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Beyond Rationality: How Behavioural Finance Shapes Investment decisions in Financial Markets

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Abstract

This research paper explores the impact of behavioral finance biases on investment decisions in the Indian stock market. It examines three key aspects: the disposition effect among traders, the influence of herding behavior and availability bias during significant market events like the GameStop short squeeze and the COVID-19 tech boom, and the quantification of loss aversion in risk profiling methods. Using data from the National Stock Exchange and case studies, the paper analyzes how psychological factors drive investor behavior, often leading to suboptimal decisions. The study highlights the importance of incorporating behavioral biases into financial models and risk assessment tools to better understand and predict market dynamics in an increasingly interconnected financial landscape.

Keywords: Behavioral finance, disposition effect, herding behavior, availability bias, loss aversion, risk profiling, portfolio management, retail investors, cognitive biases, market anomalies.

1. Introduction

In recent decades, the concept of Behavioural Finance has gained tremendous significance as the rationality of an investor further deviates from its assumption. Experts have grown to understand that in order to accurately predict a stock or take a decision, they would be required to factor in the irrationality of the general public. Behavioural finance challenges the traditional assumption that investors are fully rational, revealing that emotions and cognitive biases play a significant role in financial decision-making. In portfolio management, these biases—such as loss aversion, overconfidence, and herding—can lead investors to deviate from the optimal strategies prescribed by classical financial theory. For instance, loss aversion often causes investors to hold onto losing investments longer than rational models would suggest, or to panic sell during downturns, despite long-term goals. By understanding and addressing these behavioural tendencies, investors can develop more balanced and effective portfolio strategies that better account for the emotional complexities involved in real-world financial decisions.

2. Literature Review

Barberis, N., & Xiong, W. (2009) explore the disposition effect, where investors sell winning assets and hold onto losers. They test prospect theory models, finding that preferences based on realized gains and losses better predict this behaviour, while annual gains/losses often fail. Their study highlights the importance of modelling investor utility through realised outcomes to explain trading behaviour.

Greaves, S. P., & Ellison, A. B. (2011) found that drivers often misjudge their speeding habits and that personality traits, while influencing self-reported behavior, have limited impact on actual speeding. The research highlights the need for more accurate assessments of driving behavior, particularly speeding.

Altman, M. (2013) discusses how prospect theory, developed by Kahneman and Tversky, challenges traditional financial theories like the Efficient Market Hypothesis (EMH). He examines deviations from rational behaviour in financial markets, including loss aversion, framing effects, and the equity premium puzzle. Altman argues that these seemingly irrational behaviours can be explained through bounded rationality and cognitive biases, offering a deeper understanding of how individuals make decisions under uncertainty. His analysis expands on the relevance of prospect theory in behavioural finance.

Yadav, Y., & Shivanand. (2014) provide an overview of behavioral finance concepts, including anchoring, mental accounting, confirmation bias, gambler's fallacy, herd behavior, overconfidence, overreaction, and prospect theory. The paper offers suggestions for mitigating these psychological pitfalls and highlights how understanding these biases can explain market anomalies and irrational investor behavior.

Nawrocki, D., & Viole, F. (2014) review the integration of behavioural finance with market, utility, and portfolio theories. They critique traditional financial models for their reliance on unrealistic assumptions, such as the idea that investors are rational. The authors suggest the use of nonparametric statistics and partial moments to better capture real-world investor behaviour. They emphasise the role of utility theory in portfolio theory and call for a shift in how market disequilibria are approached, offering a fresh perspective on how investor behaviour deviates from classical financial models.

Guillemette, M. A., Yao, R., & James, R. N. II (2015) highlight the importance of considering loss aversion in financial planning. Traditional risk tolerance questionnaires don't account for this bias, which can significantly impact investment decisions. The article proposes incorporating questions that measure loss aversion into risk assessment questionnaires to help financial planners make better recommendations.

Prosad, J. M., Kapoor, S., Sengupta, J., & Roychoudhary, S. (2016) provide empirical evidence of overconfidence and the disposition effect in the Indian equity market (2006–2013). Using vector autoregression (VAR) and impulse response functions, they find evidence of both biases, with overconfidence being more dominant. The study highlights how these behavioural biases contribute to market inefficiencies and increased trading volume, particularly in developing markets like India. Their work emphasises the impact of overconfidence on the equity market and its role in distorting investor decisions.

Hunt, K. (2016) proposes a novel approach to risk profiling in financial planning based on psychological factors like self-control, optimism, financial literacy, and risk tolerance. It argues that understanding these factors can enhance client engagement and lead to more tailored financial plans. The first stage of the research involves developing a risk profiling system based on this theoretical framework.

Khanna, Kamini and Chauhan, Veena, (2017) explores the association between various demographical factors, risk profile and investment decision of retail investors. The findings revealed that the investors do not always behave rationally and their choice of investments is decided by their risk profile and other demographical factors such as age, gender, income, wealth etc. This research is also useful for portfolio managers to construct the right portfolio for the investors according to their needs and preferences.

Patel, R., & Patel, M. (2018) explore behavioral finance in Indian investment decisions, challenging traditional assumptions about investor rationality. The study analyzes savings and investment choices among faculty members in Uttarakhand, considering factors like age, marital status, education, and income. It emphasizes the importance of psychological factors in understanding investment behavior, moving beyond traditional financial models.

Akkaya, M. (2021) explores and builds upon the Tversky and Kahneman experiment of the anchoring bias. The research utilises functions of BAPM and Markowitz to create a distinct and diverse portfolio to satisfy the needs of an investor. The paper overall explores how a simple psychological experiment has caused the entire financial market to change its perspective.

Michael, G., & Irina, K. (2022) examine the 2021 GameStop phenomenon, chronicling how a single investor (DFV/Roaring Kitty) transformed r/WallStreetBets from a casual investment forum into a coordinated movement challenging Wall Street narratives. The study analyzes the conflict between traditional media's top-down approach and Reddit's community-driven information sharing. It details how DFV's contrarian GME analysis, supported by Michael Burry's insights, sparked a retail investor revolution that questioned established financial media's authority and expertise.

Van Dolder, D., & Vandenbroucke, J. (2022) explore the integration of loss aversion into client risk classifications. They present a method to measure loss aversion in a large-scale setting, finding it to be independent of risk-return preferences. Additionally, the study correlates loss aversion with education and risk aversion with gender, age, and financial status, suggesting they are complementary factors in understanding investor intent.

Mensah, M., & Peprah, W. (2022) explore the impact of heuristics and cognitive errors that occur while investors attempt to minimize losses and maximise returns. The aim was to test the modern theory against traditional market dynamics and locate the inefficiencies caused in the process. Overall, the conclusion stated that biases are inefficient as they contribute to inaccuracy and in order to tackle this problem, financial literacy is a vital prerequisite.

Bhanushali, J. S., & Jhansi Rani, M. R. (June, 2023) generate an overall view of different types of cognitive and emotional biases that have affected investment decision making throughout the course of history. Key biases include herding behaviour, overconfidence bias, anchoring bias, availability bias, regret aversion, loss aversion and recency bias. The study stresses on the importance of appropriate education and the need for well-informed decisions to take place. While the research paper steers toward a conceptual base, it gives clarity on the different categories that exist and ways in which investors must apply the growing theory of behavioural finance.

Kajol, K., Biswas, P., Singh, R., Moid, S., & Das, A. K. (2023) investigate the factors influencing the disposition effect in equity investment using Social Network Analysis (SNA). They identify key factors such as social trust and investor emotions as significant contributors. Their research establishes relationships between 30 identified factors, demonstrating how psychological and behavioural elements, including regret aversion and mental accounting, affect investor behaviour in holding losing stocks and selling winners. This study provides a detailed analysis of the social and emotional factors driving investment decisions.

Kim, K., Lee, S. T., & Kauffman, R. J. (2023) examine the GameStop short squeeze of 2021, highlighting how social media platforms facilitated coordination among individual investors. The study explores the concept of social informedness and its role in triggering collective investor behavior, drawing on work by Barber et al. (2022) and Kelley and Tetlock (2013). It illustrates the power of social influence and herding behavior in disrupting traditional market dynamics.

Hossain, A., Al-Masum, & Xu, J. (April 2023) analyze the positive impact in the Technology Sector during COVID-19. The model uses a combination of Stock Price Crash Risk and a quasi-natural setup to test the theory of uncertainty contributing to this very growth. It is essential to view this as a breakthrough in perceiving biases to be a beneficial factor.

Nizar, M. (January 2024) focuses on the root cause of the biases that occur in the financial market, introducing FOMO. Written in 2024, the language used, "FOMO" refers to the fear of missing out. It is also an answer to why most biases like herding behaviour may occur in decision making. The cognitive error is often not inherited but is instead caused by the environmental factors that contribute to one being left out while making a choice.

3. Research Gap and Objectives

The literature on behavioral finance extensively explores individual biases such as overconfidence, herding behavior, and loss aversion across various markets and timeframes. Several studies have magnified the impact of emotional and cognitive biases on investment decisions, portfolio management, and market inefficiencies. However, key gaps remain:

1. **India-specific Studies on Emerging Behavioral Trends:** While some research aims to address biases in Indian markets, there is limited analysis on how recent market events and how they may influence Indian retail investors specifically. This study aims to fill that void by examining these biases in an Indian context.

2. **Inclusion of Loss Aversion in Risk Profiling:** Although behavioral finance emphasizes loss aversion, many financial institutions overlook it in their risk assessments. There is a need for a model that quantifies loss aversion in practical terms to make risk profiling more robust and personalized. This paper assesses models to measure loss aversion, highlighting the importance of incorporating this bias into modern financial tools for improved investor outcomes.

3. **Study on new media impact**: Limited research explores the impact of retail herding during market crises and its effects on institutional investors in volatile periods. Another gap exists in analyzing how technological advancements, and new media impact

This study bridges gaps between theoretical frameworks and practical applications, offering a comprehensive understanding of how behavioral finance impacts investments in the Indian financial landscape. The above is explored via the following research objectives.

1. To analyze whether the disposition effect occurs among traders in the Indian stock market.

2. To identify the quantification of loss aversion as a behavioral bias in current risk profiling methods

3. To analyze the impact of herding behavior among retail investors on stock market dynamics and institutional investor outcomes

4. To examine the role of availability bias in driving investor decisions with a focus on its influence on the technology sector's market performance.

4. Hypothesis

Ho: The behavioural finance biases do not significantly influence the investment decision of stakeholders in the financial market

5. Methodology

This research investigates how behavioral biases—such as the disposition effect, herding behavior, availability bias, and loss aversion—impact investor decision-making and portfolio management in the Indian stock market. It adopts a multimethod approach, utilizing quantitative data analysis, case studies, and behavioral models to comprehensively address these biases.

Data Collection

1. Stock Market Data:
   - Collected from the National Stock Exchange (NSE), focusing on volatile companies (e.g., TATA Steel, ZEEL, and One97 Communications).
   - Data points include Open, High, Low, Close prices, and trading volumes to analyze trading patterns.

2. Case Study Data:
   - GameStop short squeeze (2021) and COVID-19 tech boom are used to explore herding behavior and availability bias.
   - Social media data from Reddit (r/WallStreetBets), news reports, and stock price trends are analyzed to highlight investor sentiment and collective actions.

3. Risk Profiling Data:
   - Existing risk assessment questionnaires from financial institutions are reviewed to analyze how they address or overlook loss aversion.

Data Analysis Techniques

1. Behavioral Patterns in Stock Trading (Disposition Effect):
   - Identify winning and losing days based on 52-week highs and lows.
   - Calculate average trading volume and classify days with deviations as “abnormal.”
   - Use these deviations to infer risk aversion (higher trades on winning days) and risk-seeking behavior (holding losing stocks).

2. Case Study Analysis (Herding and Availability Bias):
   - Analyze GameStop and COVID-19 tech boom events to identify how herding behavior and availability bias influenced retail investors.
   - Assess the social and media triggers that drove collective actions and stock market trends.
   - Track the impact of these behaviors on both retail and institutional investors.

3. Comparative Analysis of Risk Profiling Tools (Loss Aversion):
   - Review existing risk profiling methods to identify gaps in measuring loss aversion.
   - Incorporate behavioral finance models (e.g., Guillemette et al.’s lambda (λ) coefficient) to simulate investor responses to gain/loss scenarios.

Tools and Presentation

1. Descriptive Statistics: Use charts and tables to present stock trading trends and case study findings.

2. Sentiment Analysis: Examine social media data to track retail investor sentiment and herding behavior.

3. Comparative Graphs: Compare Nifty 50 and Nifty IT index performances during the tech boom to highlight availability bias.

This unified methodology provides a holistic approach by integrating quantitative stock market data, qualitative case studies, and behavioral finance models. It ensures that all four objectives—disposition effect, herding behavior, availability bias, and loss aversion—are addressed cohesively, demonstrating the interconnectedness of behavioral finance biases in shaping investment decisions.

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6. Data Analysis and Findings

Objective 1 :

1 **Data Source**:

- The stock data (including Open, High, Low, Close prices, and the number of trades) is obtained from the National Stock Exchange of India (NSE).
- The study focuses on highly volatile stocks that frequently break their 52-week high or 52-week low multiple times within a year. This volatility makes them ideal for observing investor behaviour over a short-term period (1/08/2023-1/08/2024).

2 **Winning Day and Losing Day**:

- A Winning Day occurs if the high price of the stock on a particular day equals or exceeds the 52-week high.
- A Losing Day occurs if the low price of the stock on a given day is equal to or below the 52-week low.

3 **Average Number of Trades**:

- The average number of trades per day is calculated by summing all trades over the year and dividing by the total number of trading days. This value acts as a benchmark for normal trading behaviour.

4 **Abnormal Trading Days**:

- A Winning Day is identified as an abnormal trading day if the number of trades on that day is greater than the average number of trades for the year.
- A Losing Day is considered an abnormal trading day if the number of trades on that day is less than the average number of trades for the year.

5 **Behavioural Interpretation of Abnormal Trading Days**:

- If there are more trades than average on Winning Days, it suggests **risk aversion** during gains, where investors tend to sell quickly to secure profits.
- If there are fewer trades on Losing Days, it indicates **risk-seeking behaviour** during losses, where investors hold onto positions, hoping for a rebound.

Companies:

1. Engineers India (Table 1)
2. ZEEL Ltd. (Table 2)
3. Pearl Polymers (Table 3)
4. TATA STEEL (Table 4)
5. Future Retail Ltd. (Table 5)
6. One 97 Communications (Table 6)

Key Findings:

1. Abnormal Trading Volumes:

- **Winning Days:** All six companies exhibited significantly higher trading volumes on days when the stock price reached their 52-week highs, compared to their respective average trading volumes. This indicates that investors were actively selling to lock in profits. For example, Engineers India recorded 239,399 trades on 12-Dec-23 when it reached its 52-week high, far exceeding its average of 28,255 trades per day.

- **Losing Days:** Four of the six companies also showed abnormal trading volumes on losing days, suggesting a reluctance to sell at a loss. ZEEL Ltd., Future Retail Ltd., and One 97 Communications exhibited particularly high trading volumes on losing days, indicating a strong tendency to hold onto declining positions.

2. Behavioural Response:

- **Risk Aversion on Winning Days:** Investors consistently demonstrated risk aversion on winning days, selling their positions to secure gains. This is evident in the consistently higher trading volumes on winning days across all companies.
- **Mixed Behaviour on Losing Days:** The behaviour on losing days was more varied. Engineers India, ZEEL Ltd., Future Retail Ltd., and One 97 Communications exhibited risk-seeking behaviour, holding onto their positions despite declining stock prices. TATA STEEL showed some signs of risk-seeking behaviour, but also exhibited periods of normal or below-average trading volumes on losing days. Pearl Polymers did not have any losing days in the observed period.

3. Cultural and Market-Specific Factors:

The observed behaviour aligns with the disposition effect, which is often amplified in markets dominated by retail investors. Indian retail traders (not so experienced) may be influenced by fear of missing out (FOMO) and emotional attachment to their investments, leading to irrational decision-making.

4. Connection to Prospect Theory:

The findings are consistent with Prospect Theory, which explains the psychological mechanisms underlying risk aversion in gains and risk-seeking in losses. Investors tend to overweight losses compared to gains, leading to a reluctance to sell at a loss and a preference to lock in profits.

Company-Specific Observations:

- **Engineers India:** Strong disposition effect, with investors selling winners early and holding onto losers.
- **ZEEL Ltd.:** Strong disposition effect, with investors selling winners early and holding onto losers, particularly on losing days.
- **Pearl Polymers:** Consistent selling of winners, no losing days observed.
- **TATA STEEL:** Strong disposition effect, with some risk-seeking behaviour on losing days.
- **Future Retail Ltd.:** Strong disposition effect, with consistent holding of losers.
- **One 97 Communications:** Mixed behaviour, with both selling winners and holding onto losers, indicating a more balanced approach.

The analysis demonstrates a strong prevalence of the disposition effect across the six Indian companies studied. Investors consistently exhibit a preference for selling winners early and holding onto losers, driven by factors such as cultural influences, market-specific dynamics, and psychological biases outlined in Prospect Theory. While the degree of this effect varies among companies, it is a prevalent phenomenon in the Indian market.

Objective 2 :

A risk profile is a quantitative analysis of the types of threats an organization, asset, project or individual faces. The goal of a risk profile is to provide a non-subjective understanding of risk.

After viewing multiple risk assessments, I have concluded that they fundamentally measure a client's:

- **Preferences (risk tolerance)** – measures the portion of money an investor is willing to lose for potential gains. Investors who have a higher risk tolerance are more comfortable in portfolios with higher volatility/return profiles

- **Goals (risk requirements)** – a client's primary intentions for their financial assets
- **Constraints (risk/loss capacity)** – a client's capacity to pursue various goals, driven by age, income, assets, tax policy, and other considerations

The results these methods categorize investors and the company allocates assets on the basis of that.

One of the central components of risk profiling is loss aversion, the assumption that people treat losses and gains differently and are more sensitive to losses than commensurate gains. Despite the empirical evidence for the importance of loss aversion, financial institutions typically do not take this concept into account and instead measure risk preferences under the (implicit) assumption that clients make rational trade-offs between risk and expected returns, in line with traditional financial models.

There are 2 reasons why loss aversion isn't included in risk profiling :

1. Loss aversion is often interchanged with risk tolerance :

The fear of losses might cause investors to miss out on profitable opportunities. Hartford funds, a fund with an AUM of 135 Billion dollars assessed a sample to find out their risk tolerance and loss aversion. It was found that people with high risk tolerance may have high loss aversion.

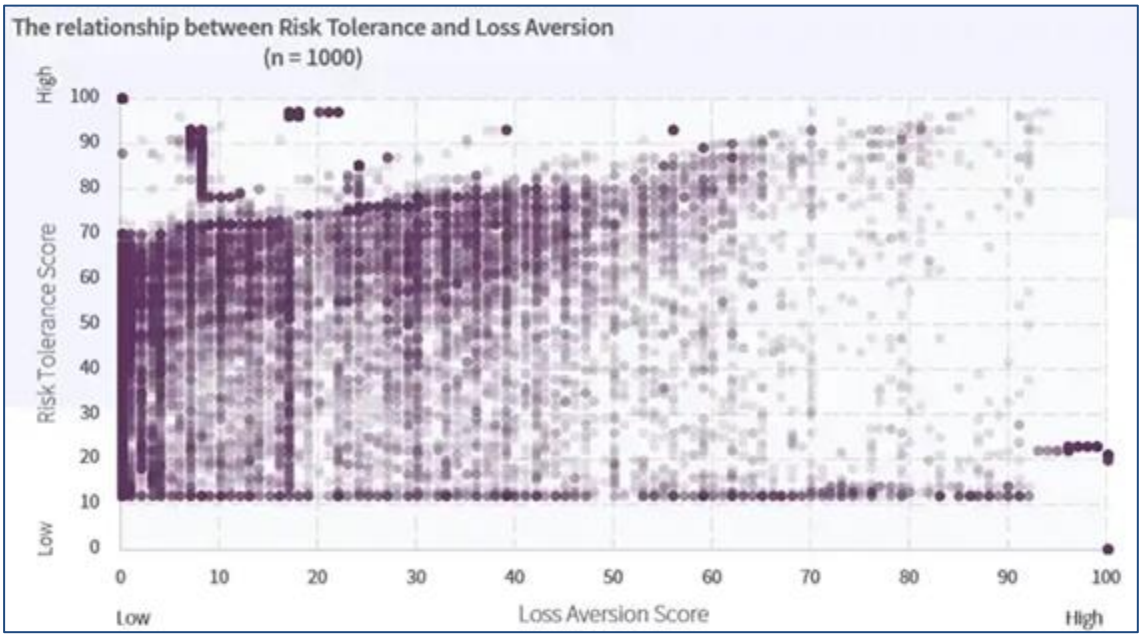

Figure 1 : Study of Relationship between risk tolerance and loss aversion (source :https://capitalpreferences.com/blog/foundations-risk-tolerance-and-loss-aversion)

Essentially, people who are comfortable with high return portfolios, may react differently when it comes to being sensitive to losing money compared to gaining. This results in panic selling when the stock is moving with a higher momentum. This could inadvertently lose potential high returns. Now this is rather contradictory and we could have prepared for such an event if we knew a persons quantified loss aversion.

2. Lack of measurability: This can be solved by the following models developed by Michael A. Guillemette , Rui Yao and Russell N. James II. This model was inspired by Arrow Pratt.

Model to calculate loss aversion:

<u>Equation 1</u>**: AR = gain * β1 + loss * β2 + certainty * β3 +PMO * β4 + HCL * β5 + e**

AR = accept or reject uncertain monetary choice; gain = gain of the uncertain monetary choice; loss = loss of the uncertain monetary choice; certainty = certain monetary choice; PMO = previous monetary outcome; HCL = high cognitive load

Equation 1 displays the model used to derive the coefficient of loss aversion (λ) (equation 2) for each participant

This equation is trying to understand why people choose to take or avoid a gamble (an uncertain choice involving money). Imagine you're offered a gamble where you could win or lose money, or you can just take a guaranteed amount of money instead. Several things influence your decision:

1. **Gain:** How much you could win from the gamble. People are more likely to take the gamble if the amount they could win is bigger.
2. **Loss:** How much you could lose in the gamble. People are more likely to take the gamble if the potential loss isn't too bad.
3. **Certainty:** This is the sure amount of money you can take instead of the gamble (like $0). If the guaranteed amount is high, people are less likely to take the risk and go for the gamble.
4. **Previous Outcome (PMO):** This is what happened in previous rounds of gambling. If you won money before, you might feel more comfortable taking another gamble because you feel like you're "playing with house money"—it's less risky.
5. **Cognitive Load (HCL):** This is about how mentally busy or distracted you are. If you're under a lot of pressure or have a lot on your mind, it might affect how you make decisions.

So, this equation is trying to predict whether someone will **accept or reject** a gamble based on how much they could win, lose, their past results, the guaranteed option, and how mentally focused they are.

<u>Equation 2:</u> **Derivation of the coefficient of loss aversion**

λ = -βloss/βgain

To measure this, we look at how sensitive people are to **losses** compared to **gains**. Equation 2 does this by dividing how much people are affected by potential losses (represented by **β_loss**) by how much they are affected by potential gains (represented by **β_gain**). The result is called **λ** (lambda), the **loss aversion coefficient**.

- If **λ** is greater than 1, it means the person hates losing more than they enjoy winning, which is typical.
- If **λ** is equal to 1, the person values losses and gains equally.
- If **λ** is less than 1, the person cares more about winning than losing, meaning they are more likely to take risks.

Let's see how it can be applicable in a risk profile:

Here's a risk profiling question with three options:

"Imagine you're offered three different investment opportunities with varying risk and reward profiles. Which one would you be most comfortable choosing?

Option A: You have a 70% chance of gaining $500, but a 30% chance of losing $500. (λ > 1)

Option B: You have a 50% chance of gaining $1000, but a 50% chance of losing $1000. (λ = 1)

Option C: You have a 30% chance of gaining $1500, but a 70% chance of losing $1500. (λ < 1)

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Questions like these were used to measure loss aversion and a score for assessment was given.

This model concluded that risk assessment questions that included loss aversion, explained more variation in individuals' portfolio allocation scores and their recent investment changes and showed a 15% marginal benefit However the sample was very small to test the models true applicability. Moreover, Capital preferences have developed a financial fingerprint that is outsourced to upcoming wealth management firms and it heavily takes loss aversion into account.

Objective3:

Case 1: Background

The GameStop (GME) saga began in January 2020 when DFV (Deep F**cking Value/Roaring Kitty), a financial educator, posted his initial GME investment thesis on r/WallStreetBets. Despite the stock trading at around four dollars, DFV's detailed analysis and research garnered significant attention within the community. By August 2020, he expanded his reach through YouTube videos, presenting a contrarian view that challenged Wall Street's prevalent short-selling position. "In one of his detailed YouTube videos (https://www.youtube.com/watch? v=GZTr1-Gp74U), DFV provided an extensive analysis of his GME position when the stock was valued at approximately four dollars per share." .His analysis was notably supported by Michael Burry, a renowned investor featured in "The Big Short."

The situation dramatically escalated in January 2021 when a remarkable short squeeze occurred, driven by r/WallStreetBets users. With approximately 140% of GameStop's public float sold short, the stock price surged from $17.25 to over $500 per share (split-adjusted $125) by January 28. This unprecedented rise had severe implications for hedge funds and affected other heavily shorted stocks and cryptocurrencies.

The event reached a controversial peak when several brokerages, most notably Robinhood, restricted GME purchases, citing clearing house collateral requirements. This phenomenon marked a pivotal shift in financial markets, demonstrating social media's power in enabling retail investors to coordinate actions against institutional players. It forced Wall Street to recognize the influence of retail traders and highlighted how social media platforms could facilitate collective action capable of challenging traditional market dynamics.

Phenomenon

Since, behavioral finance plays a major role in today's world, the same happened with the retail investors here. The bias experienced by them was the Herding Behaviour (a part of regret aversion bias). Herding behavior refers to the tendency of individuals to follow the actions or decisions of a larger group, often leading to collective movements in financial markets. This phenomenon can amplify trends, causing rapid price changes as investors buy or sell based on the actions of others rather than their own analysis.

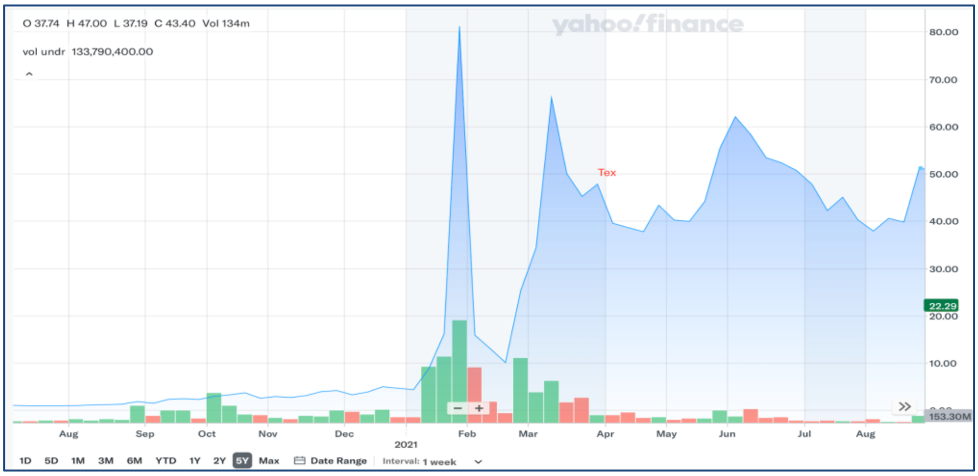

Figure 2. Price movement for GME stock (Source : https://yhoo.it/3tGpPND)

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The GameStop saga of January-February 2021 exemplifies herding behavior in financial markets. A group of retail investors, primarily coordinating through social media platforms like Reddit, collectively decided to buy GameStop shares, driving the price up dramatically. This action attracted more investors who, seeing the rapid price increase, joined in fear of missing out (FOMO). The herd mentality snowballed, causing the stock price to skyrocketed in a matter of weeks. This event demonstrated how social influence and group dynamics can override individual decision-making processes, leading to extreme market movements that may not reflect fundamental company values. The phenomenon highlights the power of collective action in modern, interconnected financial markets.

Facts and Figures (Part 1)

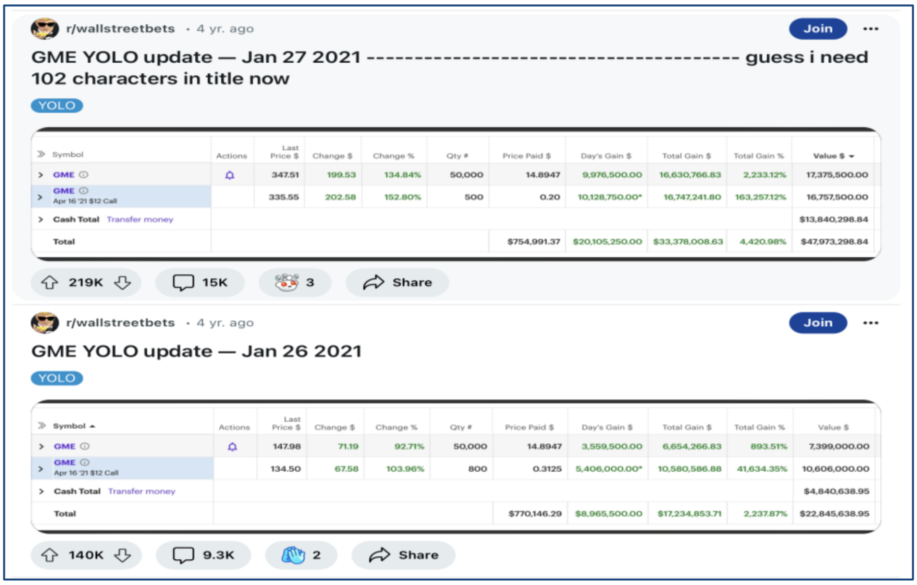
r/wallstreetbets • GME YOLO month-end update — Apr 2020
DeepFuckingValue OP replied to nckw90 4 yr. ago

The business is easily worth $700m, but could be worth up to $1.5b. So somewhere in the general vicinity of that range.

Plus there's now an opportunity for a short squeeze of some sort, though that was never a part of my original thesis. I still think it's unlikely but when the shorts exceed the float the possibility needs to be factored in.

121 Reply Share ...

Figure 3. Reddit comment (source: https://www.reddit.com/r/wallstreetbets/)



r/wallstreetbets • 4 yr. ago Join ...

GME YOLO update — Jan 27 2021 -- guess i need 102 characters in title now

YOLO

Symbol	Actions	Last Price $	Change $	Change %	Qty #	Price Paid $	Day's Gain $	Total Gain $	Total Gain %	Value $
GME		347.51	199.53	134.84%	50,000	14.8947	9,976,500.00	16,630,766.83	2,233.12%	17,375,500.00
GME Apr 16 '21 $12 Call		335.55	202.58	152.80%	500	0.20	10,128,750.00*	16,747,241.80	163,257.12%	16,757,500.00
Cash Total Transfer money										$13,840,298.84
Total						$754,991.37	$20,105,250.00	$33,378,008.63	4,420.98%	$47,973,298.84

219K 15K 3 Share

r/wallstreetbets • 4 yr. ago Join ...

GME YOLO update — Jan 26 2021

YOLO

Symbol	Actions	Last Price $	Change $	Change %	Qty #	Price Paid $	Day's Gain $	Total Gain $	Total Gain %	Value $
GME		147.98	71.19	92.71%	50,000	14.8947	3,559,500.00	6,654,266.83	893.51%	7,399,000.00
GME Apr 16 '21 $12 Call		134.50	67.58	103.96%	800	0.3125	5,406,000.00*	10,580,586.88	41,634.35%	10,606,000.00
Cash Total Transfer money										$4,840,638.95
Total						$770,146.29	$8,965,500.00	$17,234,853.71	2,237.87%	$22,845,638.95

140K 9.3K 2 Share

Figure 4. Reddit comments (source : https://www.reddit.com/r/wallstreetbets/)

The GameStop saga of 2020-2021 presents a fascinating case study in herding behavior and the power of social media in financial markets. As evidenced by the images, a Reddit user named '*DeepF*ingValue'* (Keith Gill, known on YouTube as Roaring Kitty) posted analyses suggesting GameStop was undervalued, with a potential for a short squeeze. His April 2020 post estimated the company's worth between $700 million and $1.5 billion, far exceeding its market valuation at the time.

The subsequent images reveal the dramatic impact of this analysis and the resulting retail investor frenzy. By January 26-27, 2021, DeepF*ckingValue's initial investment had skyrocketed to over $22 million, with a single-day gain exceeding $17 million. This exponential growth is mirrored in the Yahoo Finance stock chart, which shows GameStop's share price surging from under $20 in early January to a peak of nearly $350 by month's end.

This phenomenon exemplifies herding behaviour in financial markets. Retail investors, coordinating through social media platforms like Reddit's r/wallstreetbets, collectively drove up GameStop's stock price. The rapid price increase triggered a short squeeze, further amplifying the stock's momentum. The saga demonstrates how social media can facilitate mass coordination among retail investors, challenging traditional market dynamics and the positions of institutional

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investors. It also highlights the potential volatility and risks associated with such coordinated investment strategies driven by social media influence.

Hedge Funds Involved

Firm	Losses	Notes
Melvin Capital	-30% (by Jan 28, 2021)	Lost 53% by the end of January; received $2.75 billion in investments; closed position Jan 26.
	22% gain (Feb 2021)	Needed much more to break even; further losses during GME's resurgence in May 2021.
		Shut down on May 18, 2022.
Andrew Left (Citron)	100% loss (at ~$90 per share)	Closed majority of short positions; shifted focus to long investments.
D1 Capital Partners	$4 billion (20% of capital)	Significant losses due to shorting GameStop.
Short Sellers (Total)	$6 billion (as of Jan 26, 2021)	Cumulative losses reported due to the squeeze.
Morgan Stanley Hedge Funds	Varied losses	Covered short positions and reduced leverage in some of the largest actions in 10 years.
Light Street Capital	>20% loss (during 2021)	Affected by GameStop's price spikes.
White Square Capital	"Double-digit" losses	Announced shutdown on June 22, 2021.
Short Interest Change	39% (Feb 1, 2021)	Down from 114% in mid-January; signaled potential easing of the short squeeze.
Specific Loss (Mar 8, 2021)	$609 million	Reported losses from short sellers.

Figure 4. List of hedge funds involved (Source: https://hedgefundalpha.com/how-did-hedge-funds-lose-money-on-gamestop/#:~:text=This%20resulted%20in%20eight%20major,sudden%20brake%20in%20the%20pattern.)

The image details the substantial financial impact of the GameStop short squeeze on several major hedge funds and investment firms. Melvin Capital experienced a 53% loss by January's end and ultimately shut down in May 2022. Other notable casualties included Andrew Left's Citron (100% loss), D1 Capital Partners ($4 billion loss), and Light Street Capital (>20% loss). Cumulatively, short sellers reported $6 billion in losses as of January 26, 2021. The squeeze forced Morgan Stanley hedge funds to cover short positions in one of their largest actions in a decade. Even White Square Capital announced its shutdown in June 2021 due to "double-digit" losses. This widespread financial damage across multiple firms underscores the unprecedented scale and impact of the GameStop short squeeze on institutional investors who had heavily shorted the stock.

Facts and Figures (Part 2)

The image and scatter plot illustrates the significant influence of social media, particularly YouTube and Reddit, on the GameStop (GME) stock phenomenon of 2020-2021. The table shown captures data on the relationship between

Roaring Kitty's YouTube video releases and GME stock traded volume, suggesting a correlation between his content and market activity.

Youtube Video Date	Stock traded Volume
05/08/20	1,96,77,200
06/08/20	76,04,800
07/08/20	1,33,64,400
08/08/20	-
09/08/20	-
10/08/20	1,82,47,200
11/08/20	1,25,55,200
12/08/20	1,22,30,400
13/08/20	85,13,200
14/08/20	1,38,97,600
15/08/20	-
16/08/20	-
17/08/20	94,84,000
18/08/20	1,53,37,600
19/08/20	1,04,50,400
20/08/20	97,64,800
21/08/20	**4,25,70,400**

Table 7. 3/8/20 to 21/8/20 GME stock prices (source : Yahoo finance)

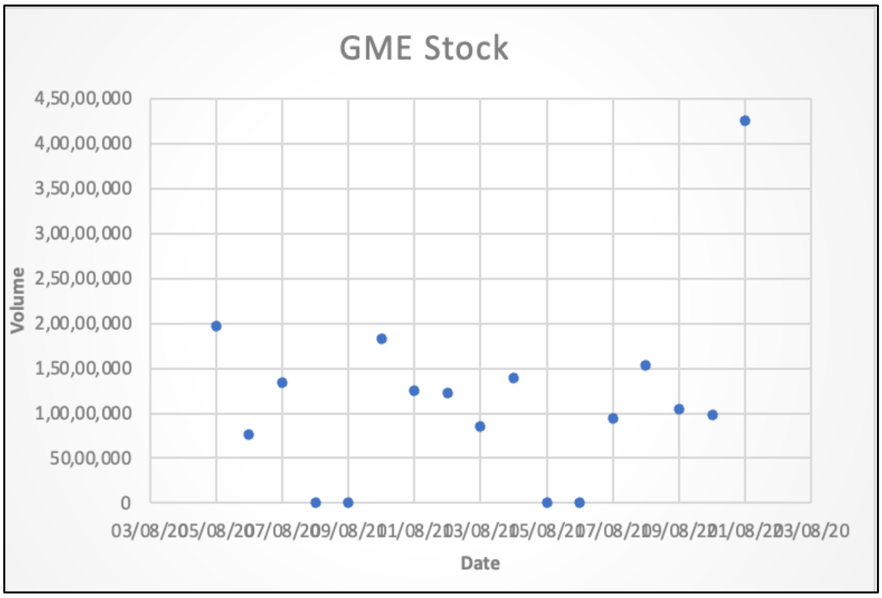

Figure 6: 3/8/20 to 21/8/20 GME stock prices on a scatter plot (source: Yahoo finance)

The chart in the image shows sporadic spikes in trading volume, potentially corresponding to Gill's video releases. This visual representation supports the notion that his content directly influenced trading activity. The dramatic price increase -

from a low of $2.57 in April 2020 to an intraday high of $483.00 on January 28, 2021 (nearly a 190-fold increase) - exemplifies the extraordinary impact of this retail investor movement.

This phenomenon demonstrates the power of social media platforms in mobilizing retail investors and challenging traditional market dynamics. The GameStop short squeeze, driven by this coordinated buying pressure, not only resulted in astronomical gains for early investors but also caused significant losses for hedge funds with short positions. This event has become a landmark case study in the intersection of social media, retail investing, and market volatility, highlighting the potential for decentralized online communities as well as herding behaviour to disrupt established financial paradigms.

Special Mention (Highlighted content in table): Dates 08/08/20, 13/08/20 and 18/08/20 specifies the Youtube release. Figure ‘4,25,70,400’ signifies huge increase in traded volume.

Objective 4:

Case 2

Background

In 2020, the world changed as Covid put a halt to the lives of billions. In person human interaction or any kind of daily activity was disallowed leaving only the online world as a saving grace. In this phase, technology and innovation had no boundaries as the sectors soared to heights. While Covid brought miseries to many, it definitely brought success and growth to the Information and Technology sectors throughout the world.

As human beings were glued to their screens from morning to night, completing their work, talking to their friends and fulfilling entertainment, investors saw a chance to invest into an exciting new opportunity. Tata Consultancy Services (TCS) shares rose from ₹1,860 in March 2020 to ₹3,840 in September 2021 while Infosys too, saw its stock price jump from ₹550 to over ₹1,700 in the same time frame. The sector experienced a tremendous surge. The aftermath of Covid did not only evoke misfortunes, but defined the dramatic rise in demand for IT stocks. Investors solely focused on the resilience of the choice, fuelling the continued investment and sparking what came to be known as ‘The Tech boom”.

Phenomenon

The course of this paper has aimed to evaluate the very instances that have not only changed the perception of the market but have explained the irrationality of an investor. One such concept is the availability bias. Availability bias is defined as a cognitive error where an investor’s tendency to rely on easily recalled information clouds their judgement while making an accurate decision. Throughout history, many investors have experienced getting influenced by this bias and thus making a decision that they may regret later on.

The error occurs due to four factors- Recency, Vividness, Personal Experience and Media Exposure. Each factor was seen during the boom.

1. Recency: The pandemic’s sudden shift to online life made tech advancements feel urgent, contributing to the surge
2. Vividness: Companies like Zoom, Netflix, and many edu-tech apps were used on a daily basis increasing their recall power
3. Personal Experience: Each individual experienced dependency on digital transformation making it a crucial aspect of their Covid experience
4. Media Exposure: News Channels like NDTV 24x7 constantly covered the rise of above-mentioned stocks while tabloids like Hindustan Times, The Economist etc. informed readers about new apps, AI and start-ups in the tech realm.

Together, the factors contributed to forming the availability bias in the minds of the consumers.

Facts and Figures

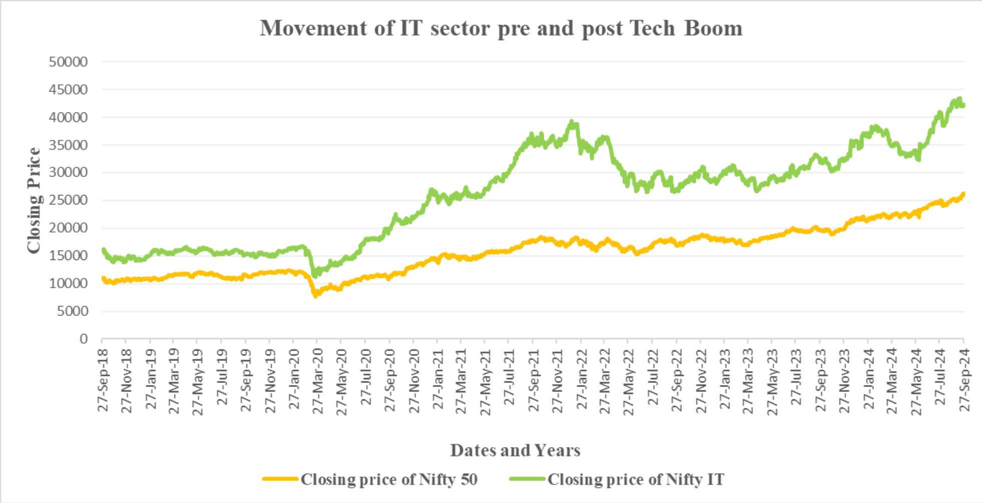

Figure 7: Movement of IT sector and post Tech Boom

Source (Excel)

Figure 7 illustrates the comparison between the closing prices of the indices Nifty 50 (yellow line) and Nifty 50 IT (green line) through a timeline of seven years from 27-09-2018 to 27-09-2024. The graph signifies that the IT sector always performed better than the overall index. However till 27 March 2020, the movement between the two indices was roughly the same. After the announcement of the pandemic isolation took place, the performance of each index dipped, thereafter changing the correlation between the two. Throughout Covid, the IT sector experienced a surge while the Nifty index stayed relatively consistent due to the poor performance of various other sectors. This signifies the Tech boom. In September 2021, the IT index experienced an all-time high with the prices of TCS and Infosys almost doubling within the span of a year as previously mentioned.

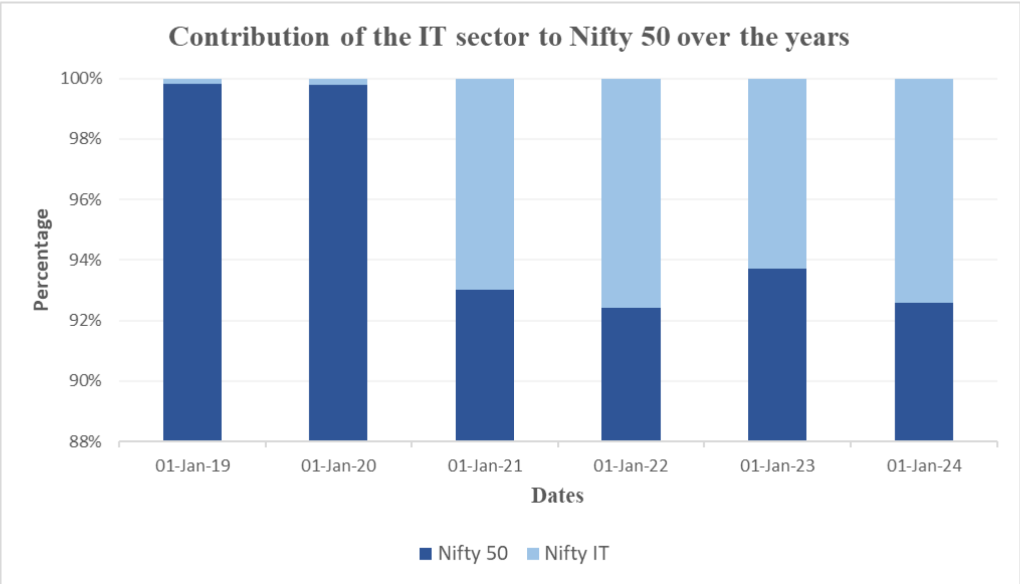

Figure 8: Contribution of the IT Sector to Nifty 50 over 6 years

Source (Excel) (Refer to Appendix)

Figure 8 highlights the contribution of the IT sector through the years. The contribution of the sectors in based on market capitalization of the IT sector divided by the market capitalization of the Nifty 50 Index and converted into a percentage format. As clearly seen, by Jan 2020, the world had not yet experienced the ill-effects nor the tech boom caused by Covid.

However, from January 2021, a spike in the contribution of the tech industry is clearly visible. The percentage contribution heavily increased suggesting and further validating the rise in demand for digital stocks.

While the tech industry has benefited from the spill over effects of the availability bias, the dramatic growth did stabilise in 2023. This viewpoint is magnified through the graphs seen above. As the lockdown was lifted, digital dependency reduced and life returned to normal. The two indices seem to move in tandem once again increasing the correlation between the two. The effect of the bias did decrease but it hasn't completely stopped. The market still continues to associate investment in the tech realm as a sensible choice and still perceives it as a growing industry.

The phenomenon of the availability bias is a prime example of how the human mind can tend to generate a mental shortcut toward processing information. Even though the bias may have probably contributed to an inaccurate decision, it overall concluded to have a dramatic, but positive effect in the long run.

7. Conclusion

Objective 1: Conclusion

The disposition effect strongly influences trader behavior in the Indian stock market. Traders tend to sell winning stocks too early to lock in realized gains, driven by risk aversion in the face of potential profits. This often leads to missing out on paper gains that could have been realized with a longer holding period. Conversely, traders hold onto losing stocks too long, hoping for a recovery, reflecting loss aversion. This reluctance to accept realized losses turns potential small losses into larger ones. Overall, the disposition effect leads to inefficient trading decisions, driven by emotional biases as explained by prospect theory.

Objective 2: conclusion

Traditional risk profiling often overlooks loss aversion, a behavioral bias that significantly influences investment decisions. A novel model calculates loss aversion by analyzing factors such as gain, loss, certainty, previous outcomes, and cognitive load. Incorporating loss aversion into risk profiling can enhance investor categorization and asset allocation decisions, leading to more accurate and tailored recommendations.

Objective 3 and 4: Conclusion

The two scenarios presented above illustrate the significance of behavioural finance and behavioural portfolio theory in the modern market. In the GameStop Saga, the herding behaviour drove retail investors to collectively purchase a large volume of shares that resulted in a surge in the market. This unusual market activity eventually causes a loss for institutional investors. In contrast, the Covid Tech Boom was a result of impulsive action and easily recalled information. The availability bias in investors fuelled the optimism lens with which their decisions were viewed.

To encapsulate, both cases magnify the irrationality of investors that ultimately impact the market toward inaccuracy, no matter how beneficial.

To summarise the findings of the research paper, the analysis showcases the different ways in which behavioural finance and portfolio theory have had an impact on the decision making of individual investors in the market. Therefore we reject the null hypothesis and conclude that the theory does indeed have a significant influence on the investment decision of stakeholders in the financial market.

8. Limitations and Future Scope

<u>Limitations</u>:

Qualitative aspects: The study conducted through the research paper focuses majorly on the qualitative aspects of the concept. The financial market relies heavily on numbers and therefore, lack of quantitative outputs acts as a drawback.

Secondary Data: The data used in the study is majorly secondary data as we did not have access to the required samples and resources to conduct a study at the adequate magnitude. Therefore, lack of primary data could reduce the reliability and validity of our conclusion.

Scope:
Relevance: Behavioural finance and portfolio theory is an upcoming and growing field of study. Therefore, the research conducted needs to be tested repeatedly to justify the relevance

Cause and effect: The basic research needs to be tested on a larger magnitude with a larger sample size in order to accurately develop a cause and effect relationship between biases and the market performance.

Quantitative Modelling: Till now, the biases have been considered to be qualitative factors that lack accurate measurement. With adequate resources and knowledge, the development of a quantitative model that accounts for such risk can be of great use.

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10. Appendix

Table 1

ZEEL Ltd
Average Trades 88146.27935

Winning Days

Date	OPEN	HIGH	LOW	close	52W H	52W L	No of trades	Winning Days	Losing Days	No of trades (Winning Days)	Abnormal Trading (Winning)	No of trades(Losing Day)	Abnormal trading (Losing)
12-Dec-23	285.9	299.7	282.5	289.05	299.7	170.1	239,399	1	0	239399	YES		
10-Aug-23	245.05	290.7	239.05	282.35	290.7	170.1	402,693	1	0	402693	YES		

Losing Days

Date	OPEN	HIGH	LOW	close	52W H	52W L	No of trades	Winning Days	Losing Days	No of trades (Winning Days)	Abnormal Trading (Winning)	No of trades(Losing Day)	Abnormal trading (Losing)
4-Jun-24	158.2	158.3	125.5	138.85	299.7	125.5	151,267	0	1			151267	NO
13-May-24	131.8	132.6	129.25	129.8	299.7	129.25	42,214	0	1			42214	YES
10-May-24	133	133.9	130.15	131.25	299.7	130.15	46,840	0	1			46840	YES
9-May-24	134.95	137.65	130.5	132.15	299.7	130.5	84,808	0	1			84808	YES
6-May-24	145	145.2	135.9	136.4	299.7	135.9	115,199	0	1			115199	NO
28-Mar-24	143	144.65	138	138.55	299.7	138	89754	0	1			89754	YES
20-Mar-24	141.9	143.6	138.35	140.65	299.7	138.35	57,097	0	1			57097	YES
19-Mar-24	143.3	144.8	139.9	140.7	299.7	139.9	51,765	0	1			51765	YES
15-Mar-24	146.95	149.1	141	141.7	299.7	141	93,294	0	1			93294	NO
13-Mar-24	157.5	159.45	141.7	145.25	299.7	141.7	106,793	0	1			106793	NO
6-Mar-24	155.5	156.3	150	154.05	299.7	150	74,754	0	1			74754	YES

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Engineers India
Average Trades 28,255

Date	OPEN	HIGH	LOW	close	52W H	52W L	No of trades	winning days	losing Days	No of tardes (Winning Days)	AbnormaL trading (Winning)
1-Jan-24	172.45	184.8	170.25	181.75	184.8	70.05	125,417	1	0	125417	YES
29-Dec-23	174.3	177.35	169.2	171.45	177.35	70.05	59,553	1	0	59553	YES
28-Dec-23	163.5	175.25	162.05	172.5	175.25	70.05	153,049	1	0	153049	YES
15-Dec-23	169.5	172.6	167	168.2	172.6	70.05	60,614	1	0	60614	YES
14-Dec-23	160.9	171.75	157.7	169	171.75	70.05	165,488	1	0	165488	YES
5-Sep-23	165.75	167.3	161.05	162.3	167.3	62.4	62,305	1	0	62305	YES
24-Aug-23	165.5	166.5	160.15	161.5	166.5	62.4	23,008	1	0	23008	YES
23-Aug-23	160.6	165.9	160	164.1	165.9	62.4	53,550	1	0	53550	YES
22-Aug-23	152.4	161.4	152.05	158.8	161.4	62.4	75,663	1	0	75663	YES
1-Aug-23	158.5	160.7	152.05	155.5	160.7	62.4	45,803	1	0	45803	YES
31-Jul-23	155	160	152.7	158.65	160	62.4	42,577	1	0	42577	YES
28-Jul-23	148	155.6	145.45	154.55	155.6	62.4	54,662	1	0	54662	YES
26-Jul-23	149.15	149.8	145	147.75	149.8	62.4	29,858	1	0	29858	YES
25-Jul-23	142.9	149.8	142	148.25	149.8	62.4	77,219	1	0	77219	YES
24-Jul-23	135.9	142.4	135.6	141.45	142.4	62.4	63,034	1	0	63034	YES
21-Jul-23	129.3	136.8	128	135	136.8	60.6	49,278	1	0	49278	YES
17-Jul-23	130	133.15	127.5	128.75	133.15	60.6	64,292	1	0	64292	YES
14-Jul-23	124	128	122	126.75	128	60	34,866	1	0	34866	YES
13-Jul-23	122	126.8	121.1	122.9	126.8	60	43,457	1	0	43457	YES
12-Jul-23	120.55	124.65	119.5	121.45	124.65	60	36,099	1	0	36099	YES
7-Jul-23	120.15	124.4	119.35	121.75	124.4	58.35	40,727	1	0	40727	YES
6-Jul-23	116.95	123.85	116.2	119.7	123.85	58.35	68,319	1	0	68319	YES
21-Jun-23	121	122.45	117.65	119.4	122.45	56	33,563	1	0	33563	YES
20-Jun-23	115.25	121.45	114.65	120.75	121.45	56	57,082	1	0	57082	YES
19-Jun-23	113.2	115	111.5	114	115	56	24,172	1	0	24172	YES
7-Jun-23	111.95	114.5	111.6	113.3	114.5	56	31,602	1	0	31602	YES
29-May-23	108.65	113.45	105	110.7	113.45	56	95,032	1	0	95032	YES
25-May-23	108.45	111	107.15	110.4	111	56	48,732	1	0	48732	YES
24-May-23	100.4	109.15	99.95	108.55	109.15	56	120,633	1	0	120633	YES
16-May-23	97.4	103.35	96.1	100.3	103.35	56	66,675	1	0	66675	YES
11-May-23	100.6	101.5	97.6	100.05	101.5	56	35,316	1	0	35316	YES
8-May-23	99.4	101.5	97.2	98.9	101.5	56	57,010	1	0	57010	YES
5-May-23	91.9	101.5	91.5	97.5	101.5	56	148,044	1	0	148044	YES
4-May-23	93	98.55	90.3	91.65	98.55	56	91,385	1	0	91385	YES
3-May-23	82.7	97.7	82.1	94.85	97.7	56	178,456	1	0	178456	YES
23-Jan-23	88.9	90.75	87.95	88.9	90.75	56	56,754	1	0	56754	YES
20-Jan-23	84.45	89.35	84.1	87.9	89.35	56	64,140	1	0	64140	YES

Table 2

Table 3

Pearl Polymers
Average Trades 1297.717949

Date	OPEN	HIGH	LOW	close	52W H	52W L	No of trades	Winning Days	Losing Days	No of Trades (Winning Days)	Abnormal Trading (Winning Days)
3-May-24	46.1	48.4	42	42.5	48.4	5.15	7366	1	0	7366	YES
2-May-24	38	44.6	37.6	44.6	44.6	5.15	5463	1	0	5463	YES
27-Feb-24	41.05	43.2	40.25	41.4	43.2	5.15	3130	1	0	3130	YES
26-Feb-24	40.3	41.9	39.2	41.05	41.9	5.15	3931	1	0	3931	YES
23-Feb-24	38.65	41.4	37.65	39.75	41.4	5.15	9537	1	0	9537	YES
15-Dec-23	35.15	40.9	33.5	34.45	40.9	5.15	11561	1	0	11561	YES

Table 4

TATA STEEL
Average Trades 242,909
Winning Days

Date	OPEN	HIGH	LOW	close	52W H	52W L	No of trades	Winning Days	Losing Days	No of trades (Winning Days)	Abnormal Trading (Winning)
18-Jun-24	183.8	184.6	180.6	181.12	184.6	108.1	295,636	1	0	295636	YES
13-Jun-24	183.4	184.1	180.51	182.56	184.1	108.1	332,013	1	0	332013	YES
12-Jun-24	182.25	183.87	181.5	182.23	183.87	108.1	254,524	1	0	254524	YES
11-Jun-24	180.5	183.75	180.5	181.33	183.75	108.1	324,246	1	0	324246	YES
10-Jun-24	180.21	182.1	177.36	180.29	182.1	108.1	320,294	1	0	320294	YES
7-Jun-24	172	179.65	170.8	178.9	179.65	107.8	488,851	1	0	488851	YES
27-May-24	177.7	177.7	174.85	175.5	177.7	105.6	201,390	1	0	201390	NO
24-May-24	174.95	177.55	174.15	174.85	177.55	104.3	227,760	1	0	227760	NO
23-May-24	173.05	175.8	170.5	175.5	175.8	104.3	259,776	1	0	259776	YES
22-May-24	175.45	175.5	171.5	173.3	175.5	104.3	298,848	1	0	298848	YES
21-May-24	168.5	175.2	167.95	174.35	175.2	104.3	450,461	1	0	450461	YES
3-May-24	168.95	170.75	165.15	166.5	170.75	104.05	311,958	1	0	311958	YES
26-Apr-24	168	170.7	165.25	165.8	170.7	104.05	335,513	1	0	335513	YES
9-Apr-24	166	169.8	165.2	166	169.8	104.05	306,316	1	0	306316	YES
8-Apr-24	166.95	166.95	164.2	165.2	166.95	104.05	262,899	1	0	262899	YES
3-Apr-24	164.65	166.25	163.1	163.65	166.25	103.2	358,923	1	0	358923	YES
2-Apr-24	162.95	165.5	161.8	164.65	165.5	103.2	335,307	1	0	335307	YES
1-Apr-24	156.8	163.9	156.5	163.15	163.9	103.2	397,933	1	0	397933	YES
7-Mar-24	152.4	159.15	152.25	157.25	159.15	101.55	569,247	1	0	569247	YES
2-Mar-24	152	156.2	151	155.25	156.2	101.55	139,508	1	0	139508	NO
1-Mar-24	143	150.65	143	149.95	150.65	101.55	452,172	1	0	452172	YES
7-Feb-24	146.85	147.4	144.05	144.4	147.4	101.55	292,894	1	0	292894	YES
6-Feb-24	143	145.1	140.45	144.65	145.1	101.55	256,507	1	0	256507	YES
5-Feb-24	140	143.35	139.35	141.55	143.35	101.55	375,154	1	0	375154	YES
29-Dec-23	138.6	141.25	137.15	139.6	141.25	101.55	234,503	1	0	234503	NO
27-Dec-23	135.85	138.9	135.5	137.2	138.9	101.55	240,022	1	0	240022	NO
19-Dec-23	136.65	137.6	134.8	135.4	137.6	101.55	167,461	1	0	167461	NO
18-Dec-23	136.85	137.6	135.1	136.6	137.6	101.55	259,565	1	0	259565	YES
15-Dec-23	133.4	136.75	133	136.45	136.75	101.55	292,704	1	0	292704	YES
18-Sep-23	135	135	130.05	130.45	135	95	282,655	1	0	282655	YES
14-Sep-23	131	134.2	130.8	131.7	134.2	95	333,183	1	0	333183	YES
12-Sep-23	132.8	133.15	128.65	129	133.15	95	212,107	1	0	212107	NO
4-Sep-23	129.2	132.9	128.85	131.75	132.9	95	342,443	1	0	342443	YES
1-Sep-23	123.5	128.7	123.4	127.05	128.7	95	315,467	1	0	315467	YES

Table 5

Future Retail Ltd
Average Trades 772.6126761

Losing Days

Date	OPEN	HIGH	LOW	close	52W H	52W L	No of trades	Winning days	Losing Days	No of Trades(Losing)	Abnormal Trading (Losing)
27-May-24	1.9	2.1	1.9	2.1	3.95	1.9	750	0	1	750	YES
21-May-24	2	2.1	2	2	3.95	2	640	0	1	640	YES
28-Mar-24	2	2.1	2	2.05	3.95	2	750	0	1	750	YES
27-Mar-24	2.05	2.15	2	2.05	3.95	2	680	0	1	680	YES
7-Mar-24	2.05	2.2	2	2.2	3.95	2	1,100	0	1	1100	NO

Table 6

One 97 Communications
Average Trades 87,737

Winning Days

Date	OPEN	HIGH	LOW	close	52W H	52W L	No of trades	Winning Days	Losing Days	No of Losing Trades	No of Winning Trades	Abnormal Trading (Losing Day)	Abnormal Trading (Winning Day)
20-Oct-23	969.75	998.3	961.9	987.65	998.3	438.35	173,766	1	0		173766		YES
12-Oct-23	981	983.55	951.55	957.55	983.55	438.35	65,638	1	0		65638		NO
11-Oct-23	950	978	946	971.75	978	438.35	124,390	1	0		124390		YES
10-Oct-23	909.95	955	909.95	949.7	955	438.35	125,011	1	0		125011		YES
25-Aug-23	919	938.65	888	899.2	938.65	438.35	180,303	1	0		180303		YES
24-Aug-23	926	931.95	898.2	904.45	931.95	438.35	160,437	1	0		160437		YES
23-Aug-23	863	916.15	863	904.75	916.15	438.35	151,396	1	0		151396		YES

Losing Days

Date	OPEN	HIGH	LOW	close	52W H	52W L	No of trades	Winning Days	Losing Days	No of Losing Trades	No of Winning Trades	Abnormal Trading (Losing Day)	Abnormal Trading (Winning Day)
9-May-24	313.65	333	310	333	998.3	310	53,329	0	1	53329		YES	
8-May-24	331	332	317.15	317.15	998.3	317.15	85,365	0	1	85365		YES	
16-Feb-24	325	341.3	318.05	341.3	998.3	318.05	86,321	0	1	86321		YES	
15-Feb-24	326.7	338.45	325.05	325.05	998.3	325.05	137,126	0	1	137126		NO	
13-Feb-24	403	408	380	380.15	998.3	380	87,564	0	1	87564		YES	
6-Feb-24	395	473.55	395	451.15	998.3	395	305,033	0	1	305033		NO	
5-Feb-24	438.5	438.5	438.5	438.5	998.3	438.5	70,718	0	1	70718		YES	
2-Feb-24	487.2	487.2	487.2	487.2	998.3	487.2	73,737	0	1	73737		YES	

Dates	Nifty 50	Nifty IT
01-Sep-19	12210000	20800
01-Sep-20	12928400	28400
01-Sep-21	6955600	523000
01-Sep-22	6896300	566700
01-Sep-23	5666500	3,80,900
01-Sep-24	5819400	466300

Figure 8: Contribution of the IT Sector to Nifty 50 over 6 years (Exce