Behavioural Finance and Risk Management: Navigating Volatility in the Indian Stock Market with a Focus on Bank Nifty

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***Abstract* - Behavioral finance as well as risk management strategies influence the trading decisions in Bank nifty index in the Indian stock market, this is what this study gets into. The factors examined in the study include psychology-based bias such as overconfidence, loss aversion and herding using a quantitative research approach. It further assesses the use of risk management measures such as Value-at-Risk and performance measures and their relevance in market volatility. A structured survey was carried out on 200 traders and the results show strong evidence of a correlation between behavioral finance factors and the trading decisions made by their subjects. Value addition for this insight is the fact that risk management measures are strong determinants in curtailing the effects of volatility. These insights assist in improving decision making constructs and strengthening the trading environment, especially in very volatile markets such as Bank Nifty.**

***Index Terms*— Behavioural Finance, Risk Management, Bank Nifty, Volatility**

I. INTRODUCTION

The global financial markets have witnessed a profound change and have become more complicated and unpredictable. Political instability and macroeconomic developments can affect financial market volatility (Albulescu, 2020; Onan et al., 2014). This calls for the need to understand better the driving variables that affect trading behavior. An evolving area, behavioral finance assists in understanding how psychological biases affect trader behavior especially in times of risk and uncertainty in the market. This research explores the role of behavioral finance in influencing trading decisions with special emphasis on the Bank Nifty index, which is a representative index for the banking sector in the Indian Stock Market. In addition, it investigates the impact of employing risk management hedging strategies on the fluctuations of the trading results. The Bank Nifty index is a pivotal component of the Indian stock market, characterized by high liquidity and significant volatility, making it an ideal subject for analyzing trader behavior under dynamic market conditions. Previous studies have highlighted the prevalence of psychological biases, such as overconfidence, loss aversion, and herding, which often lead to suboptimal decision-making. Overconfidence can result in excessive trading and risk-taking, while loss aversion may cause traders to hold onto losing positions, exacerbating losses. Herding behavior, on the other hand, often leads to market inefficiencies and increased volatility. By exploring the interplay between these biases and trading decisions, this research seeks to uncover the underlying psychological factors influencing traders in the Indian context. Furthermore, analysing the correlation between index concentration and performance is increasingly pertinent in an age of rising index fund popularity. Research indicates that the equal-weighted index surpasses the market-weighted index (Tabner, 2009; Amenc et al., 2016; Malladi & Fabozzi, 2017; Abadi & Silva, 2019) and is considered for portfolio performance optimization (Taljaard & Mare, 2021). Passive investors allocate their capital to index-based funds for apparent diversification; yet, index concentration may undermine their expectations by increasing idiosyncratic risk. Sorensen et al. (2022) identified a robust association between the monetary system and the concentration of benchmark indices that enhance the significant performance benefit of stock price weighting.

Effective risk management strategies are equally crucial for navigating volatile markets. Techniques such as diversification, stop-loss orders, and portfolio rebalancing are instrumental in minimizing potential losses and stabilizing returns during turbulent periods. The interplay between risk management practices and market volatility has been extensively studied in global markets; however, their application within the Indian stock market, particularly in the context of the Bank Nifty, remains underexplored. Numerous recent research investigates the impact of economic policy uncertainty on financial volatility (Antonakakis et al., 2019, 2013; Mei et al., 2018; Strobel et al., 2018; Su et al., 2019). This study aims to bridge this gap by evaluating how traders leverage risk management strategies to counteract the effects of psychological biases and enhance trading outcomes. While the findings of this study promise to contribute valuable insights for traders, investors, policymakers, and financial institutions. This research aims to provide a comprehensive understanding of the influence of behavioral finance and risk management practices on trading decisions, with a focus on the Bank Nifty index. By examining the relationship between psychological biases, risk management strategies, and market volatility, the study seeks to offer actionable insights for improving decision-making and developing robust risk management frameworks in the Indian stock market.

II. LITERATURE REVIEW

The evaluated literature addressed behavioural finance, risk management, and market volatility to understand trading decisions in dynamic financial markets. Seven market proxies ADR, PCR, trading volume, mutual fund net flows, and IPO activity were used to create a composite investor sentiment index. After removing macroeconomic factors including inflation, interest rates, and currency rates, Principal Component Analysis (PCA) was used to generate a sentiment index indicating investor irrationality. The emotion indicator boosts market excess returns. Negative emotion lowers return, while positive sentiment raises them. Negative sentiment changes affect returns more than positive ones. The emotion measure predicts 27% of excess return changes, demonstrating its importance. Investor sentiment asymmetrically affects stock market returns and volatility. A bullish emotion change lessens volatility, while a bearish one increases it. Behavioural finance theories explain this asymmetry, gloomy mood increases risk. At three-month lags, excess returns and investor sentiment are bidirectional. Market performance strongly influences investor sentiment, suggesting that returns modify sentiment more than sentiment predicts returns (Naik & Padhi, 2016).

The sentiment index uses six market-based proxies: trade volume, put-call ratio (PCR), advance-decline ratio (ADR), market turnover, share turnover, and IPOs. The sentiment index was created using Principal Component Analysis (PCA) to capture the most important investor sentiment drivers. Investor irrationality drives Indian stock market volatility, as sentiment strongly contributes. Negative sentiment induces market withdrawal, heightening volatility, while positive sentiment encourages speculation. Positive emotion increases excess market returns, overvaluation, and speculative trading. As investors flee, negative sentiment increases market volatility and unfavorable patterns. The GARCH (1,1) model showed volatility clustering and shock persistence. A weak-efficient market was indicated by high mean-reversion rates. Investor mood Granger drives market volatility, but not sentiment. This shows that irrational investor sentiment drives volatility rather than reacting to it (PH & Rishad, 2020).

Futures markets responded more strongly to shocks than spot markets, and spot and futures markets had bidirectional volatility spillovers, indicating mutual influence. Large-cap firms influenced mid-cap firms' volatility more than vice versa. Total volatility spillovers peaked during COVID-19, according to dynamic analysis. Large-cap corporations often received volatility from Brexit and COVID-19 in the Greek stock market (Apostolakis et al., 2021). Latent uncertainty had a longer lasting and greater impact on stock market volatility, especially in post-2007, and the latent macroeconomic uncertainty factor beat VIX in projecting volatility and jump risks. The financial sector was most sensitive to latent macroeconomic uncertainty, indicating its vulnerability to shocks. Clear macroeconomic policies can minimize latent macroeconomic uncertainty, stabilizing stock market volatility and reducing financial sector risks (Megaritis et al., 2021).

Higher U.S. economic policy uncertainty (EPU), financial uncertainty (VIX), credit market instability, rising commodity prices, and pandemic news boost emerging market stock market volatility. EPU increases asymmetries and macroeconomic spillovers, affecting stock volatility. The 2008 financial crisis and COVID-19 pandemic increased macroeconomic drivers' volatility-causing systemic danger. Crisis-era bond spreads and commodity prices generate considerable spillovers, heightening volatility. The pandemic-induced infectious disease news index (ID EMV) drove volatility, especially during COVID-19. Compared to GARCH specifications, the macro-augmented HEAVY model predicted volatility better. The addition of high-frequency macroeconomic variables greatly increased modelling accuracy (Karanasos et al., 2022; Wang, 2020).

NASDAQ 100, JSE 40, and NIFTY 100 have increased concentration, while CSI 100 have declined. Only NASDAQ 100 showed a high positive association between index variance and concentration. Component securities' variance rarely counteract index variance, especially in high concentration (Pandey & Sharma, 2023). NSE indices were more volatile during the COVID-19 epidemic. The Nifty Realty Index was the most volatile during the pandemic, whereas Nifty FMCG and Nifty Auto were less volatile. The highest returns pre-COVID-19 were in Nifty IT, but post-COVID-19, Nifty FMCG outperformed. During the epidemic, Nifty Bank, Nifty Metal, and Nifty IT returned more than before. Advanced GARCH models (GARCH (1,1), GJR-GARCH (1,1), and EGARCH (1,1)) for volatility dynamics. EGARCH models better captured volatility's asymmetric effects across all periods. The epidemic increased investor risk but also offered superior profits in some indices. Volatility clustering and leverage effects increased return sensitivity to market shocks (Mamilla et al., 2023).

Brazil and New York benefited from Indian market volatility, but China, Russia, and Mexico did not. China, Russia, and New York caused negative volatility spillovers to India. India saw moderate negative spillovers from Mexico, indicating increased interconnection and market sensitivity. India was closely tied to Brazil, Russia, and New York pre-COVID-19. India and Mexico correlated better post-COVID-19, while Brazil and New York correlated less. Global market interdependencies have changed. The VAR-BEKK-GARCH model showed that volatility persistence increased post-COVID, particularly for Brazil, Russia, and China. Post-COVID, India's volatility increased in response to market shocks. Pre-COVID, Indian market shocks had a limited, short-term impact on foreign markets. Post-COVID, India's response to global market shocks was stronger in the short term but less so over time, demonstrating efficient market adjustments. Indian IT and healthcare sectors recovered faster from the epidemic (Maharana et al., 2024). Overall, the evaluated research explains stock market volatility

III. OBJECTIVES AND METHODOLOGY

This study examined risk management strategies in addressing market volatility and employed a quantitative research methodology to assess the impact of behavioral finance and risk management techniques on trading decisions in the Bank Nifty index. The target audience comprises traders engaged in the Bank Nifty market, with a sample size of 200 traders chosen via non-probability convenience sampling. A survey methodology is utilized for data collection through a structured electronic questionnaire. The research seeks to elucidate trader behavior and decision-making, especially under volatile market conditions, thereby aiding the formulation of more effective trading and risk management strategies.

Input-Process-Output Model

Input	Process	Output
Behavioural Finance Factors (e.g., overconfidence, loss aversion, herding behaviour)	Analysis of psychological biases impacting trading decisions.	Impact on Trading Decisions in Bank Nifty
Market Volatility (e.g., price fluctuations, uncertainty)	Evaluation of risk management practices and their adaptation to volatility.	Effectiveness of Risk Management Practices
Risk Management Practices (e.g., risk-adjusted performance metrics, Value-at-Risk)	Examination of the relationship between market volatility and trading behaviour.	Correlation between Volatility and Trading Outcomes

Analysis and Discussions

For descriptive analysis of the demographic data of 200 respondents, the analysis would typically involve summarizing the frequency distribution of each demographic response.

Table 1: Demographic profile of the respondents

Response Options	Frequency (N=200)	Percentage (%)
Age		
a) 18-25	45	22.5%
b) 26-35	60	30%
c) 36-45	50	25%
d) 46-55	30	15%
e) 55+	15	7.5%
Occupation		
a) Student	30	15%
b) Professional/ Employee	100	50%
c) Business Owner	40	20%
d) Retired	15	7.5%
e) Other	15	7.5%
Trading in the Stock Market		
a) Less than 1 year	40	20%
b) 1-5 years	80	40%
c) 6-10 years	50	25%
d) More than 10 years	30	15%
Type of Trading		
a) Positional Trader	90	45%
b) Option Trader/Investor	50	25%
c) Hedger	40	20%
d) Other	20	10%
Sector You Trade		
a) Banking & Financial	150	75%
b) Others	50	25%

Source: Primary Data

The bulk of traders are 26–35, followed by 36–45, reflecting a young, active population. The lower percentage of elderly traders (55+) shows that younger generations are more likely to trade stocks, especially in high-volatility markets like Bank Nifty. Half of the respondents are professionals, showing that stock trading appeals to working people as well as business owners and retirees. Part of it is in business, showing stock market entrepreneurship. Most responders are somewhat experienced traders, with 40% having 1-5 years of experience and 25% 6-10 years. The 20% shows new traders are becoming more interested in less than a year. Positional traders make up the majority, demonstrating they prefer medium-term tactics to speculative or long-term investments. The large number of option traders and hedgers suggests risk management and short-term speculation. Given Bank Nifty, many traders focus on banking and finance. Only 25% trade in other sectors, demonstrating that while diversification occurs, banking remains the focus. This descriptive research of Bank Nifty traders' demographics and trading preferences might inform volatility management and trading behavior analysis.

Table 2: Behavioral Finance Factors and Trading Decisions in Bank Nifty

Variables	Overconfidence	Loss Aversion	Herding Behavior	Trading Decisions
Overconfidence	1.00	0.55**	0.60**	0.63**
Loss Aversion	0.55**	1.00	0.50**	0.45**
Herding Behavior	0.60**	0.50**	1.00	0.55**
Trading Decisions	0.63**	0.45**	0.55**	1.00

Source: Primary Data – SPSS Output

Significant positive correlations were found between behavioral finance factors (overconfidence, loss aversion, and herding behavior) and trading decisions in the Bank Nifty. This suggests that psychological biases influence trading decisions in Bank Nifty.

Table 3: Risk Management Practices and Market Volatility

Variables	Value-at-Risk	Performance Metrics	Volatility Navigation
Value-at-Risk	1.00	0.62**	0.58**
Performance Metrics	0.62**	1.00	0.71**
Volatility Navigation	0.58**	0.71**	1.00

Source: Primary Data – SPSS Output

Risk management practices, including Value-at-Risk and performance metrics, show significant positive correlations with market volatility navigation. This implies that effective risk management is critical for navigating periods of market volatility in the Indian stock market.

Table 4: Market Volatility and Trading Outcomes

Variables	Market	Trading	Trading

	Volatility	Strategies	Outcomes
Market Volatility	1.00	0.72**	0.72**
Trading Strategies	0.72**	1.00	0.64**
Trading Outcomes	0.72**	0.64**	1.00

Source: Primary Data – SPSS Output

There is a strong significant relationship between market volatility and trading outcomes, demonstrating that changes in volatility directly affect traders' decisions and behaviours in the Indian stock market.

IV CONCLUSION

The research underscores the profound impact of behavioral finance and risk management practices on trading decisions and outcomes in the Bank Nifty index. Psychological biases such as overconfidence, loss aversion, and herding significantly shaped trader behavior, often leading to suboptimal decisions during volatile market conditions. Effective risk management strategies, particularly those involving Value-at-Risk and performance metrics, play a pivotal role in mitigating these challenges by enhancing traders' ability to navigate market fluctuations. The study emphasizes the need for improved investor education and adaptive strategies to address psychological biases and foster disciplined trading practices. These findings provide actionable insights for traders, policymakers, and financial institutions, aiming to develop more robust frameworks for risk management and decision-making in the Indian stock market.

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