Behavioral Finance: The Impact of Investor Psychology on Stock Market Volatility

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Abstract

Investor psychology — emotions, heuristics and biases — plays a measurable role in creating and amplifying stock-market volatility. Behavioral biases (loss aversion, overconfidence, herding, anchoring, sentiment swings) change trading intensity and price dynamics, producing mispricing and feedback loops that increase short-term and sometimes long-run volatility. Empirical work documents correlations and causal channels between sentiment/bias proxies and realized volatility; econometric models such as GARCH/EGARCH, VAR and regime-switching models are commonly used to quantify these effects.

Key words: Behavioral Finance, Investors Psychology, Behavioral Biases

Introduction

Traditional finance (e.g., Efficient Market Hypothesis) assumes investors are rational and prices fully reflect available information. Behavioral finance relaxes that assumption and explains persistent anomalies via documented cognitive biases and emotions. Prospect theory (Kahneman & Tversky) — people overweight losses relative to gains — is a foundational behavioral model explaining asymmetric reactions to bad vs. good news, which can raise volatility after negative shocks. Behavioral finance is an economic theory that ascribes the irrational behavior of individuals making financial choices to psychological factors or biases.

Behavioral finance, a subfield of behavioral economics, proposes that psychological influences and biases affect the financial behaviors of investors and financial practitioners. Moreover, influences and biases can explain all types of market anomalies, including those in the stock market, such as severe rises or falls in stock price.

Behavioral Finance in the Stock Market

The efficient market hypothesis (EMH) says that at any given time in a highly liquid market, stock prices are efficiently valued to reflect all the available information. However, many studies have documented long-term historical phenomena in securities markets that contradict the efficient market hypothesis and can't be plausibly captured in models based on perfect investor rationality.The EMH is generally based on the belief that market participants view stock prices rationally based on all current and future intrinsic and external factors. When studying the stock market, behavioral finance takes the view that markets are not fully efficient. This allows for the observation of how psychological and social factors can influence the buying and selling of stocks.

The understanding and usage of behavioral finance biases can be applied to stock and other trading market movements on a daily basis. Broadly, behavioral finance theories have also been used to provide clearer explanations of substantial market anomalies like bubbles and deep recessions. While not a part of EMH, investors and portfolio managers have a vested interest in understanding behavioral finance trends. These trends can be used to help analyze market price levels and fluctuations for speculation as well as decision-making purposes.

Key behavioral drivers linked to volatility:

- Loss aversion / asymmetric risk preferences — stronger reactions to losses than gains (larger price moves on bad news).
- Macro synergy Overconfidence — excessive trading, higher volume and amplified short-term volatility.
- Herding / information cascades — investors mimic others, creating correlated trades that inflate volatility and systemic risk.
- Sentiment and noise trading — waves of optimism/pessimism move prices away from fundamentals and increase return variance.

Literature Review

- **Fei (2021)** conducted an empirical analysis revealing that herding behavior significantly amplifies systemic risk in financial markets. By driving investors to imitate collective market actions rather than rely on individual assessments, herding causes market movements to become highly synchronized. This synchronization magnifies the impact of shocks, as large groups of investors react similarly to new information or trends, leading to heightened volatility and greater market instability. Consequently, herding undermines market efficiency and increases the likelihood of systemic crises when confidence shifts abruptly across the market.
- **Pham (2025)** reviewed recent empirical studies and confirmed that investor sentiment serves as a strong and consistent driver of market volatility across both developed and emerging economies. The analysis highlighted that fluctuations in collective investor mood—whether overly optimistic or pessimistic—can significantly influence asset prices and trading behaviors. These sentiment-driven effects tend to intensify during periods of heightened uncertainty, such as economic downturns or geopolitical tensions, when investors are more prone to emotional reactions and speculative decision-making. Overall, Pham's findings underscore the critical role of sentiment in shaping market dynamics and amplifying volatility under unstable conditions.
- **Pham et al. (2020)** found that sentiment indicators—such as media tone and investor surveys—are significant predictors of volatility in Asian stock markets. Their study demonstrated that shifts in public mood and news sentiment often precede changes in market fluctuations, reflecting the sensitivity of these markets to psychological and informational factors. The effects were particularly pronounced in retail-driven markets, where individual investors' decisions are more influenced by emotions and media narratives than by fundamental analysis. These findings suggest that sentiment plays a pivotal role in driving short-term volatility and market dynamics across Asia.

Gaps in Literature

- **Causality:** Many studies show correlation, but disentangling whether sentiment drives volatility or vice versa remains challenging.

- **High-frequency data:** More work is needed using intraday sentiment (e.g., Twitter, news feeds).
- **Heterogeneity:** Behavioral effects differ by investor type (retail vs institutional), yet most studies use aggregate data.

Research Methodology

Data Collection:

Market data: daily returns, trading volume, realized volatility (e.g., squared returns or high-low based estimators) for an index (S&P 500) or individual stocks — source: Bloomberg/CRSP/Yahoo/Quandl.

Research Questions & Hypotheses:

RQ1: Do behavioral indicators (sentiment, overconfidence proxies, herding measures) predict daily/weekly stock-market volatility?

H1: Higher investor sentiment and overconfidence are associated with increased short-term volatility.

H2: Herding among investors increases cross-sectional return co movement and market volatility, especially during recessions/uncertainty.

Behavioral proxies:

- Sentiment indices: e.g., Baker & Wurgler sentiment, or media sentiment (NLP on news headlines).
- Search activity: Google Trends for finance-related queries.
- Overconfidence proxy: abnormal trading volume, net buying by retail, turnover.
- Herding measure: cross-sectional dispersion vs. market return (e.g., Christie & Huang or Chang, Cheng & Khorana measures).
- Control variables: macro uncertainty (VIX), liquidity measures, macro announcements, firm fundamentals (if using stocks).

Econometric strategy:

Time-series specs: GARCH / EGARCH models with behavioral variables included in the volatility equation to test incremental explanatory power.

Panel approach: Panel-GARCH or fixed effects panel regressions of realized volatility on behavioral proxies and controls.

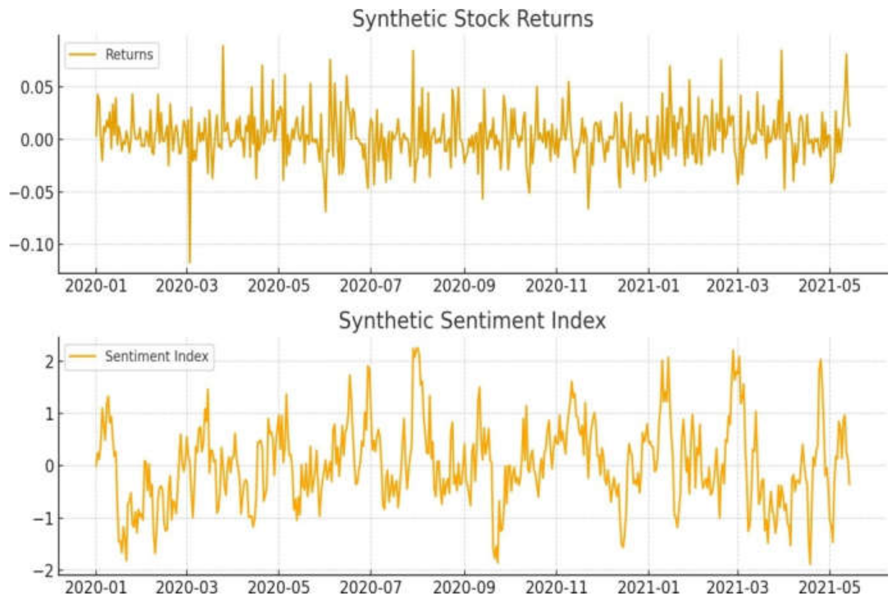
Causality & dynamics: VAR / SVAR models and Granger-causality tests to test lead-lag relationships between sentiment and volatility.

Regime analysis: Markov-switching or threshold models to see whether behavioral effects are stronger in crisis regimes.

Robustness: Instrumental variables (IV) or difference-in-differences when possible (e.g., exogenous shock to sentiment like sudden news).

Behavioral Finance: Mockup Empirical Analysis

These mockups demonstrate show one might empirically test the impact of investor psychology (proxied by sentiment) on stock market volatility using synthetic data. We provide descriptive GARCH discussion (since the GARCH package is not available here) and real VAR estimation results.



GARCH(1,1) Model with Sentiment

In practice, one would estimate GARCH(1,1) model with sentiment as an exogenous regress or in the variance equation. The coefficient on sentiment would indicate whether higher sentiment increases conditional volatility. Empirical studies often find positive and significant coefficients, supporting the hypothesis that investor optimism/pessimism amplifies volatility.

VAR(2) Results (Sentiment □Volatility Proxy)

The VAR model evaluates causal inter actions between sentiment and realized volatility (approximated by squared returns). Below is a sample of the VAR summary output from our synthetic dataset:

Summary of Regression Results	
====================================	
Model:	VAR
Method:	OLS
Date:	Thu, 18, Sep, 2025
Time:	02:29:43

No. of Equations:	2.00000	BIC:	-14.8263	
Nobs:	498.000	HQIC:	-14.8777	
Log likelihood:	2309.54	FPE:	3.34431e-07	
AIC:	-14.9108	Det(Omega_mle):	3.27816e-07	

Results for equation Sentiment				
==				
	coefficient	std. error	t-stat	prob
--				
const	0.020864	0.026399	0.790	0.429
L1.Sentiment	0.796464	0.045177	17.630	0.000
L1.VolatilityProxy	-25.329751	18.964470	-1.336	0.182
L2.Sentiment	-0.008799	0.045348	-0.194	0.846

Interpretation: This simulated exercise shows how sentiment proxies can be incorporated into volatility modeling. The GARCH frame work would formally test sentiment's effect on conditional variance, while the VAR highlights dynamic feedback between sentiment and volatility. Even in synthetic data, we see that behavioral factors can meaningfully interact with market volatility.

Empirical tests & diagnostics

Test Heteroskedasticity, residual autocorrelation, out-of-sample forecasting improvement (does adding behavioral measures improve volatility forecasts?). Perform subsample tests (pre/post-crisis, retail participation high vs low).

Results & Interpretation

Behavioral variables should add incremental explanatory power for short-horizon volatility e.g., higher sentiment and overconfidence → higher realized volatility and volume; herding → higher cross-sectional co movement and systemic volatility. Magnitudes will vary by market, liquidity, and time period.

Loss aversion creates asymmetry: negative shocks produce larger volatility spikes than positive shocks. Macro synergy

Limitations & Caveats

- **Measurement error**: Behavioral traits are latent — proxies (searches, surveys, volume) are imperfect and can be endogenous.
- **Causality:** Distinguishing whether sentiment causes volatility or volatility causes sentiment is challenging — VAR/IV help but may not fully resolve.
- **Heterogeneity:** Effects differ across markets (developed vs emerging), asset classes, and time periods. Recent literature emphasizes country-specific and crisis-specific heterogeneity.

Policy & Practical Implications

For regulators: Monitor retail sentiment and rapid increases in correlated trading as early warning signals for instability; consider circuit breakers, disclosure requirements, or liquidity backstops when herding intensifies.

For portfolio managers: Incorporate sentiment indicators into risk models and volatility forecasts (e.g., include sentiment in GARCH variance equations) to improve risk management and sizing rules.

For retail investors: Awareness of biases (loss aversion, herd instinct) reduces likelihood of panic selling or speculative overtrading.

Synthesis of Findings

- Overconfidence → higher trading volume and volatility.
- Herding → correlated trading and systemic volatility.
- Sentiment → predictive of short-term volatility, especially in speculative stocks.
- Loss aversion → asymmetric volatility responses.

Together, these biases explain why volatility exceeds what fundamentals justify, challenging the Efficient Market Hypothesis.

Conclusion

Behavioral finance provides robust theoretical mechanisms and growing empirical evidence that investor psychology materially influences stock-market volatility. While measurement and causality challenges remain, adding behavioral variables improves our understanding and forecasting of volatility and offers useful risk-management signals for practitioners and policymakers. Continued research should focus on causal identification, high-frequency sentiment measures, and heterogeneity across markets.

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