A Review of Investor Sentiment and Asset Pricing from the Perspective of Behavioral Finance

Yuhan Cheng
Financial Technology Major, School of Finance, Shanxi University of Finance and Economics, Taiyuan, Shanxi, China

Abstract: This review examines investor sentiment and asset pricing via behavioral finance, challenging the traditional rational paradigm. It synthesizes global findings on behavioral influences, integrating cognitive biases and prospect theory to refine investor behavior analysis.The study contrasts traditional CAPM/APT with behavioral models (incorporating sentiment indicators), revealing how sentiment shapes investment behaviors, prices, and volatility. It analyzes sentiment measurement techniques (surveys, market proxies) and their predictive power, focusing on China's A-share market-retail-dominated, informationally asymmetric-through case studies of bubbles, panics, and policy shocks.Based on these analyses, the research develops a sentiment-integrated investment framework to enhance portfolio performance and risk management, providing investor guidelines. It also proposes targeted regulatory and investor education reforms to improve market efficiency and mitigate biases. This study bridges behavioral finance theory and practice, delivering actionable insights for professionals, policymakers, and regulators in emerging markets.

Keywords: Behavioral Finance; Investor Sentiment; Asset Pricing; Cognitive Bias; Investment Strategy

1. Introduction

This study examines investor sentiment and asset pricing from a behavioral finance perspective, challenging the long-dominant rational investor paradigm. [4]Investor sentiment-investors' collective market attitude-is a key driver of asset price deviations, creating mispricings, opportunities, and risks. Its measurement has evolved from surveys to advanced proxies incorporating market data, social media analytics, and machine learning, with critical implications for investment management, risk assessment, and financial regulation.

China's A-share market, with over $11 trillion capitalization and 80% retail trading volume, presents a unique context where behavioral biases and sentiment-driven trading are pronounced. This research systematically investigates the interplay between investor sentiment and asset pricing, addressing how cognitive biases and collective sentiment shape investment behaviors and price dynamics unexplained by traditional rational models, while exploring sentiment transmission mechanisms and measurement techniques.

Adopting a systematic review approach, this study synthesizes decades of behavioral finance literature, conducts comparative analysis of traditional and behavioral asset pricing models, and develops context-specific frameworks for China's market. It bridges theoretical behavioral finance and real-world applications, proposing sentiment-integrated investment strategies and regulatory recommendations to enhance market efficiency and investor protection in emerging markets.

2. Theoretical Foundations of Behavioral Finance and Investor Sentiment

2.1 Evolution from Traditional Finance to Behavioral Finance

The shift from traditional to behavioral finance revolutionized financial economics,as illustrated in Figure 1. Traditional finance, grounded in the EMH and rational actor model, assumes investor rationality, with core models (CAPM, APT) asserting prices reflect intrinsic values[3].

1980s-1990s empirical anomalies challenged these foundations, leading to behavioral finance, which integrates cognitive psychology to explain unaccounted-for market phenomena.

Kahneman and Tversky's prospect theory revolutionized decision-making by documenting systematic deviations from rational choice, while subsequent work identified pervasive investor biases, establishing behavioral finance as a more realistic framework.

2.2 Cognitive Biases and Psychological Factors in Investment DecisionMaking

The Cognitive biases form the behavioral bedrock of investor sentiment, driving systematic pricing errors. Key biases and their implications are summarized in Table 1[7].

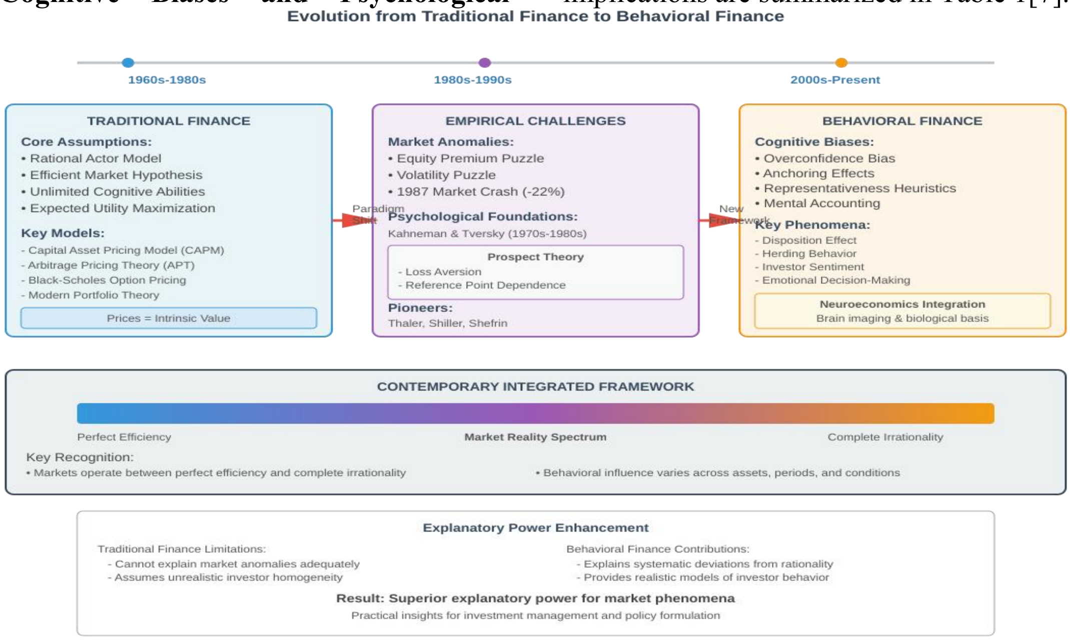

Figure 1. Evolution from Traditional Finance to Behavioral Finance

Table 1. Cognitive Biases and Their Market Implications

Cognitive Bias	Definition	Market Manifestation	Impact on Pricing
Overconfidence	Excessive faith in personal abilities and information	Excessive trading volume, momentum effects	Temporary mispricings, delayed corrections
Anchoring	Overreliance on initial information	Price stickiness around reference points	Systematic deviations from fundamental value
Confirmation Bias	Seeking information that confirms existing beliefs	Bubble formation, delayed reaction to news	Persistent overvaluation or undervaluation
Loss Aversion	Asymmetric sensitivity to gains versus losses	Disposition effect, equity premium puzzle	Higher required returns, momentum patterns
Mental Accounting	Compartmentalized financial decision-making	Inconsistent risk preferences across accounts	Suboptimal portfolio allocation
Herding	Following crowd behavior	Increased volatility during market stress	Amplified price movements, bubble formation
Representativeness	Judging probability by similarity to prototypes	Overreaction to trends, hot-hand fallacy	Momentum and reversal patterns

These biases interact synergistically to shape sentiment and asset pricing, making their understanding critical for modeling investor behavior.

2.3 Prospect Theory and Its Applications in Asset Pricing

Developed by Kahneman and Tversky, prospect theory challenges expected utility theory by modeling decisions relative to a reference point[3]. Its core components: reference dependence, loss aversion, diminishing sensitivity, and probability weighting (formalized as above).

Key applications include the disposition effect, behavioral portfolio theory, and explaining market anomalies. Cumulative Prospect Theory extends the framework, and integrating psychological insights with asset pricing improves explanatory power for sentiment-driven phenomena.

The core components and applications of prospect theory are visualized in Figure 2[12].

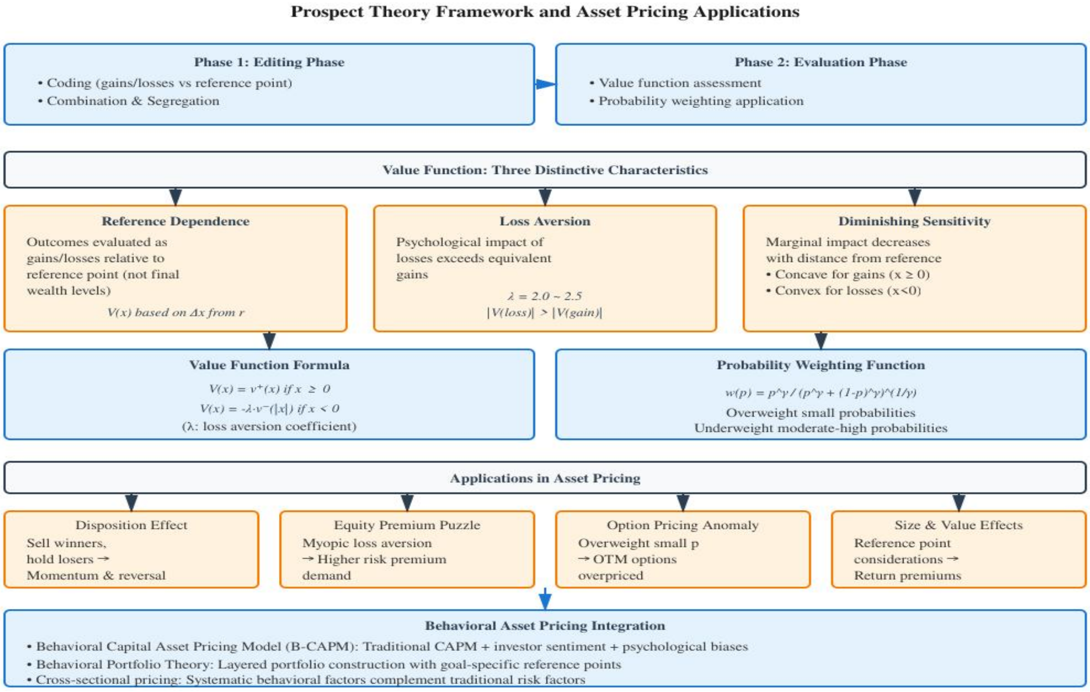

Figure 2. Prospect Theory Framework and Asset Pricing Applications

2.4 Theoretical Framework of Investor Sentiment

Investor sentiment theory challenges the EMH, holding that prices deviate systematically from fundamentals due to collective investor psychology.

Central to this framework is the noise trader-arbitrageur distinction: noise traders create sentiment-driven mispricing, while arbitrageurs' constraints prevent full correction.

Sentiment propagates via herding and information cascades, amplified by media, especially in retail-dominated markets like China's A-shares.

Key dimensions include sentiment measurement, temporal dynamics, and cross-sectional variation. Integrating sentiment into pricing requires hybrid frameworks, as sentiment distorts capital allocation and increases volatility, necessitating regulatory safeguards.They are presented in Figure 3.

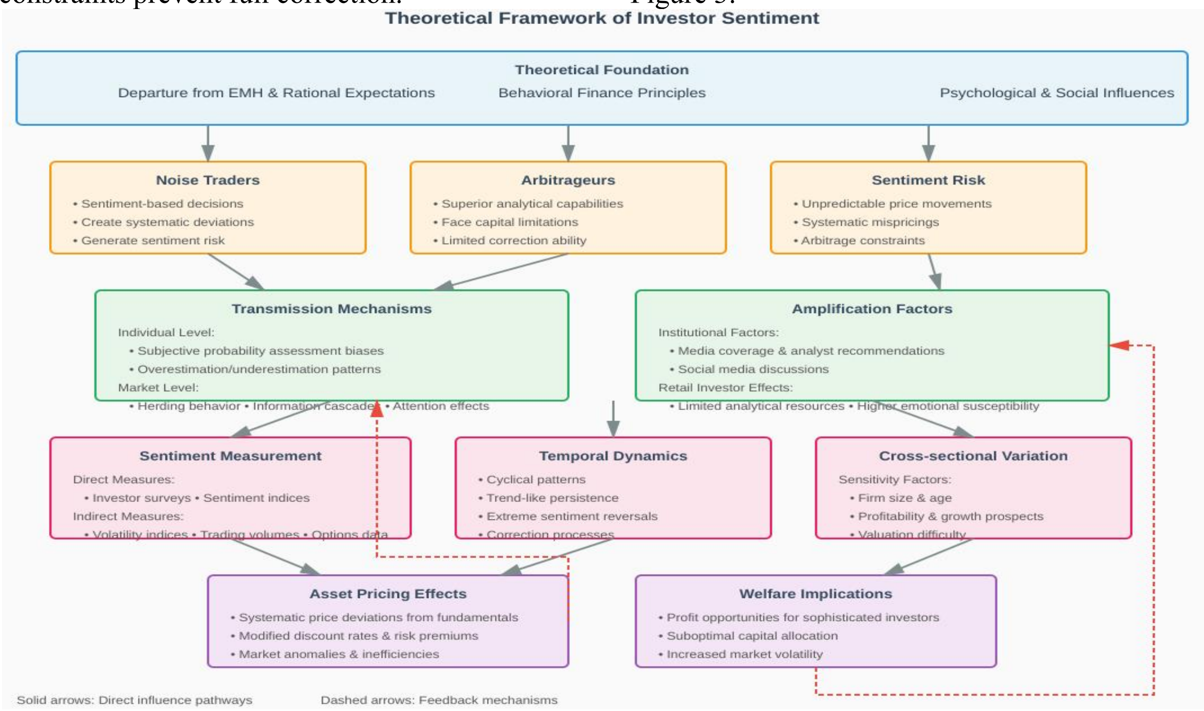

Figure 3. Theoretical Framework of Investor Sentiment

3. Asset Pricing Models: From Traditional to Behavioral Perspectives

3.1 Traditional Asset Pricing Models

3.1.1 Capital Asset Pricing Model (CAPM) Theory and Limitations

Developed by Sharpe, Lintner, and Mossin in the 1960s, the Capital Asset Pricing Model (CAPM) is a cornerstone of modern finance, built on Markowitz's portfolio theory[4]. It establishes a linear equilibrium relationship between systematic risk (measured by beta) and expected return, with the core formula:

$$E(R_i)=R_f+\beta_i[E(R_m)-R_f] \quad (1)$$

where E(Ri) represents the expected return on asset i, Rf denotes the risk-free rate, βi represents the beta coefficient measuring the asset's sensitivity to market movements, and E(Rm) signifies the expected return on the market portfolio. The beta coefficient itself is calculated as:

$$\beta_i=\frac{Cov(R_i,R_m)}{Var(R_m)} \quad (2)$$

CAPM relies on idealized assumptions: rational utility-maximizing investors, homogeneous return expectations, unlimited risk-free borrowing/lending, frictionless efficient markets, and perfectly divisible/liquid assets. These assumptions restrict the model to systematic risk as the sole return driver[15].

Despite its elegance and widespread use, CAPM faces critical empirical challenges. Its single-factor structure fails to explain real-world market anomalies: small-cap stocks (size effect, Banz, 1981) and high book-to-market value stocks (value effect, Fama-French) generate risk-adjusted returns exceeding CAPM predictions. From a behavioral finance perspective, CAPM's rationality and market efficiency assumptions are also inconsistent with investor cognitive biases, heterogeneous expectations, and real-world market frictions[3].

3.1.2 Arbitrage Pricing Theory (APT) and Multifactor Models

Proposed by Stephen Ross in 1976, Arbitrage Pricing Theory (APT) addresses CAPM's limitations by grounding asset pricing in the no-arbitrage principle, allowing multiple systematic risk factors. APT assumes asset returns follow a K-factor linear model:

$$R_i=E(R_i)+\beta_{i1}F_1+\beta_{i2}F_2++\beta_{iK}F_K+\varepsilon_i \quad (3)$$

Under no-arbitrage, expected returns are:

$$E(R_i)=\lambda_0+\lambda_1\beta_{i1}+\lambda_2\beta_{i2}++\lambda_K\beta_{iK} \quad (4)$$

APT's practical application spurred multifactor models, most notably the Fama-French 3-factor model (market, size, value) and 5-factor model (adding profitability, investment), which outperform CAPM in explaining cross-sectional returns. The table below summarizes key models:

Table 2. Multifactor Models

Factor Model	Factors Included	Average R^2	Key Advantages	Primary Limitations
CAPM	Market factor only	0.65-0.75	Simplicity, widespread acceptance	Single factor inadequacy
Fama-French 3-Factor	Market, Size, Value	0.85-0.90	Size and value premium capture	Limited factor scope
Fama-French 5-Factor	Market, Size, Value, Profitability, Investment	0.90-0.93	Comprehensive factor coverage	Model complexity
Carhart4-Factor	FF3 + Momentum	0.87-0.92	Momentum effect inclusion	Factor stability issues

A key limitation of APT is its lack of guidance for factor selection, introducing model specification risk.

3.1.3 Efficient market hypothesis and its challenges

Formulated by Eugene Fama, the Efficient Market Hypothesis (EMH) posits asset prices fully reflect all available information, precluding consistent abnormal returns. It defines three forms:

1) Weak-form: Reflects historical price/volume data (invalidates technical analysis)

2) Semi-strong form: Reflects all public information (invalidates fundamental analysis)

3) Strong-form: Reflects all public/private information (empirically rejected)

EMH underpins passive index investing, but empirical anomalies (calendar effects, momentum, mean reversion) contradict it. These are explained by investor cognitive biases and market microstructure frictions.

3.2 Behavioral Asset Pricing Models

3.2.1 Sentiment based asset pricing models

Sentiment-based models integrate investor sentiment into valuation, explaining classical model anomalies by recognizing prices reflect both fundamentals and collective psychology.

Baker and Wurgler's framework formalizes this as:

$$R_{it}=\alpha_i+\beta_iR_{mt}+\gamma_iS_t+\varepsilon_{it} \quad (5)$$

where R_{it} represents the return on asset i at time t, R_{mt} denotes the market return, S_t captures the sentiment factor, and γ_i measures the sensitivity of asset i to sentiment fluctuations. Advanced models feature time-varying sensitivity, with sentiment proxied by market indicators and NLP. In China's A-share market, sentiment is more volatile due to retail dominance.The integrated framework of sentiment-based asset pricing models, including their components and applications, is illustrated in Figure 4[5][11].

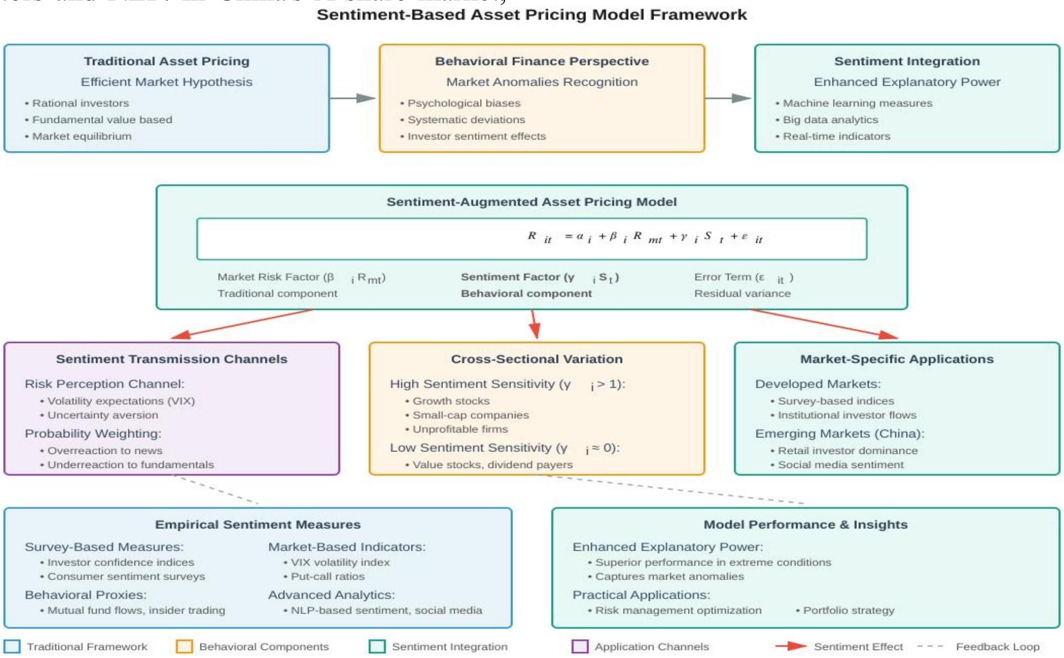

Figure 4. Sentiment-Based Asset Pricing Model Framework

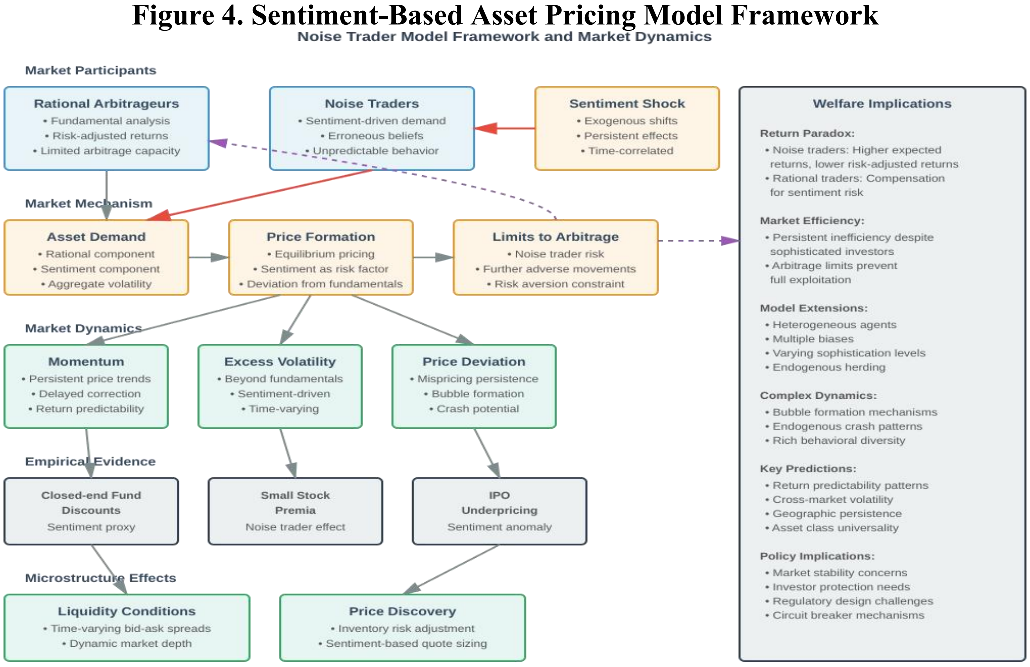

Figure 5. Noise Trader Model Framework and Market Dynamics

3.2.2 Noise trader models and market dynamics

Noise trader models formalize how irrational investors influence asset prices, challenging the efficient market hypothesis. The seminal De Long et al. (1990) model shows noise traders create limits to arbitrage: rational arbitrageurs face sentiment-driven price risk, allowing noise traders to earn excess returns and making sentiment a priced risk factor.

Key implications include:

1) Excess volatility: Sentiment-driven demand creates price volatility unexplained by fundamentals.

2) Momentum and predictability: Sentiment persistence generates momentum effects and predictable price deviations from fundamentals.

3) Empirical support: Closed-end fund discounts, small-stock premia, and IPO underpricing confirm noise trader effects.

4) Market microstructure impacts: Noise trading affects bid-ask spreads, liquidity, and price discovery.

The complete framework of the noise trader model and its market dynamics is illustrated in Figure 5[13].

3.2.3 Behavioral CAPM and Modified Pricing Frameworks

Behavioral CAPM relaxes traditional CAPM's rationality assumptions, integrating psychological biases to create more realistic risk-return relationships. Shefrin and Statman's model introduces heterogeneous beliefs and investor biases, with the formula:

$$E[R_i]=R_f+\beta_i^{behavioral}[E[R_m]-R_f]+\sum_{j=1}^{k}\lambda_j B_{ij} \quad (6)$$

where $E[R_i]$ represents the expected return on asset i, $\beta_i^{behavioral}$ denotes the behavioral beta that incorporates sentiment sensitivity, and B_{ij} captures various behavioral risk factors with corresponding risk premia λ_j. This formulation allows behavioral factors to command risk premia independently of traditional market beta, reflecting investors' aversion to assets that perform poorly during periods of negative sentiment or high uncertainty.

Modified frameworks integrate prospect theory, loss aversion, and mental accounting, explaining anomalies like the equity premium puzzle. Contemporary multi-factor behavioral models combine sentiment, momentum, and size/value effects, with time-varying factor loadings tied to market conditions.This framework is visualized in Figure 6.

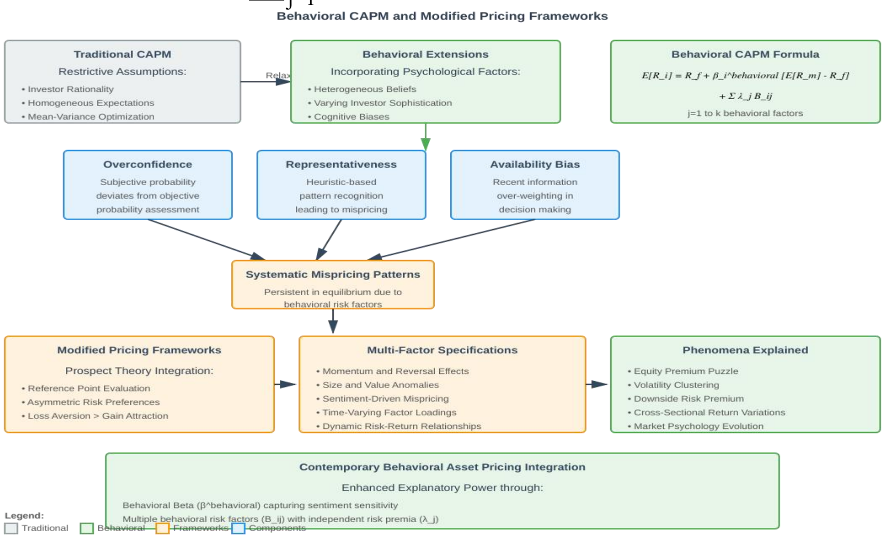

Figure 6. Behavioral CAPM and Modified Pricing Frameworks

3.3 Comparative Analysis of Traditional and Behavioral Models

3.3.1 Model performance in different market conditions

Traditional models (CAPM, APT) perform well in stable, low-volatility markets, capturing ~60-70% of cross-sectional returns. Behavioral models dominate in crisis, bubble, and transition periods, where psychological factors drive prices.These differences are summarized in Table 3.

3.3.2 Explanatory power for market anomalies

Behavioral models outperform traditional frameworks in explaining persistent market anomalies.Table 4 compares their explanatory power for key anomalies.

3.3.3 Practical applications and limitations

Traditional models remain dominant for institutional processes due to simplicity, while behavioral models offer superior anomaly prediction but face challenges in real-time implementation. These trade-offs are outlined in Table 5.

Table 3. Model Performance under Different Market Conditions

Market Condition	Traditional Models (R^2)	Behavioral Models (R^2)	Primary Explanatory Factors
Stable Periods	0.65-0.72	0.68-0.75	Systematic risk, fundamentals
Crisis Periods	0.35-0.45	0.58-0.68	Sentiment, loss aversion
Bubble Formation	0.28-0.38	0.62-0.71	Overconfidence, herding
Market Transitions	0.41-0.52	0.59-0.69	Adaptive expectations

Table 4. Comparing the Explanatory Power of Market Anomalies

Market Anomaly	Traditional Model Explanation Power	Behavioral Model Explanation Power	Key Behavioral Factors
Momentum Effect	Weak (R^2 = 0.12-0.23)	Strong (R^2 = 0.45-0.62)	Overconfidence, anchoring
Value Premium	Moderate (R^2 = 0.31-0.42)	Strong (R^2 = 0.54-0.68)	Loss aversion, mental accounting
Size Effect	Moderate (R^2 = 0.38-0.48)	Strong (R^2 = 0.52-0.66)	Attention bias, liquidity preference
Calendar Anomalies	Weak (R^2 = 0.08-0.18)	Moderate (R^2 = 0.35-0.48)	Tax-loss selling, sentiment cycles

Table 5. The Trade-off Relationship between Traditional Models and Behavioral Models

Model Category	Implementation Advantages	Implementation Limitations	Optimal Use Cases
Traditional Models	Simple computation, regulatory acceptance	Limited anomaly explanation	Passive indexing, regulatory compliance
Behavioral Models	Anomaly capture, crisis prediction	Parameter instability, complexity	Active management, tactical allocation

4. Empirical Evidence and Transmission Mechanisms

4.1 Measurement and Indicators of Investor Sentiment

4.1.1 Direct sentiment measures and surveybased indicators

Direct sentiment measures capture investor psychology via explicit surveys (e.g., Michigan Consumer Sentiment Index, AAII Sentiment Survey). Extreme readings have contrarian predictive power, and regional surveys adapt to local investor behaviors.Key characteristics of these direct survey-based measures are summarized in Table 6[1].

4.1.2 Indirect marketbased sentiment proxies

Market-based proxies derive sentiment from observable trading behaviors, avoiding survey biases. Key indicators include:

1) Closed-end fund discounts: Wider discounts signal pessimism, narrower discounts reflect optimism.

2) Trading volume: Abnormal volume spikes precede extreme price movements, with stronger predictive power during market stress.

3) Put-call ratio: High ratios indicate bearish sentiment, low ratios signal complacency.

4) Volatility indices (VIX): Capture market uncertainty, exhibiting asymmetric behavior (faster rises during stress).

5) Market microstructure proxies: Bid-ask spreads, order flow imbalances, and institutional trading patterns reveal sentiment-driven supply-demand dynamics.

The features and signals of these indirect market-based proxies are detailed in Table 7[9].

4.1.3 Composite Sentiment Indices and Construction Methods

Composite indices combine multiple sentiment indicators via statistical methods to create robust market psychology measures. The Baker-Wurgler Index (PCA on 6 market proxies, orthogonalized to macro factors) is a leading example, with strong predictive power for sentiment-sensitive stocks.A comparison of major composite sentiment indices is provided in Table 8[14]. Dynamic factor models (e.g., Kalman filtering) enable real-time updates, suitable for emerging markets.

The mathematical framework for composite sentiment index construction using principal component analysis follows the general form:

$$S_t=w_1X_{1,t}+w_2X_{2,t}++w_nX_{n,t} \tag{7}$$

Where the optimal weights are determined through eigenvalue decomposition:

$$w=\operatorname{argmax}_w \frac{w^T\Sigma w}{w^T w} \tag{8}$$

Subject to normalization constraints, where Σ represents the covariance matrix of standardized sentiment indicators.

Table 6. Direct Sentiment Measures and Surveybased Indicators

Survey Type	Frequency	Sample Size	Response Categories	Predictive Horizon
AAII Sentiment Survey	Weekly	200-400	Bullish/Neutral/Bearish	1-6 months
Investors Intelligence	Weekly	100-150	Bulls/Bears/Correction	2-8 weeks
Market Vane	Weekly	50-100	Bullish/Bearish	1-4 weeks
Conference Board	Monthly	3,000+	Positive/Neutral/Negative	3-12 months
University of Michigan	Monthly	500+	Better/Same/Worse	6-18 months

Table 7. Indirect MarketBased Sentiment Proxies

Sentiment Proxy	Data Frequency	Market Scope	Contrarian Signal	Lead Time
VIX Level	Real-time	Equity Markets	>30 (Fear), <15 (Complacency)	1-30 days
Put-Call Ratio	Daily	Options Markets	>1.2 (Bearish), <0.7 (Bullish)	3-21 days
Closed-End Fund Discount	Weekly	Fund Markets	>10% (Pessimism), <5% (Optimism)	1-12 weeks
Margin Debt	Monthly	Equity Markets	Extreme highs/lows	1-6 months
Insider Trading Ratio	Monthly	Corporate Actions	>3:1 selling (Bearish)	3-12 months

Table 8. Comparison of the Comprehensive Emotional Index

Composite Index	Components	Construction Method	Update Frequency	Geographic Scope
Baker-Wurgler Index	6 market indicators	PCA with orthogonalization	Monthly	US Markets
FEARS Index	5 sentiment proxies	Equal-weighted combination	Daily	Global Markets
CNN Fear & Greed	7 market indicators	Weighted average	Daily	US Markets
IBES Sentiment	Analyst revisions	Standardized scores	Monthly	International
Custom Composite	Variable selection	Dynamic factor model	Real-time	Market-specific

4.2 Transmission Mechanisms of Sentiment on Asset Prices

4.2.1 Individual Investor Behavior and Sentiment Transmission

Individual investors exhibit systematic behavioral biases that drive sentiment transmission:

1) Overconfidence & representativeness: Excessive trading during optimism, extrapolation of recent trends.

2) Anchoring: Persistent price deviations from fundamentals via psychological reference points.

3) Availability heuristic: Overweighting of easily recalled information (e.g., media coverage).

4) Herding: Self-reinforcing cycles driving prices far from fundamentals, especially during uncertainty.

5) Loss aversion & endowment effect: Asymmetric trading patterns explaining volatility clustering.

6) Mental accounting: Inconsistent risk preferences across portfolios creating differential demand patterns.

7) Social learning: Correlated trading via peer imitation, amplified by social media.

These individual-level mechanisms are visualized in Figure 7[7].

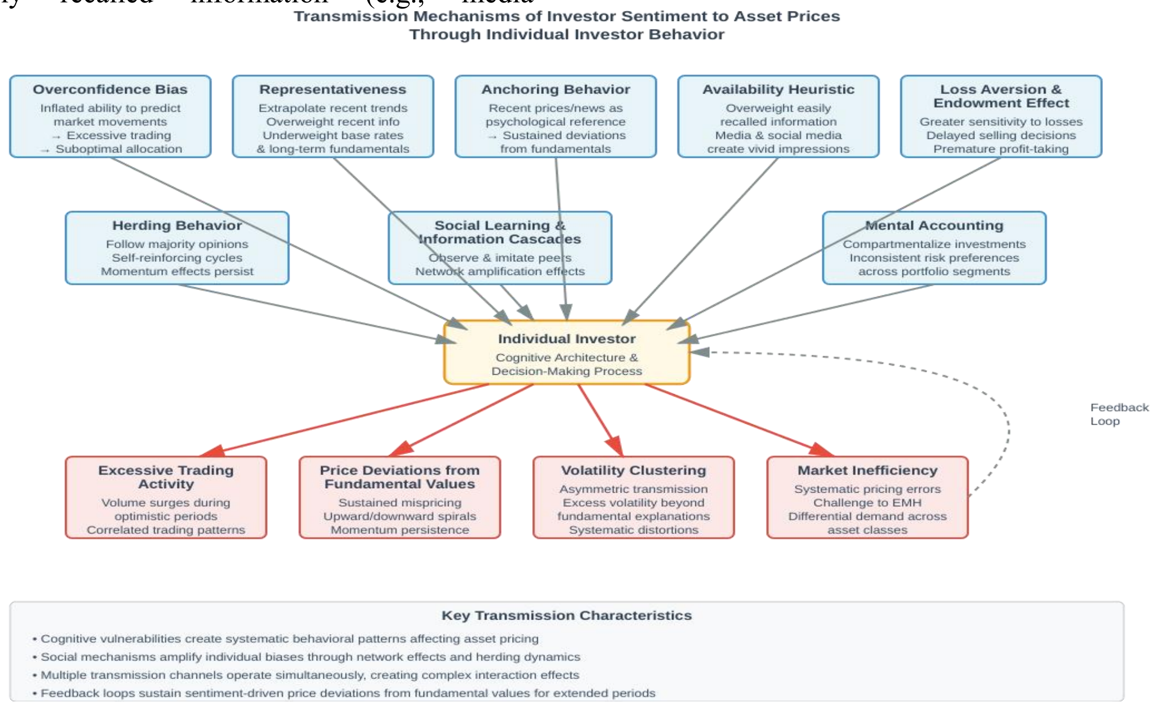

Figure 7. Transmission Mechanisms of Investor Sentiment to Asset Prices Through Individual Investor Behavior

4.2.2 Institutional investor response and market impact

Institutional investors often amplify rather than arbitrage sentiment-driven mispricings, driven by career risk, structural constraints, and behavioral biases:

1) Career risk hypothesis: Fund managers follow market sentiment to avoid benchmark underperformance.

2) Quantitative strategies: Algorithmic momentum trading creates systematic sentiment transmission.

3) Institutional constraints: Asset-liability matching, redemption pressures, and regulatory requirements amplify sentiment cycles.

4) Benchmarking behavior: Procyclical risk-taking to capture upside and limit downside deviation.

5) Risk management systems: Volatility-based position sizing creates procyclical selling pressure during stress.

6) Institutional communication: Research reports and trading activity trigger imitative behavior, amplifying sentiment.

The institutional response mechanisms are illustrated in Figure 8[10].

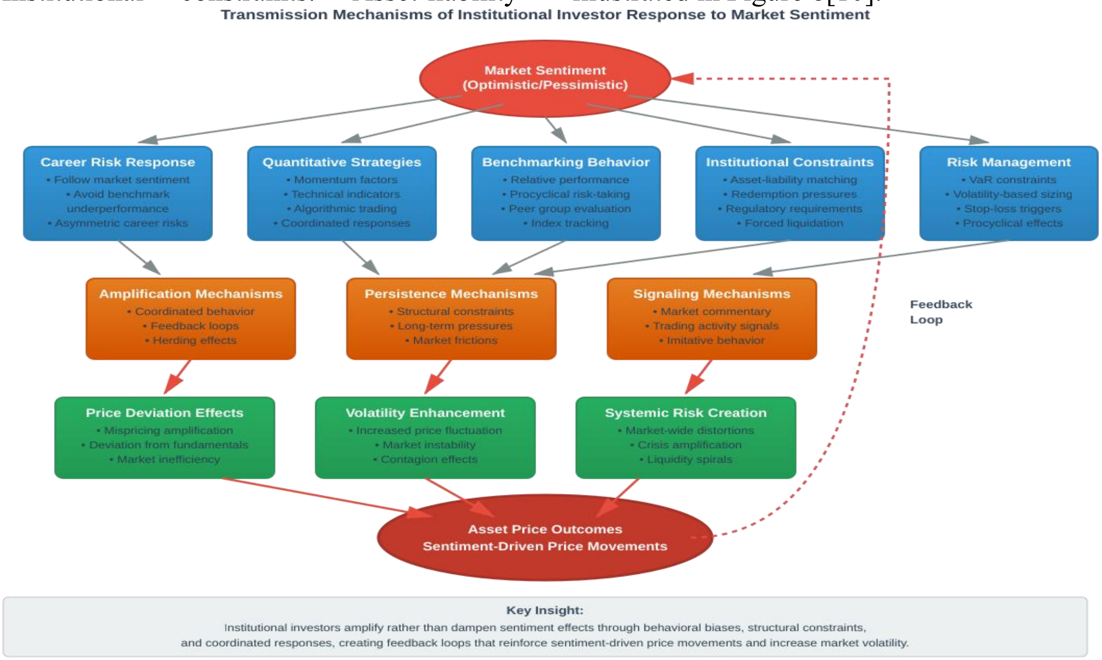

Figure 8. Transmission Mechanisms of Institutional Investor Response to Market Sentiment

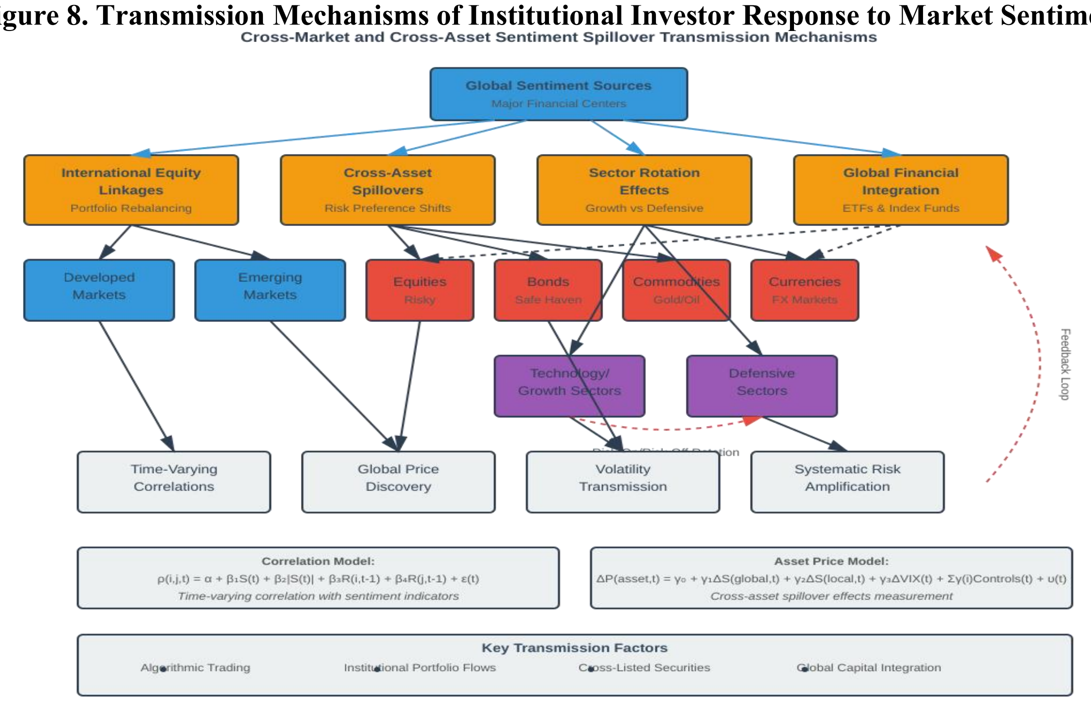

Figure 9. Cross-Market and Cross-Asset Sentiment Spillover Transmission Mechanisms

4.2.3 CrossMarket and crossasset sentiment spillover effects

Sentiment propagates globally via multiple channels:

1) International equity linkages: Institutional portfolio rebalancing transmits sentiment from major financial centers to emerging markets, creating time-varying return correlations.

2) Cross-asset spillovers: Risk-on/risk-off sentiment links equity, bond, commodity, and currency markets, creating flight-to-quality dynamics during pessimism.

3) Sector rotation effects: Growth sectors exhibit heightened sentiment sensitivity, while defensive sectors act as offsets during negative sentiment.

4) ETF and cross-listed securities: Mechanical linkages accelerate sentiment transmission across segmented markets.

The spillover model is:

$$\rho_{i,j,t}=\alpha+\beta_1 S_t+\beta_2|S_t|+\beta_3 R_{i,t-1}+\beta_4 R_{j,t-1}+\varepsilon_t \quad (9)$$

These cross-market spillover mechanisms are summarized in Figure 9[1].

4.3 Empirical Evidence from Global Markets

4.3.1 International evidence on sentimentprice relationships

Global studies confirm a negative, asymmetric sentiment-return relationship: extreme optimism precedes below-average returns, while pessimism precedes recoveries, with negative shocks having larger, more persistent effects. Sentiment effects are strongest for hard-to-value, hard-to-arbitrage stocks (small-cap, growth, unprofitable, high-volatility).

Cross-country evidence on sentiment effects is presented in Table 9[8].

Table 9. Cross-Country Evidence on Sentiment Effects Across Major Equity Markets

Market	Sentiment Proxy	Sample Period	Sentiment-Return Correlation	Persistence (months)	Volatility Impact
United States	VIX, CBOE	1990-2020	-0.34	6-12	High
United Kingdom	FTSE Volatility Index	1995-2020	-0.28	4-8	Moderate
Germany	DAX Sentiment Index	1992-2020	-0.31	5-10	Moderate
Japan	Nikkei Fear Index	1998-2020	-0.26	3-6	Low
South Korea	KOSPI Sentiment	2000-2020	-0.42	8-15	Very High
Brazil	Bovespa Volatility	2003-2020	-0.38	6-12	High
India	Nifty Sentiment	2005-2020	-0.45	10-18	Very High

Note: indicates significance at 1% level, at 5% level. Persistence measured as duration of sentiment effect significance.

Sentiment-based long-short strategies generate consistent abnormal returns across markets, with returns varying by transaction costs and accessibility.

4.3.2 China's ashare market: unique characteristics and sentiment effects

China's A-share market, dominated by retail investors (>80% trading volume), exhibits stronger, more persistent sentiment effects than developed markets, with an average sentiment-return correlation exceeding -0.5. Key features include:

1) Structural amplifiers: Capital controls, short-selling restrictions, state-owned enterprise dominance, T+1 settlement, and daily price limits.

2) Sectoral heterogeneity: Technology/growth sectors (ChiNext, STAR Market) show extreme sentiment sensitivity, while state-owned enterprises exhibit muted reactions.

3) Regulatory and media channels: Policy announcements drive sentiment independently of fundamentals; social media accelerates sentiment contagion.

4) Dividend/rights offering effects: Sentiment reactions to corporate actions often exceed economic value.

Sentiment effects across China's A-share market segments are detailed in Table 10[5].

Table 10. Sentiment Effects Across A-Share Market Segments and Comparison with International Markets

Market Segment	Sentiment Correlation	Volatility Multiplier	Persistence (days)	Turnover Sensitivity	Policy Response
A-Share Main Board	-0.52	2.8x	25-35	High	Very High
ChiNext	-0.67	4.2x	30-45	Very High	Extreme
STAR Market	-0.71	5.1x	35-50	Very High	Extreme
B-Share Market	-0.28	1.4x	10-15	Low	Moderate

US S&P 500	-0.34	1.0x	15-20	Moderate	Low
UK FTSE 100	-0.28	1.2x	12-18	Moderate	Low
Germany DAX	-0.31	1.3x	15-22	Moderate	Moderate

Note: indicates significance at 1% level, at 5% level. Volatility multiplier relative to fundamental volatility baseline.

4.3.3 Crisis events and extreme sentiment episodes

Crisis act as natural experiments, revealing sentiment as the dominant driver of asset prices during stress, while traditional models lose predictive power. Major crises (1987 Black Monday, 2000 dot-com crash, 2008 global crisis) exhibit consistent psychological dynamics: initial euphoria, sudden sentiment reversal, and prolonged pessimistic overreaction. During the 2008 crisis, sentiment shocks accounted for 60-70% of market volatility, far exceeding fundamental factors.

Key crisis episodes and their sentiment dynamics are summarized in Table 11[10].

Table 11. Major Crisis Episodes and Associated Sentiment Indicators

Crisis Event	Peak Sentiment Date	Sentiment Indicator	Market Decline	Recovery Duration	Behavioral Characteristics
Black Monday 1987	October 19, 1987	VIX >150	-22.6% (1 day)	6 months	Herding, Panic Selling
Dot-com Crash 2000	March 10, 2000	NASDAQ Fear >80	-78% (30 months)	36 months	Euphoria Reversal
Global Crisis 2008	October 10, 2008	VIX >80	-57% (18 months)	60 months	Credit Freeze, Liquidity Crisis
China Crash 2015	June 12, 2015	A-Share Sentiment <10	-43% (3 months)	24 months	Margin Liquidation, Retail Panic
COVID-19 2020	March 16, 2020	VIX >82	-34% (1 month)	12 months	Uncertainty, Flight to Safety

Note: Sentiment indicators normalized to 0-100 scale for comparison. Recovery duration measured to pre-crisis peak levels.

5. Conclusion

5.1 Main Findings and Theoretical Contributions

This review identifies investor sentiment as a foundational driver of asset pricing, marking a paradigm shift from traditional rationality-centric frameworks. Persistent sentiment-driven price deviations challenge classical efficiency assumptions, shaping individual decisions and market outcomes in ways traditional models fail to capture.

Sentiment-augmented models outperform CAPM/APT in explaining anomalies, volatility clustering, and cross-sectional returns. A comprehensive sentiment indicator taxonomy advances research, while transmission mechanisms lay foundations for future model development.

Studies on China's A-shares yield unique emerging market insights, extending frameworks beyond developed markets and validating behavioral finance globally.

5.2 Investment Strategy Framework and Practical Implications

SynthesizinThis study proposes a Behavioral-Enhanced Asset Allocation (BEAA) framework, integrating sentiment indicators, contrarian signals, and volatility patterns to capture extreme market emotions. It is implemented via systematic sentiment monitoring and threshold setting for tactical allocation adjustments.

Sentiment-based strategies deliver significant alpha in retail-dominated markets like China's A-shares. Successful implementation requires robust risk management and combining sentiment analysis with fundamental valuation to mitigate pure contrarian/momentum pitfalls.

The components of the behavioral investment strategy franework are detailed in Table 12[4].

The complete Behavioral-Enhanced Asset Allocation framework is visualized in Figure 10[11].

Table 12. Behavioral Investment Strategy Framework Components

Strategy Component	Sentiment Indicator	Implementation Threshold	Expected Market Impact	Risk Management Protocol
Contrarian Positioning	VIX > 30	Extreme Fear Events	Mean Reversion	Position Size Limits

Momentum Exploitation	Survey Optimism > 80%	Euphoric Periods	Trend Continuation	Stop-Loss Mechanisms
Volatility Harvesting	Put/Call Ratio < 0.6	Complacency Phases	Volatility Expansion	Dynamic Hedging
Sector Rotation	Margin Debt Growth > 50%	Speculative Bubbles	Sector Divergence	Correlation Monitoring
Cash Management	Sentiment Dispersion > 2σ	Uncertainty Periods	Liquidity Premium	Flexible Allocation

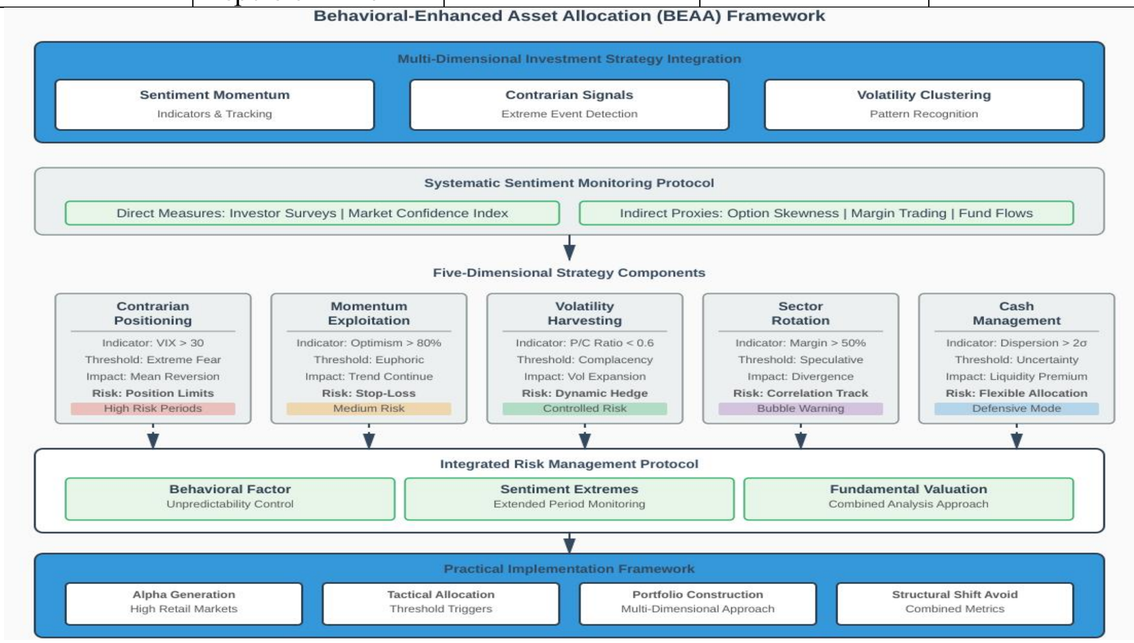

Figure 10. Behavioral-Enhanced Asset Allocation (BEAA) Framework

5.3 Policy Recommendations for Market Regulation and Investor Education

Regulators must implement behavioral-focused reforms: deploy advanced surveillance to detect sentiment-driven anomalies, curb excessive volatility, and mandate transparent disclosure of governance and risk metrics.

Supervision should integrate sentiment indices, emotion-driven trading patterns, and social media analysis for early market instability warnings. Investor education targets cognitive biases (overconfidence, anchoring, loss aversion), merging behavioral finance with traditional principles to build disciplined investing, risk management, and emotional regulation skills, with tailored programs for retail and institutional investors.

5.4 Limitations and Future Research Directions

Key limitations include imperfect sentiment measurement (partial market psychology, temporal instability, cultural bias), proxy-induced measurement errors, and cross-market investor heterogeneity limiting model universality.

Future research will advance sentiment measurement via machine learning, NLP, and big data to capture real-time investor emotions. It will also integrate neuroscience, conduct longitudinal market studies, and explore algorithmic trading-human sentiment interactions to deepen understanding of modern market dynamics.

References

[1] Qing Liu,Yanfeng Liu,Hosung Son. From emotion to action: How intraday investor sentiment drives market microstructure[J].Borsa Istanbul Review,2026,26(2):

[2] Basma Almisshal,Halil İbrahim Bulut. The dynamics of cryptocurrency market from behavioral finance perspective[J].Journal of Behavioral and Experimental Finance,2026,49

[3] Xiao Yanzhang. The Challenge of Behavioral Finance Theory to Efficient Capital Markets: A Study Based on the GameStop Short Squeeze Incident [J]. Business Observer, 2025, 11(36): 85-88 +

97.

[4] Md Rahber Alam,Asrar Ahmad,Javaid Akhter,Tariq Aziz. Mapping the field of behavioral finance: a systematic review and bibliometric analysis[J].Asian Education and Development Studies,2025,14(5):

[5] Deng Chuang, Yang Chenlong, Xie Jingxuan. Investor Sentiment and Tail Risk of Financial Asset Prices in China [J]. Systems Engineering - Theory & Practice,

[6] Rashed Jahangir,Gülfen Tuna,Hümeyra Koç,Muhammad Hassan Abbas. Financial literacy, investor sentiment, and Bitcoin returns: Panel evidence from the Eurozone[J].Borsa Istanbul Review,2025,25(S1):

[7] Alain Finet,Kevin Kristoforidis,Julie Laznicka. Investor Emotions and Cognitive Biases in a Bearish Market Simulation: A Qualitative Study[J].Journal of Risk and Financial Management,2025,18(9):

[8] Ye Lijing. Research on the Impact of Investor Sentiment on Stock Market Volatility [D]. Supervisor: Zhang Bo; He Jiangyan. Xi'an University of Technology, 2025.

[9] Liu Wenjuan. Media Sentiment, Investor Sentiment and Stock Returns [D]. Supervisor: Zhang Bo; He Jiangyan. Xi'an University of Technology, 2025.

[10] Zhangyu Wang,Qiuxuan Chen,Mengwei Liu. Group Behavior and Systemic Risk in Financial Markets: A Behavioral Finance Perspective on Crisis-Preceding and Post-Crisis Effects[J].Journal of Fintech and Business Analysis,2025,2(1):

[11] Chen Zhifang, Li Jiayuan. Short-Term Stock Price Prediction Based on BERT-BILSTM Model and Investor Sentiment [J]. Journal of Financial Theory Research, 2024, (06): 28-38.

[12] Kahneman D, Tversky A. Prospect theory: An analysis of decision under risk[J]. Econometrica, 1979, 47(2):263-291.

[13] De Long J B, Shleifer A, Summers L H, et al. Noise trader risk in financial markets[J]. Journal of Political Economy, 1990, 98(4):703-738.

[14] Baker M, Wurgler J. Investor sentiment and the cross-section of stock returns[J]. The Journal of Finance, 2006, 61(4):1645-1680.

[15] Fama E F, French K R. Common risk factors in the returns on stocks and bonds[J]. Journal of Financial Economics, 1993, 33(1):3-56.

