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A BEHAVIORAL ANALYSIS OF INVESTOR SENTIMENT DURING SYSTEMIC CRISIS

Irena Gjerasimovska, PhD (c)
Max van der Stoel Institute, South East European University
Tetovo, North Macedonia
i.gjerasimovska@seeu.edu.mk

Fatmir Besimi
Faculty of Business and Economics, South East European University
Tetovo, North Macedonia
f.besimi@seeu.edu.mk

ABSTRACT

This study examines how investor sentiment, shaped by behavioral biases, influenced decision-making during the 2007–2009 financial crisis. Focusing on two key biases—herding behavior and loss aversion - we analyze daily return data for 30 large-cap U.S. companies. To detect herding, we apply the Cross-Sectional Absolute Deviation (CSAD) methodology, which measures how closely individual returns track the market return. Regression results confirm non-linear dispersion patterns indicative of herding, particularly during periods of extreme market movement. To investigate loss aversion, we employ a GARCH (1.1) model to assess volatility clustering. The findings reveal heightened sensitivity to recent return shocks and persistent volatility, consistent with behavior driven by fear of loss. Additionally, overreaction tests using lagged-return regressions suggest investors responded irrationally to new information, leading to short-term reversals. Together, these results provide empirical support for behavioral finance theories and challenge traditional assumptions of rational investor behavior during systemic crises.

Keywords: Behavioral Finance, Investor Sentiment, Herding Behavior, Loss Aversion, Overreaction, Financial Crisis 2008

INTRODUCTION

The financial market plays a pivotal role in society as a central hub where diverse buyers and sellers interact to meet their needs. Regardless of type, investors aim to maximize returns while minimizing investment risk. The decisions investors make are largely influenced by external factors such as market performance and flow of information, as well as internal factors tied to human behavior (Sachdeva & Lehal, 2023). Financial markets also contribute to broader economic outcomes, as demonstrated by evidence from European economies showing that stock-market development significantly supports economic growth (Gallopeni et al., 2023).

Understanding common behavioral biases enables investors and financial professionals to better recognize their own decision-making patterns and anticipate the actions of others in the market (Debnath et al., 2024). These tendencies become especially significant during periods of market volatility, when geopolitical tensions or macroeconomic shocks heighten uncertainty (Nadeem et al., 2020). In such circumstances, psychological factors can alter investors' perceptions of risk. Financial risk perception is a subjective evaluation of the likelihood of incurring losses on an investment and is shaped by both individual psychological factors and external market dynamics (Tlili et al., 2023).

While prior research highlights the role of psychology in investment decisions, questions remain about how these influences interact with systemic crises. In such contexts, investor sentiment, encompassing fear, optimism, uncertainty, and confidence, becomes a critical driver of market outcomes, often moving prices beyond fundamental values (Baker & Wurgler, 2007). This paper examines three crucial behavioral tendencies, herding, loss aversion, and overreaction, using daily return data from 30 major U.S. companies during the 2008 financial crisis. By integrating behavioral theory with empirical analysis, it aims to deepen understanding of how sentiment and uncertainty shape investment behavior in times of systemic stress.

The next section reviews the theoretical and empirical literature on herding, loss aversion, and overreaction to establish the foundations for the analysis of this study.

LITERATURE REVIEW

Due to the collapse of the U.S. housing bubble and the extensive issuance of subprime mortgages to high-risk borrowers, the largest economic downturn since the Great Depression occurred in 2007-2008. Risky loans were packed into complex financial products, like mortgage-backed securities (MBS) and collateralized debt obligations (CDOs), were held by large international financial institutions. As housing prices declined and mortgage defaults surged, the value of these securities collapsed, triggering substantial losses across the financial sector (Baily, Litan, & Johnson, 2008). Lehman Brother's bankruptcy and a general decline in trust in financial markets were the crisis outcomes. To avoid a systemic collapse, the U.S. government responded by implementing emergency measures, such as the Troubled Asset Relief Program (TARP) and large interest rate from the Federal Reserve. (Baily, Litan, & Johnson, 2008).

Although the crisis has been extensively studied, a notable gap remains in analyzing its underlying causes from a behavioral-finance perspective. Conventional economic theories emphasize rationality and market efficiency, often overlooking the substantial influence of psychological factors on financial decision-making. Much of the existing literature underplays individual biases such as loss aversion and herding and rarely establishes a clear link between these tendencies and the broader systemic failures of financial institutions and markets.

At its core, herding refers to aligned patterns of behavior across individuals (Devenow & Welch, 1996). Widespread investor interest in trending or “hot” stocks may arise simply because different individuals process similar information independently. In financial markets, however, herding typically involves investors making similar decisions based on observing others rather than conducting their own analysis. This behavior often relies on a coordination mechanism, through a common signal like market price changes or direct observation of others’ actions. Theoretical perspectives vary: the non-rational view highlights psychological influences, suggesting that investors blindly follow the crowd, creating opportunities for more rational actors to profit. The rational view frames herding as a logical response to limited information or distorted incentives, where even informed agents may make suboptimal choices. A near-rational perspective bridges these positions, proposing that investors use mental shortcuts (heuristics) to reduce effort or cost, and that even rational third parties cannot fully counteract this influence. Together, these views underscore the complex drivers of collective investor behavior during periods of uncertainty such as financial crises (Devenow & Welch, 1996).

While herding reflects a collective market tendency, loss aversion highlights an individual-level bias. Prospect theory, developed by Amos Tversky and Daniel Kahneman in 1979, is widely accepted as one of the most accurate models for explaining how individuals perceive and respond to risk. A key component of this theory is loss aversion, the experimental finding that most individuals reject a 50:50 gamble to win $110 or lose $100. Tversky and Kahneman demonstrated that people derive strong emotional responses from both gains and losses, with losses generally exerting a greater psychological impact than equivalent gains (Yang, 2019).

Loss aversion provides a convincing explanation for a number of ongoing anomalies in asset pricing. It aids in resolving the “equity-premium puzzle” which refers to the empirically high average return on stocks in comparison to risk-free assets (returns) that are difficult for standard models to explain. It also sheds light on the “excess volatility puzzle,” in which stock prices fluctuate more than fundamentals would suggest, and on the “volatility clustering” commonly observed in stock returns, typically captured by GARCH-type models. Finally, loss aversion provides a behavioral basis for the “predictability of stock returns” over time and across assets, where certain factors consistently forecast returns in both time-series and cross-sectional analyses (Yang, 2019). In essence, loss aversion shapes investors’ risk attitudes, leading to behaviors that deviate from the predictions of traditional economic models.

Traditional finance theories have assumed that investors are logical beings who base their decisions on all available information. However, since human behavior has a significant influence on how financial markets are shaped, reality frequently deviates from these assumptions (Kumari & Mahakud, 2016; Baker & Wurgler, 2007). The development of behavioral finance as a separate discipline has provided fresh insights into the irrational behaviors and cognitive biases that influence how investors make decisions. A central concept in this field is investor sentiment, which encompasses the psychological factors, emotions, and beliefs that shape investor actions and, in turn, affect market dynamics (Kumari & Mahakud, 2016; Baker & Wurgler, 2007).

Based on the theoretical insights and empirical findings discussed above, the following section outlines the data sources and methodological frameworks employed to examine these behavioral biases during the crisis period.

DATA AND METHODOLOGY

Data Description

This study analyzes daily return data for 30 large U.S. companies to explore the behavior dynamics of investor sentiment during the 2007-2009 financial crisis. The sample covers the period from January 2007 to December 2009, capturing one of the most turbulent phases in modern financial history. The closing prices of the stocks were collected from investing.com, a widely used financial data provider that aggregates real-time and historical price information directly from major U.S. exchanges. The platform is frequently used in empirical finance research, which supports the reliability, accuracy and consistency of the dataset. Daily returns were calculated using standard logarithmic return calculations.

After establishing the dataset, three empirical approaches were applied to examine different behavioral dimensions: 1. herding behavior through return dispersion, 2. Loss aversion through volatility clustering, and 3. Short-term overreaction through lagged return analysis.

Herding Behavior: CSAD Model

To examine the presence of herding behavior, the study employs Cross-Sectional Absolute Deviation (CSAD) as a measurement introduced by Chang, Cheng, and Khorana (2000). CSAD captures the average absolute deviation of individual assets returns from the market return at each point in time and is widely used to detect patterns of collective investor movement (Chang, Cheng, & Khorana, 2000).

$$CSAD_t = (1/N) \times \Sigma\, |R_{i,t} - R_{m,t}|$$

Where:

$R_{i,t}$ return of stock *i* on day *t*

$R_{m,t}$ average market return on day *t*

N total number of stocks in the sample

Return dispersion increases linearly with market movements, under rational asset pricing models. However, herding behavior induces a non-linear relationship, as investors align with market consensus and tend to suppress their individual beliefs during periods of stress.
To capture this, the following regression model is estimated:

$$CSADt = \alpha + \beta1|Rm,t| + \beta2Rm,t^2 + \varepsilon t$$

Where:

$CSAD_t$ Cross-Sectional Absolute Deviation at time t - shows how spread-out stock returns are on that day

$Rm_{,t}$ Market return at time t

$R_{m,t}$	Average market return at time t (mean of all companies' returns that day)
$(R_{m,t})^2$	Square of the market return - helps test for herding during big market moves
α	Constant term in the regression - base level of dispersion
ε_t	Error term - random variation not explained by the model

A significantly negative β2 coefficient provides evidence of herding.

The analysis proceeds with a GARCH(1,1) model to examine volatility clustering and loss aversion.

Loss Aversion and Volatility: GARCH(1,1) Model

To assess how loss aversion impacts market volatility, the study applies the GARCH(1,1) modeling. The GARCH(1,1) model is widely recognized as one of the most credible and extensively used tools for modeling time-varying volatility in asset returns. Introduced by Bollerslev (1986) as an extension of Engle's (1982) ARCH model, GARCH(1,1) this model captures the phenomenon of volatility clustering, where large shocks tend to be followed by further large shocks - a common phenomenon during financial crises. The GARCH(1,1) model is used to analyze market volatility during the 2007–2009 financial crisis as follows:

$$\sigma^2_t = \omega + \alpha \cdot \varepsilon^2_{t-1} + \beta \cdot \sigma^2_{t-1}$$

Where:

- **σ^2_t** conditional variance (volatility) at time *t,*
- **ε^2_{t-1}** squared residual (shock) from the previous period,
- **σ^2_{t-1}** conditional variance from the previous period,
- **ω** constant term,
- **α** ARCH coefficient (impact of recent shocks),
- **β** GARCH coefficient (persistence of past volatility).

High and significant ARCH and GARCH coefficients indicate persistent volatility, which in behavioral finance is associated with fear-driven trading and loss aversion, as investors react more strongly to negative shocks than positive ones.

This model therefore provides a complementary behavioral perspective by quantifying how emotional responses contribute to volatility during crises.

The next step tests short-term overreaction using a lagged-return regression.

3.4. Short-Term Overreaction: Lagged Return Regression

To analyze whether investors manifest short-term overreaction, this study employs an ordinary least squares (OLS) regression model:

$$Rt=\alpha+\beta Rt-1+\varepsilon t$$

A negative and statistically significant β coefficient on the one-day lag suggests that positive (or negative) returns are followed by reversals, consistent with overreaction. According to Prospect Theory, investors overweight losses relative to gains, leading to excessive selling after negative shocks. Overreaction effects are typically short-lived and such panic-driven mispricing is corrected once sentiment stabilizes (Tetlock, 2011).

The subsequent section presents the results of the herding, volatility, and overreaction analyses.

EMPIRICAL RESULTS

Herding Behavior

To investigate behavioral responses during the 2007–2009 financial crisis, we first examine the presence of herding behavior, behavior that occurs when investors suppress their own personal information and follow the market consensus, especially during periods of increased uncertainty.

We measure this behavior using the CSAD method proposed by Chang et al. (2000), which measures the degree to which the returns of individual stocks cluster around the market return as a whole.

Table 1. Regression result for daily data

variable	**coefficient**	**std. error**	**t-statistic**	**p-value**	**95% confidence interval**
Absolute Market Return	0.4999	0.0263	19.04	0.0	[0.4483, 0.5514]
Market Return Squared	-2.5417	0.2891	-8.79	0.0	[-3.1093, -1.9741]
Constant	0.0075	0.0003	23.51	0.0	[0.0069, 0.0081]

According to the regression results, return dispersion increases with market movements, as showed by the positive and statistically significant coefficient of the absolute market return ($\beta 1=0.4999$, $p<0.01$).

The squared market return term has a negative and significant coefficient ($\beta 2=-2.5417$, $p<0.01$) which provides evidence of a nonlinear relationship consistent with herding behavior. This suggests that investors suppress their individual judgments and follow the collective market trend during times of significant market movements, which reduces the dispersion of stock returns. As market returns increased in magnitude (positive or negative), the dispersion of individual stock returns CSAD decreased, a pattern consistent with investors converging in behavior under stress.

With an R2 value of 0.43, the regression model shows that the independent variables account for roughly 43% of the variation in the Cross-Sectional Absolute Deviation. This represents a moderate explanatory power, which is considered relatively strong within the context of financial behavior studies, where behavioral patterns such as herding are influenced by multiple complexes and often unobservable factors.

Figure 1. Market Return vs. Investor Dispersion (CSAD)

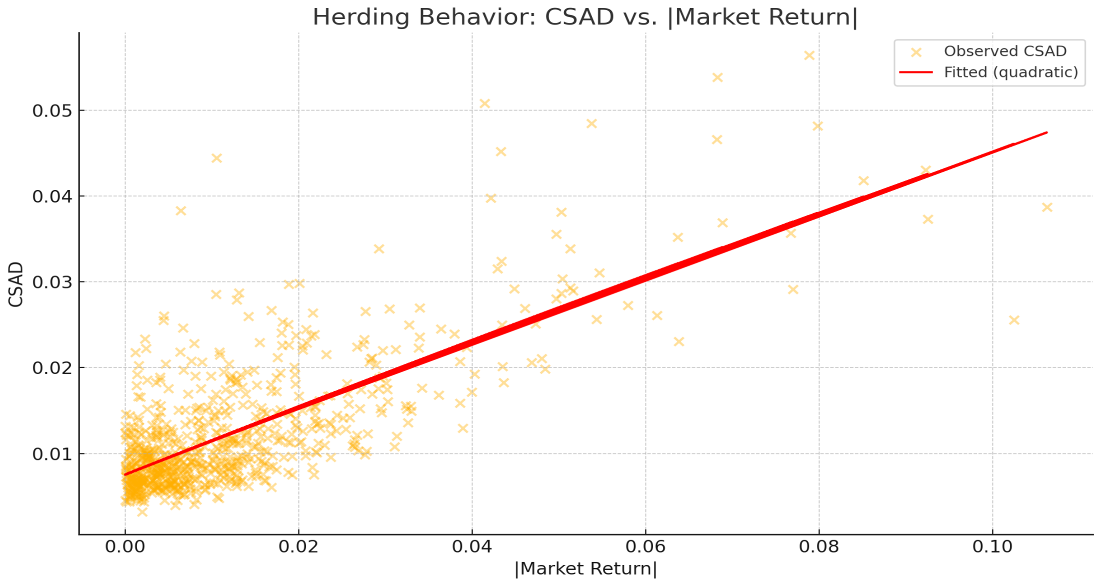
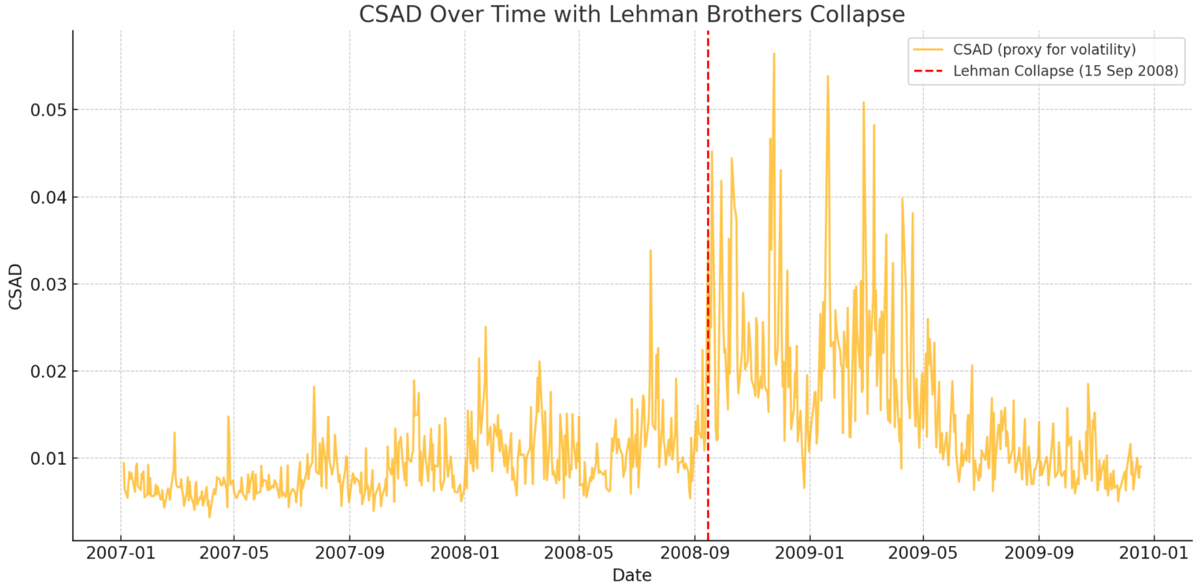


Figure 1's fitted quadratic shows a nonlinear relationship consistent with herding behavior: as market movements become more extreme, individual stock returns tend to converge, resulting in reduced dispersion. During such periods, investors are more likely to act similarly, possibly due to fear or uncertainty, thereby compressing the spread of returns.

While Figure 1 illustrates the overall relationship between market returns and investor behavior, Figure 2 contextualizes this pattern in real time. One of the biggest and most established investment banks in the US, Lehman Brothers, marked a significant shift in the course of the financial crisis (Mawutor, 2014). Its collapse on September 15, 2008, triggered widespread panic and uncertainty in global markets.

By showing how CSAD evolved throughout the financial crisis and marking the collapse of Lehman Brothers on 15 September 2008, we can observe how a major market event may have influenced investor sentiment and return dispersion. This visual adds a timeline dimension to our analysis, allowing us to connect behavioral patterns to specific market events.

Figure 2: Time series of CSAD with Lehman collapse



The red dashed line in Figure 2 marks the collapse of Lehman Brothers on September 15, 2008. A noticeable shift in return dispersion is evident around this date, reflecting heightened investor uncertainty and potential herding behavior.

The results indicate that investors tended to behave more consistently during times of significant market fluctuations, offering compelling proof of herd mentality during the financial crisis.

Next, we examine how investors responded to market losses and rising uncertainty.

Volatility and loss aversion

According to Kahneman and Tversky (1979), investors' tendency to react more strongly to losses than to equal gains is known as loss aversion. This behavior is often reflected in increased market volatility following negative news.

Table 2. GARCH (1.1) Model – Market Return Volatility (2007–2009)

component	**coefficient**	**ctd. Error**	**p-value**	**95% confidence interval**
ARCH (L1)	0.4227	0.0514	< 0.001	[0.3220, 0.5234]
GARCH (L1)	0.5495	0.0727	< 0.001	[0.4069, 0.6920]
Variance Constant	0.0000161	0.0000164	0.324	[-0.0000159, 0.0000482]

The results indicate that both the ARCH term ($\alpha = 0.4227$, $p < 0.001$) and the GARCH term ($\beta = 0.5495$, $p < 0.001$) are statistically significant. This suggests that market volatility is primarily driven by recent return shocks and the persistence of past volatility, a welldocumented feature of financial markets during periods of systemic stress. In contrast, the constant term in the variance equation ($\omega = 0.0000161$, $p = 0.324$) is not statistically significant, indicating that baseline volatility played a minimal role relative to the time-varying components. In other words, there was no steady or typical level of volatility during the crisis; the market largely responded to recent events, with each shock contributing to increased instability.

Although the statistical software used in this study (STATA) does not allow for direct testing of asymmetry with models such as EGARCH, the GARCH (1.1) results still provide valuable insights. This section presents the model results and discusses their implications for understanding investor reactions during periods of severe market stress.

Overreaction analysis

Finally, we examine whether investors tend to overreact or underreact to market news. Overreaction occurs when prices move excessively in response to new information and subsequently reverse, whereas underreaction results in prices continuing to move in the same direction.

Table 3. Overreaction test using one-day lag of market return

lagged variable	coefficient	std. error	p-value	95% confidence interval
Lag 1 Market Return	-0.1375	0.0348	< 0.001	[-0.2058, -0.0691]

The results of an ordinary least squares (OLS) regression are shown in Table 3, in which the current market return is explained by its one-day lag. This approach tests for short-term overreaction, indicated by a negative and statistically significant lag coefficient.

The results show statistically significant negative relationship ($\beta = -0.1375$, $p < 0.001$), suggesting that returns tend to reverse the following day. This implies that investors may initially overreact to information during periods of heightened uncertainty.

To evaluate whether this overreaction continues beyond a single trading day, we enhanced the model by incorporating a second lag of market returns. As shown in Table 4, the one-day lag remains negative but is only marginally significant ($p = 0.070$), while the two-day lag is statistically insignificant. These findings indicate that the overreaction effect is short-lived and corrects quickly.

Table 4. Overreaction test using one-day and two-day lags of market return

lagged variable	coefficient	std. error	p-value	95% confidence interval
Lag 1 Market Return	-0.0802	0.0441	0.070	[-0.1669, 0.0066]
Lag 2 Market Return	-0.0068	0.0379	0.858	[-0.0813, 0.0677]

Overall, these findings indicate that investors do not always act rationally during the financial crisis. According to traditional finance theory, rational investors are expected to process information objectively, avoid emotional decision-making, and make independent choices based on fundamentals (Fama, 1970). However, our results reveal clear evidence of non-rational behavior, including crowd-driven decision-making (herding), heightened sensitivity to losses, and volatility patterns consistent with emotional overreaction. These behaviors underscore the significant role that emotions and uncertainty play in shaping financial decisions during major crises.

These empirical findings provide a foundation for interpreting how behavioral biases influenced investors decision-making during the crisis and are examined in more detail in the discussion section.

DISCUSSION

The empirical results of the study highlight the significant role of behavioral biases in investors decision-making during the 2007 - 2009 crisis. The evidence of herding behavior, captured through the non-linear relationship between CSAD and market returns, illustrates that investors often set aside their individual judgement when faced with collective behavior under uncertainty. This aligns with behavioral finance theory, which suggests that people tend to rely on social cues and imitate others as heuristic responses to stressful environments (Chang et al. 2000, Devenow & Welch, 1996), leading to convergence in decision making, when faced with ambiguous situations.

The volatility spikes revealed by the GARCH(1,1) model provide further behavioral insight. The strong significance of the ARCH and GARCH terms indicates that both recent shocks and prior volatility had a significant impact on market dynamics, suggesting that investors were reacting emotionally to unfolding events rather than relying on fundamentals. This aligns with existing evidence that fear-driven trading increases volatility during crisis periods (Kumari & Mahakud, 2016). This persistent volatility pattern reflects the market's psychological state, where fear and uncertainty often overshadow rational evaluation and overweight negative information.

The short-term overreaction detected through the lagged return regressions analysis further supports the presence of loss aversion. According to prospect theory, losses carry greater psychological weight than equivalent gains, leading to sudden selloffs following negative news (Kahneman & Tversky, 1979). The rapid reversal of returns found here suggests that such reactions are often exaggerated and temporary, consistent with other prior studies showing that panic-driven mispricing is typically corrected once sentiment stabilizes (Tetlock, 2011). Other alternative explanations, such as availability bias, may also impact such rapid market movements, as investors tend to anchor on recent events rather than long-term valuations. The findings in this study indicate that investor sentiment plays a decisive role in increasing volatility and distorting the formation of the prices during the crisis. As noted by Baker & Wurgler (2007), this aligns perfectly with broader behavioral finance research, which argues that emotional responses and cognitive heuristics intensify market instability during periods of systemic stress.

However, this study faces several limitations. First, behavioral biases are indirectly measured through return patterns rather than direct investor sentiment surveys or psychological assessments. Second, the dataset covers 30 major companies, which provides useful insight but may not reflect the full heterogeneity of market behavior across sectors. Lastly, more advanced volatility models such as EGARCH or asymmetric GARCH could offer deeper insights into behavioral asymmetries but were not employed due to methodological scope and data constraints. Future research could also integrate alternative sentiment proxies, such as news-based indices or social media sentiment, to enhance the robustness of the behavioral interpretations.

These insights demonstrate how psychological forces shaped investor behavior in one of the most turbulent periods in modern finance history. The conclusions summarize these key contributions and outline directions for future research.

CONCLUSION

This study emphasizes how investor behavior during one of the most tumultuous times in contemporary financial history was influenced by behavioral biases, herding, loss aversion, and overreaction. By applying CSAD regression, GARCH modelling, and lag-based return analysis to data from the 2007–2009 financial crisis, the research uncovers non-rational behavior patterns that challenge classical financial theories. The findings emphasize that investor decisions during crises are not purely rational responses to information but are shaped by fear, cognitive shortcuts, and social influence.

These results contribute to the growing evidence that behavioral finance provides a more realistic framework for understanding systemic crises than traditional models. They underscore the importance of developing financial models and regulatory frameworks that account for psychological factors. Future studies could extend this work by using investor-level data, testing asymmetrical models such as EGARCH, or comparing behavior across different crises.

Ultimately, understanding these behavioral dynamics is essential for building resilient financial systems and informing effective policymaking.

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