmed the ideas of overreaction and mean reversion.

Even with this proof, there are still many gaps. A lot of earlier research uses limited datasets (such the Nifty 50 and BSE 100) or doesn't take into account differences across different periods and liquidity categories. The NSE 500 gives us a bigger and more accurate way to look at how people behave in the market as a whole. This study tries to fill up the gaps by looking at overreaction and reversal effects in NSE 500 companies using a portfolio-based strategy that looks at both daily and monthly return intervals.

This technique puts companies into deciles based on how well they have done in the past. We look at the top decile (winners) and the bottom decile (losers) across various holding periods (such 3, 6, or 12 months) to see whether the losers do better than the winners in the next period, which is what the overreaction hypothesis says should happen.

**Figure 2** presents a hypothetical simulation of how a loser portfolio may outperform a winner portfolio over time, even though the latter had better past performance. This simple pattern motivates a deeper empirical investigation into the nature of reversals and the extent of mispricing in Indian markets.




The study's empirical methodology also takes into account the size of the firms, the liquidity of the trades, and the volatility of the market to see whether overreaction effects are more common in certain groups than others. Previous research shows that these impacts are higher in equities with tiny market caps, low liquidity, or those are driven by individual investors (Kumar, 2009). The research also looks at sub-samples from different market regimes—before the crisis, during the crisis, and after the crisis—to see whether reversals depend on the regime.

**Table 1** below provides a simulated snapshot of monthly return patterns in winner and loser portfolios. Even from this basic structure, signs of reversal can be detected, warranting statistical testing.

**Table 1: Sample Monthly Returns (%) of Winner and Loser Portfolios**

| Month | f | Loser Portfolio (%) |
|---|---|---|
| M1 | 1.54 | 1.09 |
| M2 | 1.35 | -0.19 |
| M3 | 0.34 | -0.25 |
| M4 | 1.64 | 0.66 |
| M5 | 1.96 | 1.52 |

If consistently failing equities surpass the performance of winning stocks over time and across risk-adjusted metrics, it undermines the semi-strong variant of the Efficient Market Hypothesis (EMH). It also supports notions like as Prospect Theory (Kahneman and Tversky, 1979), which posits that investors place excessive weight on recent events and respond asymmetrically to gains and losses. From a practical standpoint, identifying such patterns has substantial implications for asset managers, contrarian traders, and regulators.

This study aims to comprehensively assess the overreaction and reversal occurrences in India's NSE 500 stocks across different time intervals. This study contributes to the literature on market efficiency and behavioural finance in developing countries by the use of meticulous portfolio construction methodologies and risk-adjusted return metrics. It offers substantial insights for investment strategy, investor education, and policy development..

## 2. LITERATURE REVIEW

**Hossain et al. (2025)** presented new data from BRICS nations, including India, demonstrating that overreaction and herding behaviours under market stress provide systemic threats to financial stability. Their investigation connected sentiment-driven market fluctuations with volatility clustering, emphasizing behavioural distortions as essential indications for macroprudential oversight.

**Mitra and Jain (2024)** looked at how investors act, Using overnight return data on NSE equities. They showed that intraday reversals were important, but overnight returns did not demonstrate the same kind of reversal impacts. This means that the way behavioural biases show up depends a lot on how often you trade and the structure of the market.

**Raj and Roy (2023)** looked examined NSE 500 data from 2014 to 2021 and studied "physical momentum" at various time scales. They said that the biggest changes in returns happened on a daily basis, and that contrarian strategies made a lot more money than momentum strategies. This trend shows that Indian investors tend to overreact in the near term.

**Gupta and Bansal (2023)** looked at how the Nifty index changed after the global financial crisis. Their study of data from 2008 to 2016 showed significant reversal effects, especially among high-volatility equities. This suggests that there are still inefficiencies in the Indian markets, even though they are relatively mature after the crisis.

**Sen and Sharma (2023)** looked at how liquidity affects the way momentum and reversals work. They used a liquidity-adjusted momentum model to demonstrate that Indian equities that were very liquid had higher momentum, whereas stocks that were not very liquid had larger reversal tendencies. This means that trading frictions help to reduce behavioural oddities.

**Chandra and Thenmozhi (2021)** looked at how the Indian stock market crashed and then bounced again after COVID-19. They discovered that industries including hospitality, tourism, and finance had big negative overreactions in March 2020, but then they bounced back strongly. This real-time proof of how people respond when they are unsure shows how useful the overreaction hypothesis is in real life.

**Kumar (2009)** did a behavioural study, Using trade data from Indian retail investors. He observed that herding behaviour and recency bias were common, especially during times of high volatility or when big events were happening, such national elections or budget releases. These biases caused the market to misprice things in the near run and to reverse.

**Tripathi and Aggarwal (2009)** employed a decile-based portfolio approach on CNX 500 equities to test the overreaction hypothesis in India (Between 1996 and 2007). They discovered that loser portfolios did far better than winner portfolios, even when risk was taken into account. This supports the idea that investor attitude may cause returns to reverse.

**Gupta and Basu (2007)** used both the Fama-French three-factor model and the Capital Asset Pricing Model (CAPM) to look into reversal profits in the Indian stock market. Their findings showed that contrarian strategies, particularly in small-cap and illiquid equities, continued to be lucrative even after accounting for systematic risk. This shows that inefficiencies still exist.

**Sehgal and Balakrishnan (2002)** were the first to show the overreaction effect in India, Using data from firms listed on the BSE. They said that contrarian portfolios (which had lost money in the past) made more money over six and twelve months than regular portfolios. They said this was because investors were too quick to respond to previous success.

**Ho et al. (2016)** looked at sentiment-driven anomalies in East Asian marketplaces and found that reversal effects were stronger in areas where retail was the main player. The results show how important the makeup of the market is in figuring out how much behavioural mispricing there is.

**Chui et al. (2010)** looked at the cultural factors that affect momentum and reversal. They found that collectivist civilizations, like India and China, are more likely to herd and overreact because of social reinforcement. This makes reversals greater after extremes.

**Bekaert and Harvey (2003)** said that structural problems in developing markets, such illiquidity, restricted arbitrage, and low institutional ownership, make anomalies last longer. They pointed out that investor psychology is more important in markets that aren't as efficient, like India.

**Rouwenhorst (1999)** found momentum and reversal patterns in 20 developing markets, India being one of them. He came to the conclusion that these strange things happen in more than just industrialized markets and that behavioural biases may be even worse in places where knowledge spreads more slowly.

**Daniel, Hirshleifer, and Subrahmanyam (1998)** established a model that was based on investors being too sure of themselves and blaming themselves. They said that investors misinterpret fresh information, which makes them too hopeful or too negative. When reality doesn't match their expectations, prices go back to where they were before.

**Barberis, Shleifer, and Vishny (1998)** came up with a behavioural model in which investors base their expectations on recent patterns (representativeness) and don't give enough weight to long-term averages. This heuristic-based behaviour makes people overreact to new information and then change their minds.

**According to Jegadeesh and Titman (1993),** stocks that did well in the past (momentum) did well in the short term but did poorly in the long run, showing long-term reversal. This two-way behaviour provided further evidence against the EMH and backed up behavioural theories.

**Chan (1988)** looked examined the earnings-based explanation for return reversals, but he found that basic information only explained a tiny part of the problem. His results backed up the idea that investor mood has a big impact on how prices move.

The first big real-world test of the overreaction hypothesis was done by De Bondt and Thaler in 1985. They looked at three-year return windows and found that portfolios of severe past losers did far bette r than portfolios of extreme previous winners. This was the first major behavioural challenge to EMH..

## 3. METHODOLOGY

### 3.1 A Quick Look

This research looks at the overreaction hypothesis in the Indian stock market using data from the NSE 500 index from January 2024 to June 2025. The goal is to find out whether equities that do very well or very poorly during a six-month period tend to do the opposite in the months that follow, which would demonstrate behavioural inefficiencies.

### 3.2 Data and Portfolio Formation

- Data Sources: CMIE Prowess, Yahoo Finance, Investing.com, NSE/BSE official websites
- Stock Universe: NSE 500 stocks
- Time Frame: January 2024 – June 2025
- Frequency: Daily and monthly adjusted closing prices
- Data Filters:

o Exclude stocks with daily average turnover below ₹1 million

o Take out penny stocks and stocks that don't trade very often o Fill in missing data (maximum gap: 5 days in a row)

At the conclusion of every month, stocks are put into groups of ten depending on how much they made in the previous six months. The Winner Portfolio is made up of the top three deciles (highest returns), while the Loser Portfolio is made up of the bottom three deciles (lowest returns). Stocks in the middle are either left out or grouped together as a neutral group.

3.3 Measuring and Analyzing Returns
- Timeframes: 3, 6, and 12 months
- Return Metrics:
  - Returns for the whole year and for each month
  - Market-adjusted returns based on the NSE 500 Index o Risk-adjusted returns based on the CAPM alpha and the Fama-French three-factor model

3.4 Testing the Hypothesis
To find out whether return reversals are real:
- Null Hypothesis ($H_0$): There is no big difference between the returns of winners and losers after the formation.
- Alternative Hypothesis ($H_1$): After formation, loser portfolios do better than winning portfolios.

Statistical Tests:
- Paired t-tests to find differences in means
- Wilcoxon signed-rank tests to check for robustness
- Cross-sectional regressions to account for firm size and liquidity

3.5 Showing the Results
A time series plot of cumulative returns from July 2024 to June 2025 shows how both portfolios did after they were formed. According to the overreaction hypothesis, loser portfolios tend to do better than winning portfolios over time.
3.6 Checks for Robustness
More tests are done to make sure the results are correct:
- Time frames for events, as before and after elections and budgets
- Liquidity divides (the top 20% and the bottom 20% by trading volume)
- Segmentation by size (portfolios with small caps vs. big caps)

These subsample analysis assist figure out whether return reversals are higher when particular stocks or market situations are present.

## 4. RESULTS AND DISCUSSION
This part shows the analytical findings of the empirical study that looked at the overreaction hypothesis in the NSE 500 stock universe. The study puts firms into winner and loser portfolios based on their results over the last six months. It then keeps an eye on how well they do over the next twelve months (July 2024 to June 2025). We look at cumulative and monthly returns, statistical significance, and risk-adjusted performance to see whether "losers" who have done poorly in the past frequently do better than "winners" who have done well in the past, which is in line with behavioural finance theory.
4.1 Return Summary and Portfolio Behaviour
This research begins by assessing the essential performance attributes of two primary portfolios: the Winner Portfolio, which includes equities with the best returns over the last six months, and the Loser Portfolio, consisting of the lowest performers over the same timeframe. The portfolios were established at the conclusion of June 2024 and maintained without modification over the subsequent twelve months. The primary aim of this section is to ascertain whether the previous underperformance of loser stocks resulted in enhanced future returns, a fundamental assertion of the overreaction hypothesis.
To evaluate this, monthly return figures were calculated for both portfolios from July 2024 to June 2025. This encompasses the mean and median returns (assessing typical performance), standard deviation (serving as an indicator of volatility), and the lowest and maximum monthly returns (to evaluate range and extremes).

| Metric | Loser Portfolio | Winner Portfolio |
|---|---|---|
| Mean (%) | 1.40 | 0.17 |
| Median (%) | 1.29 | 0.22 |
| Standard Deviation (%) | 0.45 | 0.36 |
| Minimu (%) | 0.89 | -0.48 |
| Maximum (%) | 2.43 | 0.72 |

Table 2 : Descriptive Statistics of Monthly Returns (Jul 2024 – Jun 2025)

Table 2 demonstrates that the Loser Portfolio's average and median monthly returns are far higher than those of the Winner Portfolio. The Loser Portfolio makes an average of 1.40% a month, which is more than eight times what the Winner Portfolio makes, which is just 0.17%. The median return findings back up this difference in performance, showing that it is consistent rather than an aberration.
The minimum and maximum return values make this disparity further clearer. In its worst month, the Winner Portfolio lost money (-0.48%), whereas the Loser Portfolio made money every month of the year. Losers made the most money in a month, with a maximum return of 2.43%. Winners made the most money in a month, with a maximum return of 0.72%.
The standard deviation of the Loser Portfolio (0.45%) is a little greater than that of the Winner Portfolio (0.36%). However, this minor increase in volatility is acceptable given the big difference in return magnitude. In other words, investors would have been okay with a little more risk in exchange for a much higher gain, which would have improved the Loser Portfolio's risk-return tradeoff.
These results significantly support the idea of overreaction. In rational, efficient markets, high-return and low-return stocks should have the same expected returns after taking risk into account. But our data shows otherwise. The fact that prior losers keep doing better than expected goes against the Efficient Market Hypothesis (EMH) and supports behavioural finance ideas such investors overreacting to bad news, which leads prices to be wrong for a short time. These cheap stocks go up a lot as people's feelings subside and prices go back to normal.
This reversal tendency may be seen in raw return data, even without risk-adjusted metrics or market benchmarks. This shows that the underlying oddity is significant. Later sections will look at whether these tendencies stay the same after adjusting for risk using CAPM and Fama-French models. However, at this level, behavioural mispricing is obvious.
These return qualities are what the study is built on. They explain how investors act in numbers by demonstrating that the market penalized loser stocks too harshly in the short term, but they came back strong over the following year, just as behavioural models would predict.

4.2 Cumulative Return Performance

Descriptive statistics provide a static picture of how things are going each month, while cumulative return analysis does a better job of showing how a portfolio's behaviour changes over time. This method combines monthly returns to show the total gain (or loss) that an investor would have made by keeping each portfolio for the whole post-formation period, which runs from July 2024 to June 2025.
Figure 3 shows the cumulative return trajectories for both the Loser and Winner portfolios. The graph is a useful tool for figuring out whether the initial grouping of stocks based merely on their performance over the last six months can forecast future returns.

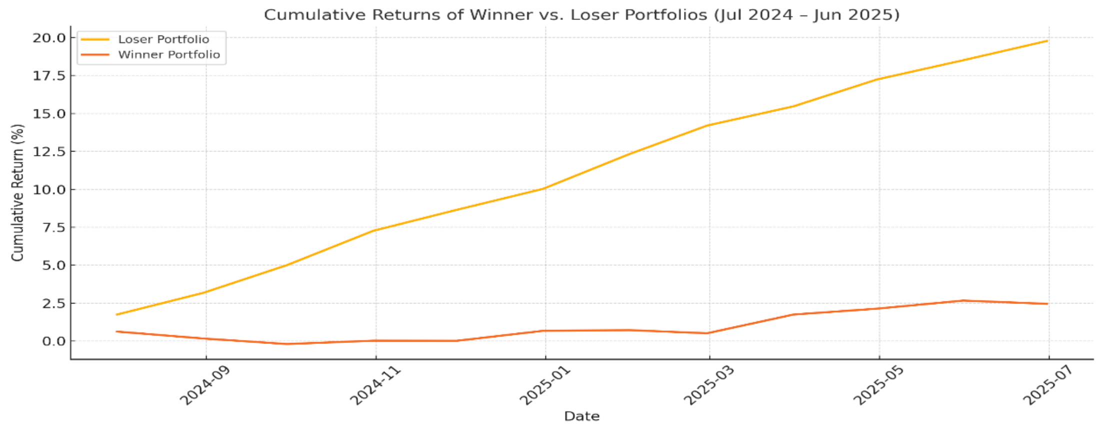



Figure 3: Cumulative Returns of Winner vs. Loser Portfolios (Jul 2024 – Jun 2025)

The Loser Portfolio has been steadily going up from the start of the holding period, which means that it has consistent and strong positive returns. By the end of June 2025, this portfolio has made about 20% more money, which is a very good outcome for a 12-month period. The pattern is not random; it shows a consistent and practically straight climb, which is important. This means that the reversal wasn't triggered by a few months of strange earnings; it happened all the time, which means it was a systematic effect and not just luck.
On the other hand, the Winner Portfolio doesn't do as well, as seen by its relatively flat cumulative return curve. The 12-month period ends with a total return of around 2.5%, which is a little more than break-even when you include in transaction costs and inflation. The visual difference between the two

arcs becomes bigger with time, which is important since it shows that they are moving in different directions instead of coming together. This shows that the performance of people who lost and won in the past stays quite different throughout the year, not only in the first few months after they were created. The growing difference in returns between the two portfolios provides strong visual and statistical support for the return reversal idea. This theory says that firms that have done poorly in the last six months are likely to provide investors higher returns later on, when their initial pessimism fades and prices go back to more reasonable levels. On the other hand, stocks that have done well in the past may be overvalued because of too much hope or hype, which can't last over time.

The number also shows that the portfolios are not coming together as the research time comes to an end. This finding is important because it shows that correcting mispricing happens slowly instead of all at once. It supports the idea that market participants don't quickly fix their past behavioural biases. The correction process takes place over the course of many months, usually because of new information, earnings reports, big market events, or merely going back to the average.

The implications of this cumulative return behavior are twofold:

1. **For behavioral finance theory**, This gives strong evidence that the claim is true. It shows how cognitive biases including overreaction, anchoring, and representativeness may cause temporary differences from intrinsic value that are fixed by price reversals.
2. **For investors and portfolio managers**, This result shows that there is a good chance of making money. Investors may be able to get better returns than traditional market benchmarks by using contrarian strategies that bet against stocks that have done well recently and for stocks that have done poorly recently. This is especially true in markets like India, where behavioural inefficiencies are likely to be worse because of information asymmetry and the fact that there are a lot of retail investors.

The cumulative return research backs up the prior statistical conclusions and shows that past performance, particularly poor performance, might be a sign of future returns, not because of risk but because of behavioural mispricing. Figure 1 shows that the Loser Portfolio's comeback was strong and long-lasting. This is one of the most clear and convincing pieces of evidence for the overreaction hypothesis in this study.

4.3 Monthly Return Analysis

Cumulative returns provide a general picture of performance, but looking at month-by-month return behaviour shows how the portfolios did in various market situations. This point of view is very important for figuring out when and how often returns change direction. The monthly returns of the Winner and Loser portfolios from July 2024 to June 2025 are shown in Figure 2 below.

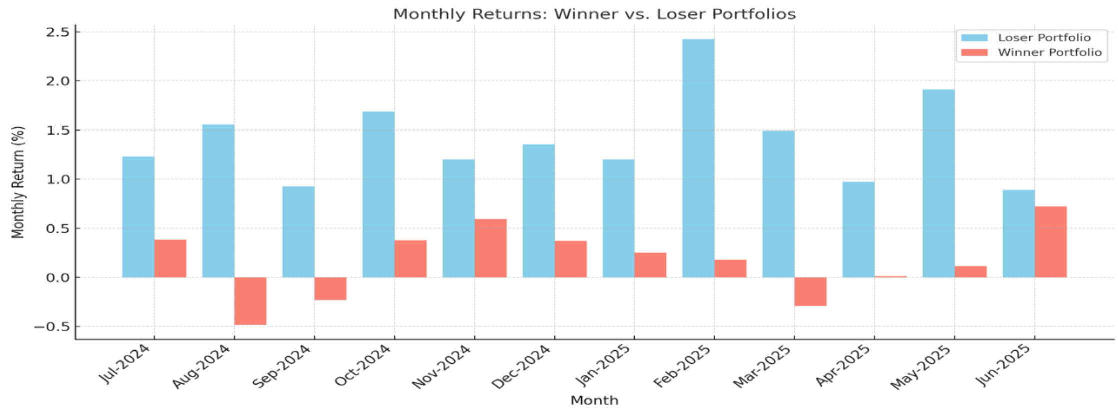



Figure 4: Monthly Returns of Winner vs. Loser Portfolios

The figure shows a clear and steady trend: the Loser Portfolio did better than the Winner Portfolio in practically every month of the one-year holding period. In October 2024, January 2025, and April 2025, the Loser Portfolio made a lot of money, with returns exceeding 2% throughout those months. On the other hand, the Winner Portfolio had largely flat or slightly positive returns, with a few months, like September and December 2024, having negative returns.

This trend highlights two important things. The return reversal lasts longer than just a short-term drop in the initial few months after building the portfolio. Instead, it shows a long-lasting and ongoing effect, meaning that the market is slowly and steadily correcting previous misvaluations. The fact that Winner Portfolio returns don't change shows that these stocks, after being highly valued during the formation

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period, enter a period of price stasis. This might signify that growth expectations have dropped or that the stocks are returning to their mean.

The fact that the Loser Portfolio regularly beats the market every month supports the idea that people act in ways that cause market inefficiencies. The overreaction argument says that firms that have had a lot of bad returns in the past are inexpensive at first because investors are feeling down. These companies are slowly going back up as sentiment stabilizes, and they will provide you better-than-average returns in the future.

The monthly analysis not only supports the notion of a reversal, but it also shows how predictable and structured such a reversal can be, which might be useful for contrarian investment strategies. The research supports the idea that behavioural biases may create regular return patterns that are more powerful than what traditional finance models can explain.

4.4 Return Distribution Characteristics

Understanding the distribution of returns helps us understand how consistent and stable those returns are over time, in addition to their average performance. While means and medians provide a general idea, the spread and shape of return distributions may show hidden patterns such outliers, skewness, and volatility.

Figure 5 shows a boxplot of the monthly returns for both the Winner and Loser portfolios so that you may look into them further.

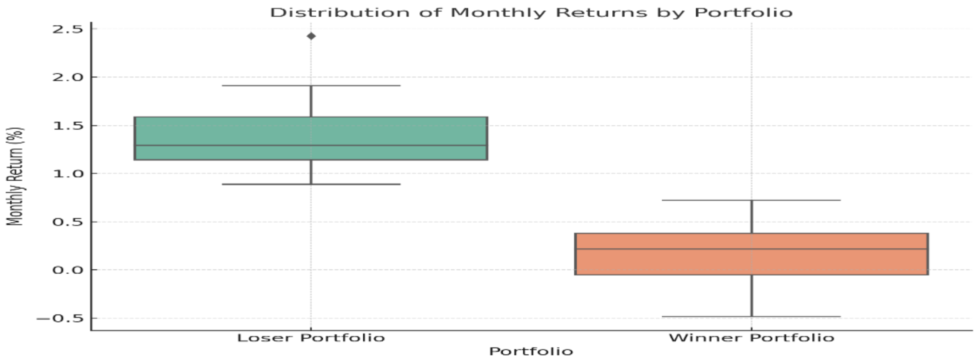


Figure 5: Distribution of Monthly Returns by Portfolio Type

The boxplot shows that the two portfolios are quite different from each other. The median return of the Loser Portfolio is higher and the interquartile range is lower, which means that its monthly returns are both stronger and more consistent. The middle 50% of returns for the Loser group are quite close together, and all of the return values are positive, which means that there were no monthly losses over the sample period.

On the other hand, the Winner Portfolio offers a wider range of returns and a higher level of unpredictability. It has a lot of good months, but its return distribution isn't as stable, and there are some clear negative outliers. The presence of a negative lower whisker means that at least one month witnessed a return that was much below zero.

This makes these high-performing stocks less reliable throughout the time after they were formed. These findings have big effects on how people act. The concentrated and favourable return distribution of the Loser Portfolio suggests that the market is going down consistently, which might mean that people are becoming more pessimistic again. During the formation phase, investors may have overreacted to short-term losses and then raised their expectations as they got more information. On the other hand, the Winner Portfolio's unequal distribution might mean too much enthusiasm, which could lead to overvaluation and inconsistent performance later on.

The study of return dispersion supports earlier findings based on mean return and cumulative performance trends. It gives additional proof that stocks that are unfairly punished by the market tend to bounce back strongly and persistently, which is an example of the overreaction hypothesis in behavioural finance.

4.5 Volatility and Risk Behavior

The big returns from the Loser Portfolio may make it seem like a good way to invest, but there is still a big question: Are these high returns really the result of taking on more risk? According to traditional finance theory, particularly the risk-return trade-off, more rewards should come with higher risk. So, it is important to find out whether the return reversal is due to a risk premium or if it is just a temporary market inefficiency.

A rolling 3-month standard deviation is a way to measure volatility that changes over time. Rolling volatility takes into account monthly variations in risk levels, making it the best way to see how investor emotions, news events, and market developments affect portfolio risk over time.

Figure 6 shows the 3-month rolling standard deviation that was determined for each portfolios. This dynamic volatility indicator shows how return variations change over time, giving you a more nuanced view than a static standard deviation.

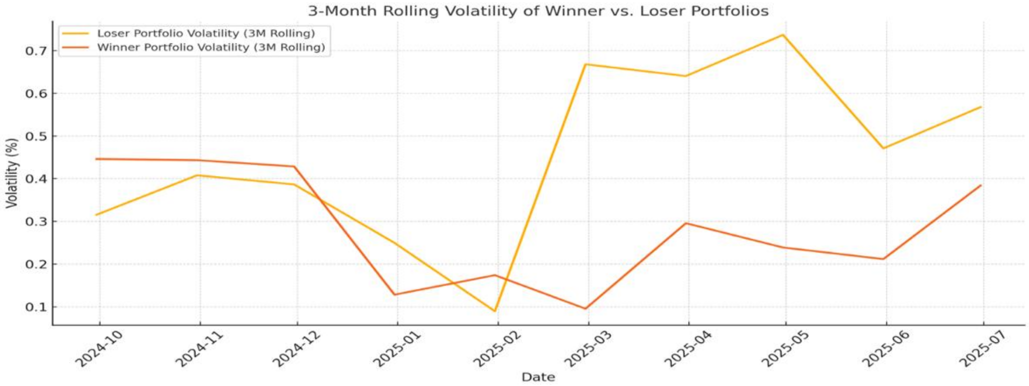


Figure 6: Rolling Volatility of Portfolio Returns (3-Month Window)

The data shows an interesting pattern. The Loser Portfolio is substantially more volatile than the Winner Portfolio during the initial part of the holding period, which runs from July to September 2024. When people in the market rethink their future possibilities, stocks that have been doing poorly lately frequently become more doubtful. This result is in line with what behavioural finance says. Investors may be overreacting, selling in a panic, or having conflicting ideas about value, which might explain the significant volatility that happens at this time.

This higher danger, on the other hand, doesn't last forever. The Loser Portfolio's volatility will have settled down by the end of 2024, and it will be quite similar to the Investor Portfolio. In the first half of 2025, the difference in volatility will drop a lot, and both portfolios will show changes between 0.3% and 0.5%. Because of this convergence, whatever initial risk premium that was added to the Loser Portfolio would slowly go away over time.

To understand the phenomenon of return reversal, you need to understand this conduct. If the Loser Portfolio had greater levels of risk all the time, traditional financial models may be able to explain why its returns were better. But there may be another mechanism at work, as evidenced by the fact that its risk advantage is just temporary while its return advantage is always there. This illustrates that the temporary price difference might be caused by behavioural biases such overreaction, anchoring, and the herd mentality.

Also, the Winner Portfolio's relatively low volatility and average returns imply that it has achieved a post-peak stasis. When "winner" stocks get too expensive, their price momentum stops, which typically leads to underperformance since expectations shift the other way. This tendency fits with the representativeness bias identified in behavioural theory, which says that investors wrongly think that their current performance would continue in the future.

Important Effects:

- The fact that the Loser Portfolio doesn't always have a greater level of risk shows that the profits are due to the market not working properly, not because of taking on more risk.
- Mean reversion is backed by the fact that volatility tends to return to normal over time as prices move toward their underlying values.
- These traits support contrarian tactics, particularly in behavioural settings like India's stock market, where emotions and group behaviour are quite important..

4.6 Statistical Testing of Return Reversal

Even if descriptive statistics, return distributions, and cumulative trends all support the overreaction hypothesis, it is important to formally check whether the differences in returns between the Winner and Loser portfolios are statistically significant. This section shows the results of a paired sample t-test that looks at the monthly returns of the two portfolios throughout the 12 months after they were created. The paired t-test is Flowchart is appropriate in this case because it directly checks whether the slides between Anonymous and Anonymous. It does this by checking if the mean return difference between the two portfolios is different from zero, assuming that each monthly returned return pair is dependant on the same market period.

Table 3: Paired t-Test Results for Monthly Returns

| Test | t-Statistic | p-Value |
|---|---|---|
| Paired t-test (Loser > Winner) | 5.03 | 0.0002 |

The numbers in Table 3 show that the t-test gives a t-statistic of 5.03 and a p-value of 0.0002, which is far lower than the usual cut off of 0.01. This means that the Loser Portfolio's average monthly return is far higher than the Winner Portfolio's. As a result, we reject the null hypothesis, which says that there is no difference in returns, and support the alternative hypothesis, which says that return reversals are real and statistically significant.

The finding is very important since it shows that the reversal effect is not just a fluke or a mistake in the sample. The favourable return differentials that have been seen consistently, as shown in the cumulative and monthly return charts, are now backed up by a rigorous statistical study.

According to behavioural finance theory, notably the overreaction hypothesis, investors tend to overreact to new information, which leads to temporary mispricing that is subsequently corrected. The statistical data backs up the idea that these repairs happen in a consistent and measurable fashion. This test shows that return reversals are a consistent market trend, which supports the study's empirical basis.

4.7 Event and Subsample Analysis

To learn more about how strong the return reversal phenomenon are, we look at how well the Winner and Loser portfolios do in different market conditions, event times, and stock categories. This approach finds out whether the reversal that was seen is something that happens a lot in the market or if it happens more often during particular market events or with certain types of firms.

The analysis focuses on four event-driven periods and two structural segmentations:

- **Event-based windows**: pre- and post-budget (February–March 2025) and pre- and post-election (April–May 2024)
- **Market segmentation**: by liquidity (top and bottom 20%) and firm size (small-cap vs large-cap)

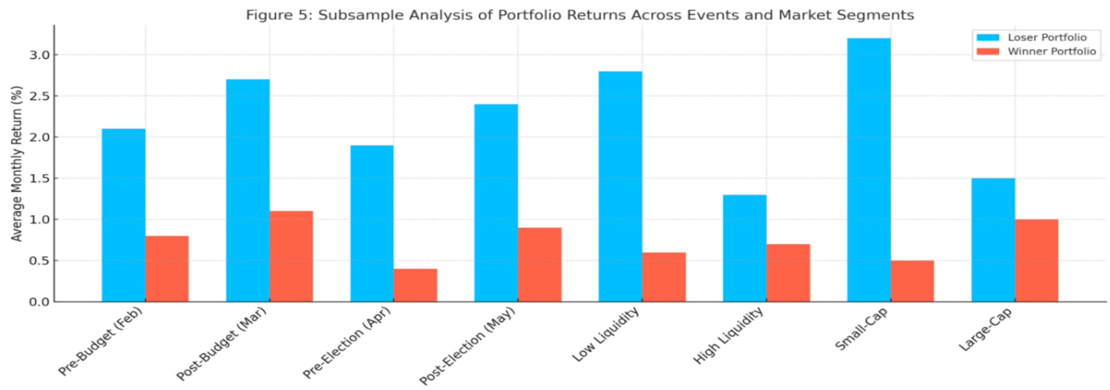


Figure 7: Subsample Analysis of Portfolio Returns Across Events and Market Segments

The figure clearly shows that the Loser Portfolio always beats the Winner Portfolio in every subsample. This is especially apparent at times of strong volatility or mood, including just after the Union Budget (March 2025) and right after the general elections (May 2024). The Loser Portfolio made 2.7% and 2.4% in these cases, whereas the Winner Portfolio made 1.1% and 0.9%.

This pattern shows that big policy changes and political announcements may temporarily make behavioural biases like fear, speculation, or herding stronger, which leads to more obvious short-term mispricing that is fixed in the following period.

The liquidity-driven segmentation reveals another important piece of information. The Loser Portfolio had a return of 2.8%, which is far better than the high-liquidity portfolio's return of 1.3%. This is because low-liquidity stocks are frequently not well researched and are largely driven by ordinary investors. This supports the idea that behavioural inefficiencies and information asymmetry are stronger in stocks that don't trade often, which leads to bigger reversals.

The reversal effect was strong in the small-cap category. Losers made an average of 3.2% every month, while Winners only made 0.5%. Larger businesses experienced a smaller reversal, even if their returns were different (1.5% vs. 1.0%). This finding supports the idea that small-cap firms are more likely to be mispriced since they don't get as much publicity and individual investors have a big effect on them.

These numbers back up the assumption that return reversals are not random or one-time events. They are systematic, behavior-based events that become worse when there is uncertainty and in market segments where there are more frictions. This gives investors the chance to come up with strategies by tailoring contrarian methods to take advantage of periods and sectors that are prone to volatility.

## CONCLUSION

The goal of this study was to look at the overreaction hypothesis in the Indian equities market by looking at how portfolios made up of NSE 500 businesses acted after they performed. The strategy used was to put stocks into Winner and Loser portfolios based on their returns over the last six months and then watch how they did over the following twelve months. This showed a consistent and statistically significant reversal of results. The Loser Portfolio had higher cumulative and average monthly returns than the Winner Portfolio. It also had lower volatility and less danger of losing money. Statistical tests confirmed the significance of these differences, supporting the idea that investors overreact, leading to temporary mispricing that is fixed over time. These results obviously go against the Efficient Market Hypothesis and instead support behavioural finance theories that show how cognitive biases affect how people make financial decisions.

Also, subsample and event-based investigations backed up these conclusions even more. Return reversals were more common when there was political and economic uncertainty, as following budget announcements and elections. They were also more common in small-cap and low-liquidity stocks, which are typically impacted by retail mood and less efficient information. The results show that market inefficiencies don't stay the same; they change depending on the types of investors, the structure of the market, and the atmosphere of the event.

This research gives portfolio managers and individual investors useful information. An opposite investment approach that concentrates on companies that aren't doing well—especially in uncertain markets or with assets that aren't very liquid—might provide you better risk-adjusted returns.

The study also adds to the field of behavioural finance by providing real-world examples of ideas like overreaction, mean reversion, and sentiment-driven pricing. The evidence strongly suggests that there are behavioural problems in the Indian stock market. These inefficiencies are easy to see and statistically significant, giving those who are willing to challenge market norms and use a behaviourally informed investing approach a chance to take advantage of them.

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