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Recalibrating Rationality: A Multidimensional Analysis Of Behavioral Biases, Herd Mentality, And Market Anomalies In Post-Pandemic Equity And Credit Markets

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***Abstract* – The COVID-19 pandemic fundamentally disrupted global financial markets, exposing profound deviations from traditional rational expectations theory and the Efficient Market Hypothesis. This study investigates the interplay of behavioral biases, herd mentality, and market anomalies in shaping post-pandemic financial dynamics across equity and credit markets. Drawing on behavioral finance frameworks and bounded rationality theory, the research examines how cognitive distortions—including overconfidence, loss aversion, and confirmation bias—influenced investment decisions, while herd behavior amplified sys- temic risks and speculative bubbles.Employing a comprehensive mixed-method approach, the study combines econometric analysis of high-frequency financial data spanning January 2020 to December 2024 with survey-based behavioral experiments. The empirical framework tests hypotheses concern- ing the persistence of irrational investor behavior and its correlation with observable market anomalies. The findings indicate that behavioral biases exhibit statistically significant uni- directional causality toward market efficiency ($F = 41.9166$, $p = 1 \times 10{-}18$), whereas mo- mentum effects demonstrate bidirectional relationships with trading volume (with p-values as low as $7 \times 10{-}97$).Panel regression results reveal that behavioral biases negatively affect daily returns (co- efficient = -0.3945, $t = -24.4895$), suggesting systematic distortions in price formation. Furthermore, Vector Error Correction Model (VECM) analysis confirms the existence of long-run equilibrium relationships with significant error correction mechanisms, highlight- ing structural adjustments in post-crisis financial systems. Variance decomposition analysis shows that momentum explains an increasing share of behavioral bias variations over time, rising from 6.11% to 55.28% across ten forecast periods.These findings necessitate a multidimensional recalibration of rationality that integrates structural, psychological, and regulatory dimensions of post-crisis financial behavior. The study contributes to behavioral finance literature and provides actionable policy recom- mendations for market regulation, investor protection frameworks, and systemic resilience strategies across developed and emerging economies.**

***Keywords* – Behavioral Finance; COVID-19; Herd Behavior; Market Anomalies; Momentum Effects; Vector Error Correction Model; Market Efficiency; Post-Pandemic Financial Markets.**

I. INTRODUCTION

The COVID-19 pandemic dramatically reshaped global financial markets, revealing the pro- found extent to which real-world investor behavior deviates from long-standing economic as- sumptions of rationality and efficiency. While the Efficient Market Hypothesis (EMH) and rational expectations models traditionally suggest that individuals calmly interpret information and make optimal utility-maximizing decisions, the panic-driven volatility observed during the pandemic exposed the psychological fragility of financial participants and the inherent limita- tions of conventional theoretical frameworks (Shiller, 2003). Historically, major financial crises including the South Sea Bubble (1720), the Great Depression (1929), the Dot-com crash (2000), and the Global Financial Crisis (2008) have repeatedly demonstrated that markets are destabi- lized by waves of optimism, fear, and herd-driven behavior (Kahneman and Tversky, 1979). Yet the pandemic amplified these behavioral tendencies to unprecedented extremes, with investors worldwide grappling with acute uncertainty, flooding into speculative assets, and contributing to meme-stock rallies, cryptocurrency booms, and credit market distortions that fundamentally defied fundamental valuation metrics (Korniotis and Kumar, 2021).

Behavioral finance provides a robust explanatory framework for understanding such pat- terns by emphasizing the role of cognitive biases including overconfidence, confirmation bias, anchoring, and loss aversion, alongside social influences that drive herd mentality (Barberis et al., 1998). These psychological factors generate momentum effects, systematic mispricing, as- set bubbles, and cascading market crashes that are not random anomalies but rather systematic and predictable deviations embedded in human psychology (Daniel et al., 1998). Herd behav- ior theories pioneered by Banerjee (1992) and Bikhchandani et al. (1992) demonstrate how information asymmetry and peer imitation create irrational cascades, while prospect theory de- veloped by Kahneman and Tversky (1979) explains why investors become risk-seeking during losses, thereby intensifying market instability. The pandemic therefore served as a real-time laboratory where bounded rationality, emotional contagion, and the proliferation of social trad- ing platforms collectively reshaped market outcomes in ways that challenge traditional financial orthodoxy.

The empirical landscape of post-pandemic financial markets presents a compelling puzzle for researchers and policymakers alike. In early 2020, global equity markets experienced one of the fastest declines in history, with the S&P 500 falling 34% in just five weeks, only to rebound with extraordinary vigor, reaching new all-time highs within months (Baker et al., 2020). This V-shaped recovery defied conventional economic logic, particularly given the simultaneous con- traction in global GDP and rising unemployment. Credit markets exhibited equally perplexing behavior, with corporate bond spreads widening dramatically during the March 2020 selloff before compressing rapidly following Federal Reserve intervention (Gilchrist et al., 2024). The emergence of meme stocks in early 2021, epitomized by GameStop and AMC Entertainment, demonstrated how retail investors coordinated through social media platforms could collec- tively challenge institutional short-sellers and fundamentally alter price discovery mechanisms (Lyo´csa et al., 2022). These phenomena collectively suggest that traditional models of ratio- nal expectations and market efficiency require fundamental recalibration to accommodate the psychological and social dimensions of investor behavior.

The theoretical foundations of this study rest upon the intersection of classical finance the- ory and behavioral economics. The Efficient Market Hypothesis, as articulated by Fama (1970), asserts that asset prices fully reflect all available information, making it impossible for investors to consistently achieve abnormal returns. However, persistent market anomalies including mo- mentum effects (Jegadeesh and Titman, 1993), value premiums (Fama and French, 1992), and post-earnings announcement drift (Bernard and Thomas, 1989) have consistently challenged the empirical validity of strong-form market efficiency. The Adaptive Market Hypothesis proposed by Lo (2004) offers a synthesis, suggesting that market efficiency is not a binary condition but rather a continuum that evolves with market conditions, institutional structures, and investor behavior. This perspective aligns with the bounded rationality framework introduced by Si- mon (1955), which recognizes that cognitive limitations and informational constraints prevent investors from achieving perfect rationality in decision-making.

The post-pandemic period provides a unique natural experiment for examining behavioral finance propositions under extreme conditions. The convergence of multiple factors includ- ing unprecedented monetary and fiscal policy responses, accelerated digital transformation in financial services, the rise of commission-free trading platforms, and the amplification of so- cial media influence on investment decisions created an environment where behavioral biases could manifest with particular intensity (Ozili and Arun, 2020). Understanding these dynam- ics is essential not only for academic theory development but also for practical applications in investment management, risk assessment, and regulatory policy design. The persistence of be- havioral anomalies in post-pandemic markets raises fundamental questions about the nature of rationality in financial decision-making and the appropriate frameworks for modeling investor behavior.

This study addresses the central research problem: How can rationality in financial markets be recalibrated by incorporating herd mentality, behavioral biases, and market anomalies in the post-pandemic period? The research objectives are: (1) to examine the causal relationships be- tween behavioral biases, momentum effects, and market efficiency in equity and credit markets; (2) to quantify the impact of behavioral factors on daily stock returns using advanced econo- metric methodologies; (3) to investigate long-run equilibrium relationships between behavioral variables and market outcomes through cointegration analysis; (4) to analyze the dynamic trans- mission of behavioral shocks through variance decomposition and impulse response functions; and (5) to develop evidence-based policy recommendations for regulatory authorities, financial institutions, and investors.

The significance of this research extends across multiple dimensions. Theoretically, it con- tributes to the ongoing paradigm shift in financial economics toward more psychologically- grounded models of market behavior by validating behavioral propositions in the important context of emerging markets while providing robust methodological frameworks for their ex- amination. Empirically, the study offers comprehensive evidence from the Indian equity market, which represents one of the world's fastest-growing major economies with distinctive institu- tional characteristics and investor demographics. Practically, the findings inform regulatory policy development, investment management practices, corporate financial decision-making, and individual investor education programs. By bridging theoretical propositions with empiri- cal validation, this research supports the continued integration of behavioral insights into both financial theory and practice.

The structure of this paper proceeds as follows: Section 2 presents a comprehensive review of the theoretical and empirical literature on behavioral finance, herd mentality, and market anomalies. Section 3 develops the theoretical framework and formulates testable hypotheses. Section 4 describes the research methodology, including data sources, variable construction, and econometric specifications. Section 5 presents the empirical results and discusses their im- plications. Section 6 concludes with policy recommendations and directions for future research.

II. LITERATURE REVIEW

Theoretical Foundations of Behavioral Finance

Behavioral finance has fundamentally reshaped financial economics by demonstrating that in- vestors are not the fully rational decision-makers assumed under traditional finance models. Instead, they are susceptible to cognitive biases and emotional influences that systematically distort judgment and lead to predictable market anomalies (Thaler, 1999). The theoretical foun- dations of behavioral finance can be traced to the pioneering work of Kahneman and Tversky (1979), who developed prospect theory as an alternative to expected utility theory. Prospect the- ory posits that individuals evaluate outcomes relative to a reference point, exhibit loss aversion (feeling losses more acutely than equivalent gains), and demonstrate diminishing sensitivity to both gains and losses. These behavioral tendencies generate systematic patterns in financial decision-making, including the disposition effect where investors hold losing stocks too long and sell winning stocks too quickly (Shefrin and Statman, 1985).

The concept of bounded rationality, introduced by Simon (1955), provides another founda- tional pillar for behavioral finance. Simon argued that cognitive limitations and informational constraints prevent individuals from achieving perfect rationality in decision-making, leading them to satisfice rather than optimize. In financial markets, bounded rationality manifests through heuristic-driven decision-making, where investors rely on mental shortcuts that may produce systematic errors (Tversky and Kahneman, 1974). These heuristics include represen- tativeness (judging probabilities based on similarity), availability (assessing frequency based on ease of recall), and anchoring (fixating on initial reference points). Barberis et al. (1998) integrated these insights into a comprehensive framework explaining how investor sentiment generates underreaction and overreaction in asset prices.

Cognitive Biases in Financial Decision-Making

Overconfidence represents one of the most extensively documented cognitive biases affecting investor behavior. Barber and Odean (2001) demonstrated that overconfident investors trade excessively, reducing their net returns, with male investors exhibiting greater overconfidence than female investors. Overconfidence manifests through miscalibration (excessive precision in probability assessments), the better-than-average effect, and illusion of control (Moore and Healy, 2008). In emerging markets, Rehman et al. (2025) identified overconfidence as a dom- inant predictor of irrational market decisions, revealing inefficiencies beyond rational financial assumptions. The persistence of overconfidence despite negative feedback suggests that this bias is deeply ingrained in human psychology and resistant to learning (Gervais and Odean, 2001).

Loss aversion, a central insight from prospect theory, explains why investors exhibit asym- metric responses to gains and losses. Oken and Odean (2000) found that loss-averse investors require substantially higher expected returns to accept risky positions, contributing to the eq- uity premium puzzle. In credit markets, loss aversion influences lending decisions, with loan officers becoming excessively conservative following default experiences (Perera and Rodrigo, 2020). Chand (2024) documented pronounced loss aversion in South Asian markets, where in- vestors cling to losing positions irrationally to avoid realizing losses, thereby delaying portfolio adjustment and amplifying downside risk exposure.

Anchoring bias occurs when individuals fixate on specific reference points when making numerical judgments. Phan and Zhou (2014) demonstrated anchoring effects in the Vietnamese stock market, where investors rely on historical price levels when valuing stocks. Kaustia (2006)

found that IPO offer prices anchor subsequent trading ranges, while George and Hwang (2004) documented anchoring in analyst earnings forecasts. Confirmation bias, the tendency to seek in- formation confirming existing beliefs while discounting contradictory evidence, leads investors to maintain positions despite contrary information (Nickerson, 1998). This bias contributes to momentum effects and delayed price adjustment to news (Rabin and Schrag, 1998).

Herd Mentality and Social Contagion

Beyond individual psychology, market behavior is fundamentally governed by collective dy- namics such as herding and sentiment contagion. Banerjee (1992) formally modeled herding behavior under uncertainty, demonstrating that rational individuals may ignore private informa- tion to follow observed actions of predecessors, generating informational cascades. Bikhchan- dani et al. (1992) extended this framework, showing that herding can arise from reputational concerns, compensation structures, and information aggregation mechanisms. Empirical ev- idence from Chang et al. (2000) established significant herding across Asian financial mar- kets, particularly during periods of market stress. Truong (2019) documented similar behavior among Vietnamese investors during turbulence, intensifying volatility and accelerating price movements.

The pandemic period witnessed unprecedented herding behavior facilitated by social me- dia platforms. Korniotis and Kumar (2021) documented a strong positive correlation between social media activity and market volatility during meme-stock episodes, with retail traders on platforms like Reddit's WallStreetBets coordinating buying pressure to challenge institutional short positions. Surveys of these new traders identified fear of missing out (FOMO), herd in- stinct, and speculative motivation as primary drivers of trading activity (Alnassar and Alsham- mari, 2021). This modern manifestation of herding demonstrates how technology amplifies traditional behavioral patterns, creating new channels for sentiment transmission and market coordination.

Investor sentiment has emerged as a crucial driver of asset prices, with extensive empiri- cal evidence supporting its influence on returns. Baker and Wurgler (2006) demonstrated that sentiment predicts cross-sectional returns, with speculative, hard-to-arbitrage stocks exhibiting greater sensitivity to sentiment fluctuations. ? showed that U.S. consumer confidence corre- lates positively with returns, underscoring that emotions often overpower fundamental valua- tions during certain market regimes. Song (2025) introduced sentiment-based volatility model- ing, finding that market optimism reduces crash probability while pessimism triggers extended downturns. Natural language processing techniques have enabled more sophisticated sentiment measurement; Zuniga-Cedillo et al. (2025) validated strong sentiment-price feedback loops in the Mexican market using web scraping and NLP methodologies.

Market Anomalies and Efficiency Challenges

The Efficient Market Hypothesis, championed by Fama (1970) and Fama (1998), claims that prices fully reflect all available information, precluding systematic profit opportunities. How- ever, persistent market anomalies challenge this proposition. Momentum effects, documented by Jegadeesh and Titman (1993) and Carhart (1997), demonstrate that past winners continue to outperform past losers over intermediate horizons, generating positive risk-adjusted returns. Hong and Stein (1999) developed a unified theory explaining momentum through gradual infor- mation diffusion and investor underreaction. Value anomalies, where stocks with low prices rel- ative to fundamentals outperform growth stocks, were documented by Fama and French (1992) and Lakonishok et al. (1994), challenging risk-based explanations.

Post-earnings announcement drift, where prices continue moving in the direction of earnings surprises for extended periods, represents another persistent anomaly (Bernard and Thomas, 1989; Chan et al., 1996). Shiller (2000) attributed speculative bubbles to psychological feedback loops rather than rational valuation, while De Bondt and Thaler (1985) documented long-term overreaction and reversal patterns. These anomalies collectively suggest that market efficiency is not a universal property but rather varies across time, markets, and institutional contexts. The Adaptive Market Hypothesis proposed by Lo (2004) reconciles these observations by arguing that markets evolve dynamically rather than maintaining static rational equilibrium, with effi- ciency emerging from evolutionary processes of learning, competition, and institutional adap- tation.

Behavioral Finance in Credit Markets

Behavioral finance research has expanded beyond equity markets to examine credit market dy- namics. In banking and credit sectors, cognitive predispositions significantly affect loan orig- ination, pricing, and repayment decisions. Perera and Rodrigo (2020) found that perceived behavioral control and subjective norms significantly influence repayment intentions among borrowers. Organizational decision-making in lending institutions is similarly vulnerable to behavioral biases, with overconfidence and herd mentality shaping credit approval decisions during boom periods and excessive conservatism during downturns (Ranjan, 2025). Elmagdob and Aboubaker (2025) demonstrated that similar behavioral patterns drive household financial welfare outcomes, highlighting the broad applicability of behavioral finance beyond institu- tional market contexts.

The pandemic exposed distinctive behavioral dynamics in credit markets. During the March 2020 selloff, investors simultaneously demanded cash and insurance, causing the safest corpo- rate bond yields to spike and inverting the usual upward-sloping term structure of credit spreads (Haddad et al., 2021). This ”dash for cash” phenomenon overwhelmed normal credit pric- ing mechanisms, requiring central bank intervention to restore market functioning. Gilchrist et al. (2024) showed that Federal Reserve announcements of corporate bond-buying programs significantly reduced investment-grade credit spreads and restored normal term structure rela- tionships. These episodes demonstrate that even sophisticated institutional investors in credit markets are susceptible to herd psychology and panic-driven behavior, eroding assumptions that credit spreads solely reflect fundamental credit risk.

Cross-Cultural Dimensions and Institutional Context

The impact of behavioral biases varies systematically across cultural and institutional contexts. Hofstede (2001) cultural dimensions framework explains how social values influence financial decision-making, with individualism, uncertainty avoidance, and long-term orientation affect- ing risk preferences and trading behavior. Empirical studies affirm such heterogeneity: Al- Tamimi (2006) linked UAE investment behavior to cultural norms, while Chand (2024) and Bangladesh (2024) highlighted pronounced loss and regret aversion driving inefficiencies in South Asian markets. Low financial literacy emerges as a structural barrier in emerging mar- kets, exacerbating susceptibility to behavioral biases (Sarin and Nair, 2019).

The institutional environment significantly moderates behavioral effects. Market regula- tions, disclosure requirements, trading mechanisms, and investor protection frameworks shape the environment within which behavioral biases manifest (La Porta et al., 2006). Morck etal. (2000) demonstrated that stock price synchronicity varies across countries based on property rights protection and corporate governance quality. In India, the Securities and Exchange Board of India (SEBI) has implemented various investor protection measures that may moderate be- havioral excesses, though their effectiveness requires systematic evaluation (Gupta and Iyer, 2024).

Computational Behavioral Finance and Methodological Innovations

A defining evolution in behavioral finance is the integration of technology and computational methods, giving rise to Computational Behavioral Finance. Machine learning models incor- porating behavioral indicators, particularly sentiment measures, deliver enhanced market pre- diction accuracy. Rezaei et al. (2025) demonstrated that hybrid models combining technical indicators with sentiment variables outperform traditional forecasting approaches. In the Indian context, Dash and Mishra (2024) showed that hybrid deep-learning approaches incorporating NLP sentiment metrics significantly outperform conventional time-series models. Bhuyan et al. (2024) enhanced prediction interpretability through knowledge-graph-based modeling, illustrat- ing how behavioral insights can be computationally operationalized for practical applications.

Natural language processing has revolutionized sentiment measurement in financial mar- kets. Loughran and McDonald (2011) developed finance-specific dictionaries for sentiment analysis, recognizing that general-purpose lexicons misclassify financial text. Tetlock (2007) demonstrated that media sentiment predicts market returns and trading volume. Zhou and Li (2022) provided comprehensive methodological guidance for NLP applications in market senti- ment analysis. These developments reflect an emergent shift toward holistic market-understanding frameworks combining behavioral theory, econometrics, and artificial intelligence.

Financial Literacy as a Corrective Mechanism

Across the literature, financial literacy emerges as a potential corrective mechanism for behav- ioral biases. Empirical evidence consistently shows that higher financial literacy reduces sus- ceptibility to biases like herding and overconfidence. Almansour et al. (2025) found that finan- cially literate investors demonstrate better risk perception and more rational decision-making. Lusardi and Mitchell (2014) documented substantial welfare costs associated with financial il- literacy, while Van Rooij et al. (2009) showed that literacy improves retirement planning and wealth accumulation. In emerging markets, low literacy exacerbates heuristic-driven trading, signaling urgent policy needs for investor education programs (Bangladesh, 2024).

Research Gaps and Contributions

Despite the expanding behavioral finance literature, several critical research gaps persist. First, post-pandemic market realities remain insufficiently integrated into financial theory, particu- larly regarding the combined and interacting influence of multiple biases under extreme stress conditions. Second, much existing research relies on cross-sectional survey data rather than longitudinal or experimental studies, limiting causal inference. Third, cultural context hetero- geneity and intervention effectiveness remain significantly underexplored, with limited empiri- cal evaluation of debiasing programs, regulatory reforms, and scalable investor education tools. Fourth, the integration of behavioral factors into formal asset pricing models remains underde- veloped, with limited guidance for practitioners seeking to incorporate behavioral insights into investment processes.

This study addresses these gaps by: (1) providing comprehensive empirical evidence from the post-pandemic period using high-frequency daily data; (2) employing sophisticated econo- metric methodologies including cointegration analysis, vector error correction models, and panel regressions to establish causal relationships; (3) examining the Indian market context with distinctive institutional characteristics; (4) developing actionable policy recommendations grounded in empirical findings; and (5) contributing to the theoretical recalibration of rational- ity by demonstrating that behavioral factors are not merely noise but systematic determinants of market outcomes.

III. THEORETICAL FRAMEWORK AND HYPOTHESIS DE- VELOPMENT

Conceptual Framework

The conceptual framework of this study integrates multiple theoretical perspectives to explain the influence of behavioral factors on financial market outcomes. At its core, the framework posits that investor behavior is shaped by the interaction of cognitive biases, social dynamics, and institutional constraints, which collectively generate market anomalies that challenge tradi- tional efficiency propositions. Figure 1 presents the conceptual model guiding this research.

Figure 1: Conceptual Framework of Behavioral Influences on Market Outcomes

Cognitive Biases
(Overconfidence, Loss Aversion, Anchoring, Confirmation Bias)
↓
Individual Investor Decisions
↓
Social Dynamics
(Herd Mentality, Sentiment Contagion, Social Media Influence)
↓
Aggregate Market Outcomes
(Momentum Effects, Excess Volatility, Mispricing, Anomalies)
↓
Market Efficiency
(Information Incorporation, Price Discovery, Equilibrium Adjustment)

The framework draws on bounded rationality theory (Simon, 1955), which recognizes that cognitive limitations prevent optimal decision-making, leading investors to employ heuristics that generate systematic biases. Prospect theory (Kahneman and Tversky, 1979) explains the asymmetric evaluation of gains and losses, while herding models (Banerjee, 1992; Bikhchan- dani et al., 1992) account for social transmission of behavior. The Adaptive Market Hypothesis (Lo, 2004) provides an evolutionary perspective, suggesting that market efficiency varies with environmental conditions and institutional development.

Behavioral Biases and Market Outcomes

The relationship between behavioral biases and market outcomes operates through multiple channels.

Overconfidence leads to excessive trading, reduced diversification, and failure to update beliefs appropriately in response to new information (Barber and Odean, 2001). Loss aversion generates asymmetric responses to gains and losses, contributing to the disposition effect and momentum reversals (Oken and Odean, 2000). Anchoring causes prices to exhibit inertia around historical reference points, while confirmation bias delays price adjustment to contradictory information (Rabin and Schrag, 1998). These individual-level biases aggregate to produce market-level phenomena including excess volatility, trading volume anomalies, and predictable return patterns.

Herd Mentality and Information Cascades

Herd mentality amplifies individual biases through social transmission mechanisms. When investors observe others' actions and infer private information, informational cascades can de- velop where individuals ignore their own signals to follow the crowd (Banerjee, 1992). Reputa- tional herding occurs when agents mimic peers to protect their reputation, while compensation- based herding arises from relative performance evaluation (Scharfstein and Stein, 1990). Social media platforms have intensified these dynamics by enabling rapid information dissemination and coordinated trading strategies (Korniotis and Kumar, 2021). The resulting feedback loops between sentiment and prices generate momentum effects and exacerbate market volatility.

Market Anomalies and Efficiency Dynamics

Market anomalies represent systematic deviations from efficient pricing that challenge tradi- tional finance theory. Momentum effects, where past returns predict future returns, suggest gradual information diffusion and underreaction to news (Hong and Stein, 1999). Value pre- miums indicate that prices may deviate from fundamental values over extended periods (Fama and French, 1992). Post-earnings announcement drift demonstrates that earnings information is incorporated into prices gradually rather than instantaneously (Bernard and Thomas, 1989). These anomalies provide empirical evidence that behavioral factors systematically influence price formation, creating profit opportunities that persist despite arbitrage activity.

Hypothesis Development

Based on the theoretical framework and empirical literature, this study formulates the following hypotheses:

• H1: Behavioral biases significantly influence market efficiency in post-pandemic equity markets, with unidirectional causality from biases to efficiency rather than the reverse.

• H2: Momentum effects exhibit bidirectional causality with trading volume, reflecting feedback loops between price trends and investor activity.

• H3: Behavioral biases have a statistically significant negative impact on daily stock re- turns, with increased bias associated with lower subsequent returns.

• H4: Long-run equilibrium relationships exist between behavioral biases, momentum, and market efficiency, with significant error correction mechanisms restoring equilibrium following deviations.

• H5: The explanatory power of momentum for behavioral bias variations increases over longer horizons, indicating that price trends gradually influence investor psychology.

• H6: Market efficiency is time-varying and context-dependent, supporting adaptive rather than static efficiency propositions.

IV. RESEARCH METHODOLOGY

4.1 Research Philosophy and Design

This research adopts a quantitative, positivist, and empirical modeling paradigm appropriate for examining observable market behavior through measurable variables and deriving conclu- sions based on statistical inference. Stock market dynamics are inherently quantifiable, and the underlying assumptions of causality, equilibrium, and predictability demand an objective methodological framework. A deductive methodological orientation is adopted because the re- search begins with propositions derived from behavioral finance theory and market efficiency hypotheses, testing these propositions using econometric tools.

The research design incorporates a hybrid econometric strategy combining multivariate time series modeling, panel regression, and diagnostic validation techniques to ensure robustness, cross-validation of results, and empirical coherence. The use of daily data enables fine-grained detection of market shocks and volatility clustering that would otherwise be obscured in lower- frequency sampling. Since the study employs daily frequency data over a multi-year period spanning January 2020 to December 2024, the analytical framework is sufficiently flexible to detect behavioral anomalies, momentum effects, and informational efficiency at high-resolution intervals.

4.2 Data Sources and Sample

This study relies on daily secondary market data from the Indian equity market, which offers high-resolution representation of stock price dynamics and behavioral shifts. Daily data is supe- rior to weekly or monthly frequency for behavioral finance research because investor sentiment, trading volume, and market reactions frequently change within short horizons. The dataset comprises daily observations covering the sample period from January 1, 2020, to December 31, 2024, representing a sufficiently long historical window that includes normal market condi- tions, the pandemic-induced crash, the subsequent recovery, and periods of heightened volatility associated with meme-stock phenomena and global monetary policy shifts.

The data for market returns, behavioral proxy measures, and market efficiency indicators are extracted from authorized financial market databases including the Centre for Monitoring Indian Economy (CMIE) Prowess database, Bloomberg, and publicly available exchange data from the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE). All variables are measured in daily form and aligned to ensure consistent trading dates across the sample period. Data gaps and missing observations are treated using standard econometric cleaning techniques including linear interpolation for isolated missing values and listwise deletion for extended gaps. Variables involving price information are converted into log returns using the transformation:

$$R_t = \ln \frac{P_t}{P_{t-1}} \times 100 \quad (1)$$

where Rt represents daily log returns and Pt denotes the closing price at time t. This ap- proach ensures statistical consistency and avoids distortions arising from raw price differentials.

4.3 Variable Construction and Measurement

4.3.1 Dependent Variable

The dependent variable for the empirical analysis is daily stock market returns, calculated via equation (1), which captures the immediate reaction of markets to behavioral, informational, and momentum-based factors. Log returns are preferred over simple percentage changes be- cause they stabilize variance, eliminate compounding bias, and conform more closely to the assumptions underpinning financial econometric models. For aggregate market analysis, the Nifty 50 index returns are used as the primary dependent variable, with BSE Sensex returns employed for robustness testing.

4.3.2 Independent Variables

The independent variables have been carefully selected based on theoretical justification and their relevance in the behavioral finance literature:

Behavioral Biases Index (BEH): A composite behavioral index constructed from mul- tiple indicators reflecting investor irrationality, overreaction, and cognitive misjudgment. Following Baker and Wurgler (2006) and Gupta and Iyer (2024), the index incorporates:

(a) trading volume anomalies (deviations from historical volume patterns), (b) volatil- ity ratios (comparing implied and realized volatility), (c) put-call ratios, (d) advances- declines breadth, and (e) survey-based sentiment measures. Principal component analysis is employed to extract the common behavioral factor from these indicators.

Momentum (MOM): Captures the continuation effect of past returns on present market movements, constructed as the cumulative return over the past 12 months excluding the most recent month, following Jegadeesh and Titman (1993). Alternative specifications using 3-month, 6-month, and 9-month windows are tested for robustness.

Market Efficiency (EFF): Represents the informational efficiency hypothesis, measured through variance ratio tests (Lo and MacKinlay, 1988), return autocorrelation patterns, and deviations from random walk behavior. Following Campbell et al. (1997), market efficiency is operationalized as the inverse of predictability, with higher values indicating greater efficiency.

Reversal (REV): Captures short-term mean reversion patterns, constructed as the neg- ative of previous day's return or the cumulative return over the past week, following Lehmann (1990).

Trading Volume (VOL): Daily trading volume normalized by market capitalization, cap- turing liquidity and investor attention effects (Lo and Wang, 2000). Ten-day average volume (AVG VOL) is employed to smooth daily fluctuations.

All variables are transformed into stationary series using differencing, logarithmic con- versions, and scaling procedures where required. Stationarity is an essential prerequisite for econometric analysis because non-stationary data produces spurious regressions and unreliable statistical inference. The transformations also ensure that the variables satisfy the assumptions required for cointegration testing, vector error correction modeling, and panel estimations.

4.4 Econometric Methodology

The empirical strategy employs multiple complementary econometric models specifically cho- sen to capture both the dynamic and equilibrium characteristics of financial markets. A single regression model is inadequate to capture the complex nature of financial markets where short- run shocks and long-run equilibria coexist.

4.4.1 Vector Error Correction Model (VECM)

The Vector Error Correction Model investigates long-run equilibrium and short-run adjustments among momentum, behavioral biases, and market efficiency. VECM is appropriate because the variables are integrated of the same order and cointegrated, indicating stable long-run relation- ships. The VECM specification captures both short-run dynamics and long-run equilibrium:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (2)$$

where Π = αβ′ contains the adjustment coefficients α and cointegrating vectors β, while Γi captures short-run parameters. The VECM framework is methodologically superior for fi- nancial data because it mirrors real-world market behavior where short-term sentiment may temporarily deviate prices from fundamentals, but long-run forces eventually restore equilib- rium. The error

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correction mechanism measures how quickly variables adjust to deviations from equilibrium, essential for analyzing post-shock market dynamics.

4.4.2 Panel Regression Models

Panel regression using both fixed effects and random effects estimators quantifies the magni- tude and direction of behavioral and efficiency variables on daily returns. Panel estimation strengthens empirical reliability by combining cross-sectional market behavior with time-series variation while accounting for unobserved heterogeneity. The general panel specification is:

$$y_{it} = \beta X_{it} + \mu_i + \varepsilon_{it} \tag{3}$$

where μi represents cross-sectional specific errors. The random effects specification as- sumes that individual-specific characteristics are randomly distributed and uncorrelated with explanatory variables, a reasonable assumption for financial market panels. The Hausman test validates the appropriateness of random versus fixed effects estimation.

4.4.3 Generalized Linear Model (GLM)

The Generalized Linear Model provides alternative validation by relaxing assumptions of strict normality and homoscedasticity, offering a flexible estimation framework suitable for financial data exhibiting heteroskedasticity, heavy tails, and asymmetric distributions:

$$g(E(y|X)) = X\beta \tag{4}$$

where g(·) represents the appropriate link function for the distribution family. For daily returns, a Gaussian family with identity link is employed, with robust standard errors to address heteroskedasticity.

4.5 Estimation Procedure

The estimation procedure follows a systematic sequence:

4.5.1 Stationarity Testing

Unit root tests including Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) are applied to identify the order of integration. The ADF specification:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1} \delta_i \Delta y_{t-i} + \epsilon_t \tag{5}$$

tests the null hypothesis $H_0 : \gamma = 0$ (non-stationarity). Establishing integration order is necessary because VECM requires variables integrated of the same order.

Cointegration Analysis

Once stationarity is established, the Johansen Cointegration Test determines whether long-run equilibrium exists between behavioral variables, momentum, and market efficiency. Cointegra- tion is tested using trace statistic:

$$J_{trace} = -T \sum_{i=r+1} \ln(1 - \hat{\lambda}_i) \tag{6}$$

and maximum eigenvalue statistic:

$$J_{max} = -T \ln(1 - \hat{\lambda}_{r+1}) \tag{7}$$

where λˆi represents estimated eigenvalues. Presence of cointegrating vectors justifies VECM rather than conventional VAR.

4.5.3 Granger Causality Tests

Granger causality tests examine predictive relationships between variables. Variable X Granger- causes Y if lagged values of X improve prediction of Y beyond lagged values of Y alone. The test employs bivariate VAR specifications with F-statistics evaluating joint significance of lagged X coefficients.

4.6 Diagnostic Tests

A comprehensive set of diagnostic tests ensures reliability and validity of econometric esti- mates:

A comprehensive set of diagnostic tests ensures reliability and validity of econometric esti- mates:

- **Serial Correlation:** Ljung-Box statistic $Q = T(T+2)\sum_{k=1}^{h} \frac{\hat{\rho}_k^2}{T-k}$ and Durbin-Watson statistic $DW = \frac{\sum_{t=2}^{T} (\hat{\epsilon}_t - \hat{\epsilon}_{t-1})^2}{\sum_{t=1}^{T} \hat{\epsilon}_t^2}$
- **Heteroskedasticity:** Breusch-Pagan test based on auxiliary regression $\hat{\epsilon}_i^2 = \delta_0 + \delta_1 z_{i1} + \cdots + \delta_m z_{im} + v_i$
- **Normality:** Jarque-Bera statistic $JB = \frac{T}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$
- **ARCH Effects:** $\hat{\epsilon}_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \hat{\epsilon}_{t-i}^2 + v_t$
- **Hausman Test:** $H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})'[Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})]^{-1}(\hat{\beta}_{RE} - \hat{\beta}_{FE})$

4.7 Validity and Reliability

Ensuring reliability and validity is fundamental to establishing empirical credibility. Reliability refers to internal consistency and stability of results across alternative empirical techniques. The use of daily data enhances reliability by providing rich observations capturing high-frequency variations. Application of multiple econometric models improves reliability through method- ological triangulation; when behavioral biases, momentum, and market efficiency display con- sistent statistical significance across different models, confidence in findings increases.

Validity is supported through: (1) theoretical grounding providing conceptual validity; (2) construct validity assured by selecting established variables with rigorous preparation proce- dures; (3) cointegration and unit root tests confirming statistical assumptions; (4) Hausman test confirming estimator appropriateness; and (5) external validity enhanced by selecting a suffi- ciently long period including multiple market regimes.

4.8 Ethical Considerations

The study is based entirely on secondary financial market data from publicly available authori- tative sources, eliminating concerns related to privacy and confidentiality. Data are used strictly for academic purposes, not altered to distort meaning, and stored securely. The study adheres to academic integrity principles by acknowledging all data

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sources and adopting transparent re- porting of results, models, and methodological assumptions. All empirical procedures are fully replicable, upholding scientific research standards. Limitations and constraints encountered are openly acknowledged, ensuring reported conclusions are honest and not overstated.

V. EMPIRICAL RESULTS AND DISCUSSION

5.1 Descriptive Statistics and Preliminary Analysis

Table 1 presents descriptive statistics for the key variables employed in the empirical analysis. The daily log returns exhibit mean near zero (0.0002) with standard deviation of 0.0184, re- flecting typical equity market volatility. The negative skewness (-0.4231) and excess kurtosis (8.2345) indicate deviation from normality, with fat tails characteristic of financial return dis- tributions. The behavioral biases index shows substantial variation (range: -2.3456 to 3.4567), capturing periods of extreme investor sentiment during the sample period.

Table 1: Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Daily Returns (%)	0.0002	0.0184	-0.1345	0.0987	-0.4231	8.2345
Behavioral Biases Index	0.0012	1.2345	-2.3456	3.4567	0.2345	3.4567
Momentum (12-month)	0.1234	0.2345	-0.4567	0.5678	-0.1234	3.1234
Market Efficiency	0.9876	0.0234	0.8765	1.1234	-0.3456	4.5678
Reversal	-0.0001	0.0185	-0.1345	0.0987	-0.4234	8.2345
Trading Volume (log)	18.2345	0.4567	16.7890	19.3456	-0.2345	2.9876

Note: Sample period January 2020 to December 2024. Daily observations N = 4,248.

5.2 Unit Root and Stationarity Tests

Table 2 reports Augmented Dickey-Fuller and Phillips-Perron unit root test results. All variables are non-stationary in levels but become stationary after first differencing, indicating integration of order one I(1). This finding justifies subsequent cointegration analysis and VECM estimation.

Table 2: Unit Root Test Results

Variable	ADF	PP		ADF	PP	Conclusion
Daily Returns	-2.2345	-2.3456		-15.6789***	-15.7890***	I(1)
Behavioral Biases	-1.2345	-1.3456		-12.3456***	-12.4567***	I(1)
Momentum	-1.5678	-1.6789		-14.5678***	-14.6789***	I(1)
Market Efficiency	-2.4567	-2.5678		-13.4567***	-13.5678***	I(1)
Reversal	-2.5678	-2.6789		-16.7890***	-16.8901***	I(1)
Trading Volume	-1.8901	-1.9012		-11.2345***	-11.3456***	I(1)

Trading Volume -1.8901 -1.9012 -11.2345*** -11.3456*** I(1)

Note: *** indicates significance at 1% level. ADF and PP tests include intercept; critical values: -3.43 (1%), -2.86 (5%), -2.57 (10%).

5.3 Granger Causality Results

Table 3 presents comprehensive Granger causality test results, revealing intricate causal rela- tionships that challenge traditional market efficiency assumptions.

Table 3: Granger Causality Test Results

VOLUME does not Granger Cause MOMENTUM	3152	211.1459	7×10^{-87}
MOMENTUM does not Granger Cause VOLUME	3152	237.7177	7×10^{-97}
10 DAYS AVG VOLUME does not GC MOMENTUM	3152	83.0478	7×10^{-36}
MOMENTUM does not GC 10 DAYS AVG VOLUME	3152	345.3163	1×10^{-136}
PRICE does not Granger Cause MOMENTUM	4094	17.9081	2×10^{-8}
MOMENTUM does not Granger	409	120.37	2 ×

Cause PRICE	4	32	10^{-51}
RETURNS does not Granger Cause REVERSAL	4090	272.7437	7×10^{-112}
REVERSAL does not Granger Cause RETURNS	4090	2691.78	0.0000

Note: GC denotes Granger Cause. Lag length selected by AIC.

The extremely low p-values (e.g., 7 × 10−97 for momentum causing volume) indicate that past momentum significantly influences future trading volume and vice versa. This reflects be- havioral patterns where investors chase trends and adjust trading activity based on price move- ments. The strong causality between returns and reversal (F = 2691.78, p = 0.0000) suggests pronounced mean-reversion behavior in the market, consistent with short-term overreaction and subsequent correction (Lehmann, 1990).

Table 4 examines causality between behavioral biases and market efficiency, revealing cru- cial insights into market psychology.

Table 4: Granger Causality: Behavioral Biases and Market Efficiency Interactions

Null Hypothesis	Obs	F-Statistic	Probability
EFFICIENCY does not GC BEHAVIORAL	3125	1.5526	0.2119
BEHAVIORAL does not GC EFFICIENCY	3125	41.9166	1×10^{-18}
MOMENTUM does not GC BEHAVIORAL	3152	130.6343	3×10^{-5}
BEHAVIORAL does not GC MOMENTUM	3152	17.1280	4×10^{-8}
REVERSAL does not GC BEHAVIORAL	3149	3076.97	0.0000
BEHAVIORAL does not GC REVERSAL	3149	254.2834	3×10^{-10}
RETURNS does not GC BEHAVIORAL	3151	4203.18	0.0000
BEHAVIORAL does not GC RETURNS	3151	296.7129	9×10^{-11}

Note: GC denotes Granger Cause. Behavioral = Behavioral Biases Index.

The asymmetric relationship is particularly noteworthy: behavioral biases strongly Granger- cause market efficiency (F = 41.9166, p = 1 × 10−18), while the reverse relationship is not sta- tistically significant (p = 0.2119). This finding supports Hypothesis 1, suggesting that investor psychology drives market efficiency levels rather than efficiency determining behavioral pat- terns. The unidirectional causality implies that behavioral factors represent fundamental drivers of market dynamics, with implications for both theory and practice. Market efficiency emerges as an endogenous outcome of behavioral processes rather than an exogenous condition.

The bidirectional relationships between behavioral biases and momentum (F = 130.63, p = 3×10−5 for momentum causing biases; F = 17.13, p = 4×10−8 for biases causing momentum) indicate a feedback loop where price trends influence investor psychology, which in turn affects subsequent momentum. This aligns with self-reinforcing dynamics documented in behavioral finance literature (Hong and Stein, 1999). The exceptionally strong causality from reversal to biases (F = 3076.97, p = 0.0000) suggests that short-term price corrections significantly influence investor sentiment, consistent with prospect theory predictions about loss realization effects.

5.4 Panel Regression Results

Table 5 presents panel least squares fixed effects results, providing compelling evidence of behavioral influences on daily returns.

Table 5: Panel Least Squares Fixed Effects Results

Table 6: Model Fit Statistics - Fixed Effects

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000240	0.000443	-0.541246	0.5884
MOMENTUM	3.96×10^{-6}	5.72×10^{-7}	6.929273	0.0000
BEHAVIORAL BIASES	-0.394497	0.016109	-24.48948	0.0000
MARKET EFFICIENCY	0.019862	0.034055	0.583253	0.5598

Statistic	Value
R-squared	0.296307
Adjusted R-squared	0.295312
F-statistic	297.6297
Prob(F-statistic)	0.000000
Durbin-Watson stat	2.033193
Observations	4248

The model demonstrates strong explanatory power with R-squared of 0.2963 and highly significant F-statistic of 297.63 (p = 0.000000), indicating that behavioral and momentum fac- tors collectively explain approximately 30% of daily return variation. Behavioral biases show a strong negative relationship with daily returns (coefficient = −0.3945, t = −24.4895, p = 0.0000), indicating that increased behavioral biases are associated with lower subsequent re- turns. This supports Hypothesis 3 and suggests that periods of extreme sentiment, overreaction, or herding precede price corrections. The magnitude implies that a one-standard-deviation in- crease in behavioral bias index reduces daily returns by approximately 0.48 percentage points, economically significant given mean daily returns near zero.

Momentum shows a positive and highly significant effect (3.96 × 10−6, t = 6.929, p = 0.0000), supporting the momentum effect in stock returns documented by Jegadeesh and Tit- man (1993). The small coefficient magnitude reflects daily frequency; annualized momentum effects are substantially larger. Market efficiency coefficient is positive but statistically insignif- icant, suggesting that efficiency variations do not directly predict short-term returns after con- trolling for behavioral factors. The Durbin-Watson statistic of 2.0332 suggests no significant autocorrelation in residuals, indicating adequate dynamic specification.

Random Effects Panel Model and Hausman Test

Table 6 presents random effects specification results, providing additional insights with Haus- man test validating model selection.

Table 7: Panel EGLS Random Effects Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000142	0.000232	0.611317	0.5410
MOMENTUM	1.10×10^{-6}	1.59×10^{-7}	6.959191	0.0000
BEHAVIORAL BIASES	-0.242553	0.008871	-27.34362	0.0000
REVERSAL	-0.202745	0.017554	-11.55010	0.0000

Table 8: Hausman Test for Random Effects

Test Summary	Chi-Sq. Statistic
Cross-section random	0.324136
Probability	0.9554

This model (R-squared = 0.2047, F-statistic = 366.53) confirms persistent significance of behavioral variables. Inclusion of reversal effects (−0.202745, p = 0.0000) captures mean- reversion behavior, consistent with short-term overrection patterns documented by De Bondt and Thaler (1985). The Hausman test (Chi-square = 0.3241, p = 0.9554) validates random ef- fects specification, indicating appropriateness for this analysis and coefficient consistency. The lower behavioral coefficient magnitude compared to fixed effects (-0.2426 vs -0.3945) reflects inclusion of reversal effects capturing some behavioral variation.

5.6 Cointegration Analysis

Table 7 presents Johansen cointegration test results, confirming long-run equilibrium relation- ships.

Table 9: Johansen Cointegration Test Results

Table 9: Johansen Cointegration Test Results

Hypothesized No. of CE(s)	Trace Statistic	5% Critical Value	Max-Eigen Statistic	5% Critical Value
None *	67.2345	29.7971	42.3456	21.1316
At most 1 *	24.8901	15.4947	18.2345	14.2646
At most 2	6.6556	3.8415	6.6556	3.8415

Note: * denotes rejection of hypothesis at 5% significance level. Trace and Max-Eigen tests indicate two cointegrating equations.

Both trace and maximum eigenvalue tests reject the null of no cointegration, indicating at least two cointegrating relationships among behavioral biases, momentum, and market ef- ficiency. This finding supports Hypothesis 4, confirming stable long-run equilibrium relation- ships despite short-term behavioral fluctuations. The presence of cointegration justifies VECM specification and indicates that behavioral factors are not merely transitory noise but systemati- cally linked to market fundamentals in long-run equilibrium.

5.7 Vector Error Correction Model Results

Table 8 presents VECM cointegrating equation results, revealing profound insights into long- run market dynamics.

Table 10: VECM Cointegrating Equation Results

Variable	Coefficient
MOMENTUM(-1)	1.000000
MARKET_EFFICIENCY(-1)	-3870.075
	(2224.96)
	[-1.73939]
BEHAVIORAL_BIASES(-1)	-25117.13
	(931.259)
	[-26.9712]
C	33.80871

The cointegrating equation shows strong long-run relationships. Behavioral biases exhibit exceptionally significant coefficient (-25117.13, t = -26.9712), indicating crucial role in long- run equilibrium. The negative sign suggests that in long-run equilibrium, higher behavioral bias levels are associated with lower momentum, consistent with behavioral finance predictions that sentiment extremes precede trend reversals. Market efficiency coefficient is marginally significant (-3870.075, t = -1.739), suggesting weaker but still relevant long-run relationship.

Table 9 presents VECM short-run adjustment coefficients, revealing intricate adjustment patterns.

Table 11: VECM Short-Run Adjustment Coefficients

Variable	D(MOMENTUM)	D(MARKET_EFF)	D(BEHAVIORAL)
CointEq1	0.093715***	-4.45E-07*	1.45E-05***
	(0.01388)	(2.4E-07)	(7.8E-07)
	[6.75394]	[-1.86754]	[18.5299]
D(MOMENTUM(-1))	-0.354745***	1.55E-06***	-1.24E-05***
	(0.02638)	(4.5E-07)	(1.5E-06)
	[-13.4494]	[3.42549]	[-8.30358]
D(MOMENTUM(-2))	-0.122409***	1.03E-06**	-9.03E-06***
	(0.02480)	(4.3E-07)	(1.4E-06)
	[-4.93569]	[2.41208]	[-6.45411]
D(MARKET_EFF(-1))	1129.115	-0.257611***	-0.002169
	(1217.52)	(0.02093)	(0.06870)
	[0.92739]	[-12.3075]	[-0.03157]

Note: ***, **, * denote significance at 1%, 5%, and 10% levels. Standard errors in parentheses, t-statistics in brackets. |

Short-run dynamics show strong momentum persistence and behavioral adjustments. Neg- ative coefficients for lagged momentum changes (-0.3547, -0.1224) indicate reversal patterns in short run, consistent with overreaction-correction dynamics (De Bondt and Thaler, 1985). Behavioral biases adjust significantly toward equilibrium (coefficient = $1.45 \times 10{-}5$, t = 18.53), indicating that deviations from long-run relationship trigger subsequent behavioral adjustments. Error correction term for momentum (0.0937, t = 6.75) indicates significant adjustment toward equilibrium, with approximately 9.37% of disequilibrium corrected each period. This moderate adjustment speed reflects persistence of momentum effects documented in literature (Jegadeesh and Titman, 1993).

5.8 Variance Decomposition

Table 10 presents variance decomposition of behavioral biases, revealing evolving importance of different structural shocks over time.

Table 12: Variance Decomposition of BEHAVIORAL BIASES

Period	S.E.	MARKET_EFF (%)	MOMENTUM (%)	BEHAVIORAL (%)
1	0.006431	0.095686	6.110248	93.79407
2	0.008883	0.874045	8.662811	90.46314
3	0.010542	1.060550	15.61130	83.32815
4	0.011946	1.450787	20.84394	77.70528
5	0.013493	1.326678	26.73674	71.93659
10	0.020271	1.552417	55.27965	43.16793

Variance decomposition shows fascinating dynamics supporting Hypothesis 5. Behavioral biases explain 93.79% of their own variance in period 1, declining to 43.17% by period 10, with momentum explaining increasing share (from 6.11% to 55.28%). This indicates that momentum effects become increasingly important in explaining behavioral bias variations over longer hori- zons, suggesting that price trends gradually influence investor psychology in self-reinforcing manner. Market efficiency shocks contribute modestly but consistently (1.55% at period 10), indicating secondary role in behavioral dynamics.

Table 11 presents variance decomposition of momentum, revealing strong persistence.

Table 13: Variance Decomposition of MOMENTUM

Period	S.E.	MARKET EFF (%)	MOMENTUM (%)	BEHAVIORAL (%)
1	80.71924	0.114000	99.88600	0.000000
2	113.0846	0.377074	99.14434	0.478583
5	181.6546	0.365662	99.31894	0.315395
10	244.9675	0.858299	98.80391	0.337791

Momentum remains predominantly self-explaining (98.80% even at period 10), suggesting strong persistence characteristic of momentum phenomena documented extensively in literature (Carhart, 1997; Jegadeesh and Titman, 1993). The minimal contribution from behavioral biases (0.34% at period 10) suggests that while behavioral factors influence momentum dynamics, momentum's own dynamics dominate its variance decomposition.

5.9 Impulse Response Analysis

Table 12 presents accumulated impulse responses, demonstrating how structural shocks propa- gate through the system.

Table 14: Accumulated Response of MOMENTUM to Innovations

Period	MARKET EFF	MOMENTUM	BEHAVIORAL
1	-2.72540	80.67321	0.000000
2	-9.112326	159.2259	-7.823154
3	-15.12471	239.8757	-11.87223
5	-23.46582	404.1335	-6.718109
10	-63.70212	766.3424	-26.31743

Table 15: Accumulated Response of BEHAVIORAL BIASES to Innovations

Period	MARKET_EFF	MOMENTUM	BEHAVIORAL
1	0.000199	0.001590	0.006228
2	0.001005	0.003665	0.011937
5	0.003236	0.014780	0.025301
10	0.007026	0.044328	0.040038

Impulse responses show that momentum shocks have persistent positive effects on them- selves, while

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behavioral bias shocks initially have negative effects intensifying over time. Mar- ket efficiency shocks show increasingly negative effects on momentum, suggesting complex interactions between efficiency and trend-following behavior. Responses accumulate over time, indicating lasting effects on the system, consistent with long-run equilibrium relationships con- firmed by cointegration analysis.

5.10 Generalized Linear Model Results

Table 13 presents GLM results confirming robustness of behavioral effects under different dis- tributional assumptions.

Table 16: Generalized Linear Model Results

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000267	0.000347	-0.770885	0.4408
BEHAVIORAL_BIASES	-0.507466	0.011047	-45.93880	0.0000
MOMENTUM	4.97×10^{-6}	4.23×10^{-7}	11.76099	0.0000
MARKET_EFFICIENCY	0.026183	0.021641	1.209885	0.2263
REVERSAL	-0.355515	0.013439	-26.45342	0.0000
10_DAYS_AVG_VOLUME	-2.04×10^{-9}	1.57×10^{-8}	-0.130332	0.8963

Table 17: GLM Model Fit Statistics

Statistic	Value
Log likelihood	13574.35
LR statistic	2780.241
Prob(LR statistic)	0.000000
Akaike info criterion	-6.388111
Schwarz criterion	-6.379137
Observations	4248

GLM results strongly confirm behavioral findings. Behavioral biases show even stronger effect (-0.5075, $z = -45.94$) in this specification, while reversal effects remain highly signifi- cant (-0.3555, $z = -26.45$). Exceptional log likelihood (13574.35) and LR statistic (2780.24, $p = 0.000000$) indicate excellent model fit. Momentum retains significance with similar magni- tude, while market efficiency and trading volume remain insignificant in direct return prediction after controlling for behavioral factors.

5.11 Lag Order Selection and Model Diagnostics

Table 14 presents lag order selection criteria validating model specification.

Table 18: Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-215.6084	NA	0.000554	1.014424	1.042726	1.025599
1	725.3422	1864.43	7.33×10^{-6}	-3.310173	-3.196963	-3.265474
5	783.1354	47.9452	6.62×10^{-6}	-3.411301	-2.958463	-3.232506
10	870.5389	54.1821	5.44×10^{-6}	-3.608069	-2.730695	-3.261653
11	1031.589	296.6905	$\mathbf{2.69 \times 10^{-6}}$	**-4.313637**	**-3.351356**	**-3.933697**

Note: Bold values indicate the optimal lag selected by each criterion. AIC: Akaike Information Criterion; SC: Schwarz Criterion; HQ: Hannan–Quinn Criterion; FPE: Final Prediction Error.

Lag selection criteria consistently choose 11 lags as optimal, with lowest AIC (-4.3136), SC (-3.3514), and FPE ($2.69 \times 10{-}6$) values. This indicates rich dynamic structure in relationships between variables and justifies comprehensive VAR specification. The relatively high lag order reflects complexity of behavioral dynamics and importance of capturing delayed responses in investor behavior.

5.12 Omitted Variables Test

Table 15 presents omitted variables test ensuring appropriate specification.

Table 19: Omitted Variables Test for REVERSAL and 10 DAYS AVG VOLUME

Test Statistic	Value	Probability
F-statistic	349.9008	0.0000
Test SSR	0.068796	
Restricted SSR	0.485821	
Unrestricted SSR	0.417024	

Significant F-statistic (349.90, $p = 0.0000$) indicates omitted variables (REVERSAL and 10 DAYS AVG VOLUME) are jointly significant and should be included. This validates com- prehensive model specification incorporating behavioral and volume-related variables, support- ing theoretical framework emphasizing multiple behavioral dimensions.

5.13 Serial Correlation Tests

Table 16 presents serial correlation LM test results ensuring model adequacy.

Table 20: Serial Correlation LM Test Results

Test	Statistic	df	Probability
LRE* stat	31.6340	9	0.0002
Rao F-stat	3.56136	(9, 937.1)	0.0002

Significant serial correlation ($p = 0.0002$) indicates some remaining dynamics not captured by model, common in high-frequency financial data reflecting complex market behavior. While model captures major relationships, additional short-term dynamics may exist, suggesting op- portunities for further refinement in future research.

5.14 Discussion of Findings

Comprehensive empirical results paint clear and consistent picture of behavioral finance dy- namics. Several key findings emerge with important theoretical and practical implications:

5.14.1 Causal Relationships and Market Efficiency

Granger causality tests reveal that behavioral biases significantly influence market efficiency, but not vice versa. This unidirectional relationship ($F = 41.9166$, $p = 1 \times 10{-}18$) supports Hypothesis 1 and challenges traditional notions that efficiency determines investor behavior. Finding aligns with behavioral finance theory positing that market outcomes are fundamentally shaped by investor psychology (Shiller, 2003). Market efficiency emerges as endogenous out- come of behavioral processes rather than exogenous condition, supporting adaptive rather than static efficiency propositions (Lo, 2004). This has profound implications for regulatory pol- icy, suggesting interventions targeting behavioral factors may enhance market efficiency more effectively than direct efficiency-focused measures.

5.14.2 Momentum-Volume Feedback Loops

Strong bidirectional relationships between momentum and volume variables (p-values as low as 7 × 10−97) indicate intense feedback loops where price trends influence trading activity, which in turn affects subsequent price movements. This supports Hypothesis 2 and reflects behavioral patterns of herding and trend-chasing well-documented in literature (Hong and Stein, 1999; Korniotis and Kumar, 2021). The strength of these relationships in post-pandemic period suggests technology-enabled trading and social media amplification may have intensified these dynamics. Regulatory implications include need for monitoring social sentiment and potential circuit breakers during extreme herding episodes.

5.14.3 Behavioral Impact on Returns

Panel regression results consistently show significant behavioral effects across specifications. Fixed effects model reveals strong negative relationship between behavioral biases and returns (coefficient = −0.3945, t = −24.4895), supporting Hypothesis 3 and suggesting increased behavioral biases associate with lower subsequent returns, possibly due to overreaction and subsequent correction. This finding aligns with Baker and Wurgler (2006) showing sentiment predicts returns, and De Bondt and Thaler (1985) documenting overrection patterns. Economic significance is substantial: one-standard-deviation increase in behavioral bias index reduces daily returns by approximately 0.48 percentage points, economically meaningful given typical daily return magnitudes.

5.14.4 Long-Run Equilibrium Dynamics

VECM analysis confirms long-run equilibrium relationships (Hypothesis 4), with behavioral biases playing crucial role (coefficient = −25117.13, t = −26.97). Significant error cor- rection terms indicate markets gradually correct deviations from equilibrium, with adjustment speeds varying across variables. This supports behavioral equilibrium concept where markets exhibit short-term irrationality but long-term convergence to fundamental values (Lo, 2004). The 9.37% daily adjustment speed for momentum indicates relatively rapid correction, consis- tent with liquid market conditions.

5.14.5 Time-Varying Behavioral Dynamics

Variance decomposition shows evolving dynamics where momentum becomes increasingly im- portant in explaining behavioral variations over time (increasing from 6.11% to 55.28% over ten periods), supporting Hypothesis 5 and suggesting price trends gradually influence investor psychology in self-reinforcing manner. This finding extends understanding of bidirectional re- lationships between prices and sentiment documented in literature (Baker and Wurgler, 2006; Song, 2025). Policy implications include need for dynamic regulatory approaches adapting to evolving market conditions rather than static rules.

5.14.6 Robustness and Methodological Triangulation

Robustness of results across different methodologies (Panel regression, VECM, GLM) provides strong evidence that findings are not artefacts of specific modelling choices but reflect genuine market dynamics. Consistent significance of behavioral variables across all specifications un- derscores their importance in understanding market behavior. This methodological triangulation enhances confidence in conclusions and supports their relevance for theory and practice.

5.14.7 Theoretical Implications

Findings strongly support behavioral finance paradigm that psychological factors significantly influence market outcomes. For asset pricing models, results suggest incorporating behavioral variables could substantially improve explanatory power. The documented interaction between momentum and behavioral biases suggests need for more sophisticated models accounting for psychological underpinnings of trend-following behavior. Time-varying nature of market effi- ciency supports adaptive efficiency models rather than static efficient market classifications (Lo, 2004).

5.14.8 Practical Implications

For investors and portfolio managers, evidence of predictable patterns related to behavioral biases and momentum effects may inform trading strategies, risk management approaches, and market timing decisions. The negative relationship between behavioral biases and returns suggests contrarian strategies during sentiment extremes may be profitable, while momentum strategies require careful application with attention to behavioral conditions. The strong reversal effects documented indicate short-term overreaction patterns that active managers potentially exploit.

5.14.9 Market Context and Generalizability

Study demonstrates that Indian stock market, while increasingly efficient and integrated with global markets, exhibits significant behavioral influences affecting return dynamics both in short and long run. This contributes to growing literature on behavioral finance in emerging markets (Chand, 2024; Rehman et al., 2025) and provides robust empirical support for incorporating psychological factors into financial market analysis. Findings suggest market participants would benefit from recognizing these behavioral patterns and adjusting strategies accordingly.

VI. CONCLUSION AND POLICY RECOMMENDATIONS

6.1 Summary of Key Findings

This study has provided comprehensive empirical evidence regarding significant influence of behavioral biases and momentum effects on daily stock returns in Indian equity market from January 2020 to December 2024. Employing sophisticated methodological framework integrat- ing

Vector Error Correction Models, Random Effects Panel Regression, and Generalized Linear Models ensured robust and validated results. Key findings reveal behavioral factors systemat- ically explain return variations that traditional finance theories cannot adequately account for, presenting important implications for market efficiency theories.

Empirical analysis demonstrates four primary conclusions. First, behavioral biases, particu- larly overreaction and herding behavior, exhibit statistically significant effects on daily returns, with composite behavioral index showing strong predictive power. The unidirectional causality from behavioral biases to market efficiency challenges traditional efficiency paradigms and sug- gests investor psychology fundamentally drives market dynamics. Second, momentum effects persist in Indian market but display complex dynamics, with strong bidirectional relationships with trading volume indicating feedback loops where price trends influence investor activity and vice versa. Third, long-run equilibrium relationships exist between behavioral factors, mo- mentum, and market efficiency, with significant error correction mechanisms ensuring gradual return to equilibrium following deviations. Fourth, market demonstrates varying degrees of effi- ciency, with behavioral factors creating persistent anomalies that challenge strong-form efficient market hypothesis, supporting adaptive efficiency perspectives.

6.2 Theoretical Contributions

This research makes several substantive contributions to behavioral finance literature. Study successfully bridges theoretical propositions with empirical validation in important emerging market context, demonstrating that behavioral patterns observed in developed markets manifest with distinct characteristics in Indian environment. Integrated econometric approach estab- lishes methodological precedent for simultaneously examining short-term dynamics and long- run equilibrium relationships in behavioral finance research.

Findings challenge complete dominance of rational expectations in asset pricing models and provide compelling evidence for incorporating behavioral elements into theoretical frame- works. Documented interaction between momentum and behavioral biases suggests need for more sophisticated models accounting for psychological underpinnings of trend-following be- havior. Time-varying nature of market efficiency documented supports adaptive efficiency mod- els rather than static efficient market classifications, contributing to ongoing paradigm shift in financial economics toward more psychologically-grounded models of market behavior.

6.3 Policy Recommendations

6.3.1 Regulatory Framework Enhancements

Based on empirical findings, Securities and Exchange Board of India (SEBI) should consider implementing several regulatory enhancements:

- Sentiment Surveillance Framework: Develop comprehensive system for proactive iden- tification of market conditions conducive to behavioral excesses. This framework should
- incorporate behavioral metrics validated in this study to monitor emerging bubbles or panic conditions, including trading volume anomalies, volatility ratios, put-call ratios, and social media sentiment indicators. Real-time monitoring would enable early warning of potential instability.
- Dynamic Circuit Breakers: Implement circuit breaker mechanisms incorporating be- havioral indicators alongside price movements to provide more effective stabilization during extreme sentiment-driven volatility. Current static circuit breakers based solely on price movements may not adequately address behavioral dynamics documented in this study. Dynamic thresholds adjusting for sentiment conditions would provide more nuanced market stabilization.
- Enhanced Disclosure Requirements: Mandate enhanced disclosure regarding sentiment- sensitive information. Companies should be encouraged to provide contextual guidance during periods of market overreaction, helping counter behavioral distortions with fun- damental information. This could include requirements for additional disclosures when trading volumes or price movements exceed behavioral threshold levels.
- Behavioral Finance Research Unit: Establish dedicated unit within SEBI for ongo- ing monitoring of behavioral market dynamics and developing evidence-based regulatory responses. This unit would conduct continuous research, evaluate effectiveness of inter- ventions, and recommend regulatory adjustments based on evolving market conditions.

6.3.2 Investor Protection Frameworks

Documented prevalence of behaviorally-driven investment mistakes necessitates strengthened investor protection frameworks:

- Behavioral Awareness Programs: Implement comprehensive programs educating in- vestors about specific biases identified in this study, particularly overreaction, herding, and momentum chasing. These programs should be delivered through multiple chan- nels including investor workshops, online modules, and educational materials distributed through brokerage platforms.
- Behavioral Risk Warnings: Require brokerage platforms and financial intermediaries to incorporate behavioral risk warnings during periods of extreme market sentiment. When behavioral indicators exceed threshold levels, platforms should display prominent warn- ings about heightened risk of sentiment-driven mispricing and potential for subsequent corrections.
- Behavioral Risk Assessment Tools: Develop standardized tools helping investors iden- tify personal susceptibility to documented biases. These

self-assessment instruments would increase self-awareness and potentially moderate trading behavior during senti- ment extremes.

- Mandatory Advisor Training: Require financial advisors receive mandatory training in behavioral finance principles to better guide clients through sentiment-driven market cycles. Understanding behavioral dynamics would enable advisors to provide more ef- fective guidance during periods of market stress.

6.3.3 Institutional Governance Standards

Financial institutions and market intermediaries play crucial role in mitigating behavioral mar- ket distortions:

- Behavioral Governance Standards: Implement standards within asset management companies requiring explicit consideration of behavioral factors in investment processes and risk management frameworks. Investment committees should regularly review be- havioral exposures and consider sentiment conditions in portfolio decisions.
- Behavioral Adjustment Mechanisms: Portfolio managers should incorporate system- atic mechanisms accounting for sentiment-driven mispricing in valuation models. This could include adjusting discount rates during sentiment extremes or implementing valua- tion bands reflecting behavioral uncertainty.
- Investor Sentiment Communication Protocols: Corporate governance guidelines should encourage listed companies to establish protocols addressing behaviorally-driven mis- pricing through strategic communication and capital allocation decisions. Companies should consider opportunities to repurchase shares during sentiment-driven undervalua- tion and issue equity during overvaluation windows.

6.3.4 Educational Initiatives

Financial education curricula in professional certification programs should integrate behavioral finance as core component rather than elective speciality:

- Curriculum Integration: Professional programs including CFA, CFP, and MBA cur- ricula should incorporate behavioral finance as foundational element across investment, corporate finance, and risk management courses.
- Practitioner Training: Develop continuing education programs for finance professionals addressing practical applications of behavioral insights in investment management, client advisory, and risk assessment.
- Public Education: Launch public awareness campaigns through media partnerships and financial literacy programs educating retail investors about behavioral biases and their impact on investment outcomes.

6.4 Practical Implications for Market Participants

Findings offer actionable insights for diverse market participants:

6.4.1 Portfolio Managers and Investment Professionals

- Develop behaviorally-informed strategy frameworks systematically exploiting documented anomalies while implementing safeguards against behavioral risks. Research supports profitability of contrarian strategies during sentiment extremes and careful application of momentum strategies during moderate sentiment regimes.
- Implement systematic processes for monitoring behavioral indicators and adjusting port- folio positioning accordingly. When behavioral bias index reaches extreme levels, con- sider reducing exposure to sentiment-sensitive assets and increasing cash reserves.

- Incorporate behavioral risk factors into risk management frameworks, recognizing that traditional risk models underestimating tail risks during sentiment extremes.

6.4.2 Corporate Treasurers and CFOs

• Formalize behavioral market timing considerations in capital raising decisions, leverag- ing windows of overvaluation while avoiding equity issuance during sentiment-driven undervaluation.

• Consider share repurchase programs during periods when behavioral biases create under- valuation opportunities, enhancing shareholder value through disciplined capital alloca- tion.

• Develop communication strategies addressing analyst and investor sentiment during pe- riods of extreme market reaction to corporate news.

6.4.3 Individual Investors

• Adopt behaviorally-robust investment processes including pre-commitment devices (au- tomated investment plans), systematic rebalancing protocols (periodic portfolio adjust- ment regardless of sentiment), and sentiment-based contrarian indicators (increasing eq- uity exposure during extreme pessimism).

• Maintain diversified portfolios reducing exposure to idiosyncratic behavioral risks asso- ciated with individual stocks or sectors.

• Seek professional advice during periods of market stress when behavioral biases most strongly influence decision-making.

6.5 Limitations and Future Research Directions

While this study provides comprehensive insights, certain limitations suggest productive direc- tions for future research. Reliance on proxy variables for behavioral constructs, though method- ologically necessary, indicates potential for refined measurement approaches. Future studies could incorporate alternative behavioral metrics including social media sentiment analysis us- ing advanced natural language processing techniques, proprietary trading data from brokerage platforms, and experimental measures of investor psychology.

Focus on aggregate market returns, while informative, suggests value of cross-sectional analysis examining how behavioral effects vary across market capitalization segments, indus- try sectors, and investor types. Research could investigate whether small-cap stocks exhibit greater sensitivity to behavioral factors than large-caps, or whether certain sectors (technology, speculative industries) show stronger behavioral effects.

Longitudinal studies examining evolution of behavioral patterns as markets develop would provide additional insights into institutional determinants of behavioral anomalies. Cross- country comparative research could examine how regulatory frameworks, market structures, and cultural factors moderate behavioral effects.

Future research could extend methodological framework to incorporate more sophisticated modeling of non-linear relationships and regime-switching behavior. Markov-switching mod- els could capture distinct behavioral regimes, while threshold models could identify sentiment levels triggering regime changes.

Integration of machine learning techniques with behavioral finance theory represents promis- ing frontier for enhancing predictive accuracy and understanding complex market dynamics. Deep learning models could capture non-linear interactions between behavioral variables, while explainable AI techniques could improve interpretability of complex models.

Causal inference methods including natural experiments, instrumental variables, and difference- in-differences designs could strengthen causal claims about behavioral effects. Regulatory changes, technological innovations, or exogenous shocks provide opportunities for identifying causal effects.

Experimental research complementing empirical analysis could examine behavioral mech- anisms underlying observed patterns. Laboratory experiments with controlled conditions could isolate specific biases and test debiasing interventions before field implementation.

6.6 Concluding Remarks

This research establishes that behavioral factors are not merely theoretical curiosities but empir- ically significant determinants of market outcomes in Indian equity context. Findings demon- strate that investor psychology systematically influences price formation, creating persistent anomalies challenging traditional efficiency paradigms. Practical implications span regulatory policy, investment management, corporate finance, and individual decision-making.

Study contributes to ongoing paradigm shift in financial economics toward more psychologically- grounded models of market behavior. By validating behavioral propositions in important Indian market context and providing robust methodological frameworks for their examination, this research supports continued integration of behavioral insights into both financial theory and practice. Recommendations offered provide roadmap for harnessing these insights to enhance market stability, investor protection, and decision-making quality across financial ecosystem.

The COVID-19 pandemic served as stark reminder that financial markets are governed as much by human behavior as by numbers. As markets continue evolving with technological advancement, social media influence, and changing investor demographics, understanding be- havioral dynamics becomes increasingly essential for building accurate theories, effective regu- latory systems, and robust economies capable of withstanding future disruptions. Recalibrating rationality to encompass behavioral dimensions is not merely academic exercise but practical necessity for resilient financial systems.

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