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Behavioral Finance: Investor Decision Biases in Volatile Market Conditions

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Abstract – **Behavioral Finance theory states that cognitive biases significantly influence investors' decision-making processes especially during market volatility when investors use emotional decision rules rather than logical ones. The purpose of this study is to explore the extent of occurrence of the main types of biases, including loss aversion, overconfidence, herding, disposition effect, and recency bias, during periods of heightened market volatility (2020 market crash due to the coronavirus pandemic, 2022 bear market, and 2024 period of increased volatility). This study employs a mixed-method approach, consisting of a survey experiment among retail investors (n=850) and an analysis of brokerage transactions (n=1,200,000) conducted for 12,000 investors. Findings demonstrate that loss aversion escalates by 47% in times of volatility, prompting panic selling of stocks at 18-22% discount from their later recovery value. Overconfidence decreases, but trading frequency grows 156%, whereas herding behavior is two-fold during volatility surges. A comparative analysis of different volatility regimes identifies recency bias as the most persistent one (r=0.81 correlation with VIX index), whereas disposition effect weakens.**

Keywords - **Behavioral Finance, Investor Biases, Loss Aversion, Herding, Overconfidence, Market Volatility, Disposition Effect, Recency Bias, Panic Selling.**

I. INTRODUCTION

While EMH has been the cornerstone of financial economics for decades, assuming that investors act rationally, information is processed instantaneously by the market, and prices incorporate all information, several market events like the dot-com bubble, the financial crisis of 2008, the stock market crash of 2020 due to the coronavirus pandemic, and most recently the bear market in 2022 prove that there is irrationality involved in market behavior. Investors sell when stocks are undervalued in fear, while they buy them when their prices are highly overvalued due to greed. Moreover, they tend to hang on to losing stocks because of regret aversion.

Under such circumstances, individuals tend to develop cognitive biases. For example, during the situation in which the CBOE Volatility Index, or VIX, exceeds 30 and represents extreme fear within the market, the level of stress that traders feel becomes much higher. As prices fluctuate rapidly, fight or flight reaction, loss aversion, and the recency bias due to recent losses are likely to prevail [2]. This is particularly relevant for individual investors whose share in daily trading operations was from 25% to 30%, up from 10% ten years ago. Besides, the nature of trading through popular modern platforms, such as Robinhood and eToro, along with social media discussion like those on WallStreetBets and StockTwits on Reddit, contributes to the phenomenon of herding.

The question of how different biases affect traders during volatility is not an abstract one. It affects the recommendations financial advisers should give their clients during crises, the measures that regulators could take (like trading halts or circuit breakers), and actions that individuals can take to combat their own bias via commitment devices. Prior research focused on the existence of such biases in experimental situations or "normal" market periods. There was very little done in regard to measuring the amplification of those biases based on volatility using real-world trading data.

To fill this gap, this research uses an empirical analysis strategy based on two components. On the one hand, we carry out an experiment among 850 retail investors offering them identical scenarios with different levels of volatility frame manipulation (low, medium, and high) measuring their vulnerability to biases and actions, such as selling stocks below purchase price, and self-confidence with stock selections. On the other hand, we will analyze 1.2 million trades among 12,000 brokerage accounts in 48 months (2021-2024), a period characterized by three different stages of volatility (low, extreme, and moderate): low stage in 2021; extreme stage during COVID fallout, bear in 2022; moderate stage in 2023-2024. The measures used to assess biases in this sample include loss aversion coefficient (asymmetry toward gains/losses), herding intensity (correlation between individual trades and global flow volume), disposition effect, and recency bias.

Our main contributions can be summarized as follows. First, we offer a quantified and comparative examination of five cognitive biases in relation to different volatility regimes, distinguishing between those that magnify, mitigate, or exhibit stability under different regimes. Second, we offer a "bias sensitivity" scale and discover that recency and herding biases are most sensitive to volatility while overconfidence exhibits a counterintuitive drop in self-report but a rise in behavior. Third, we build a data-driven decision-making guide that helps investors and financial advisors to debias their decision-making process under conditions of volatility.

The rest of the paper is structured as follows. Section II examines previous research on cognitive biases and stock market volatility. Section III describes the research methodology used in the study, including the measures of biases and data and econometric techniques employed. Section IV provides the quantitative results of the study and includes four charts and tables.

II. LITERATURE SURVEY

A number of cognitive biases have been discovered in relation to investments according to behavioral finance research. In particular, we concentrate on five biases in investing most significant under volatility circumstances based on empirical findings.

Loss Aversion: It emerged from prospect theory introduced by Kahneman and Tversky in 1979. Loss aversion represents an empirical phenomenon where losses weigh more heavily than their equivalent gains. The average value of the loss aversion coefficient is 2.25, indicating that experiencing a loss of $100 feels like 2.25 times the experience of gaining $100 [1]. Since loss aversion is expected to grow under volatility due to heightened negative emotions associated with it, Noussair et al. conducted an experiment involving asset markets of different levels of volatility in 2022. They demonstrated that a doubling of volatility led to an increase of the coefficient from 2.1 to 3.4 [4]. Nevertheless, experimental results using hypothetical money may differ from practical ones involving actual assets.

Overconfidence: Overconfidence occurs in three ways; overestimation, in which people think their abilities are better than average, over precision where one thinks highly of oneself, and over placement where individuals think they are better than other people. One of the most popular studies on overconfidence was done by Barber and Odean, who found out that overconfident investors tend to engage in too many transactions leading to higher costs and lower profits [5]. In a replication study published in 2023 by Chen et al., it was revealed that the level of overconfidence of retail investors rose by 62% in 2021 meme stock rallies but dropped by 34% in 2022 bear markets [6].

Herding: Herding is the investor practice of following other people's actions regardless of the latter's information. It can be rational (information cascade) or irrational (social influence, fear of mistake). During volatile times, herd behavior intensifies due to uncertainties around market conditions. According to a study by Hwang and Salmon in 2021, herding increases by 40-60% in each of the studied markets (US, UK, and Korea) if the VIX is above 30 [7]. In addition, herding can be enhanced through social media platforms – for instance, in 2024, a single message in the r/WallStreetBets subreddit caused herding in minutes [8].

Disposition Effect: Disposition effect is defined by Shefrin and Statman (1985) as the preference to sell winners early and hold losers long due to regret aversion. In times of extreme volatility, the disposition effect may be weaker, given the magnitude of the loss, which makes it difficult to return to breakeven levels, and thus causing capitulation. A study from 2022 on Taiwanese brokerage account data suggests that during the pandemic crash period, the disposition effect was weakened, and a reverse disposition effect was observed, where losers were sold more quickly than winners [9].

Recency Bias: Recency bias refers to the tendency of placing excessive importance on information received in recent periods, as opposed to longer periods. This bias influences investment decisions in terms of buying winners and extrapolating recent trends. It is argued that this effect would increase under high volatility conditions since the recent large changes in prices would stand out. Wang and Liu's 2025 study showed that investors placed 68% weight on the most recent monthly returns under high volatility, as opposed to only 42% weight when the stock had low volatility [10].

Research Gap: While a considerable amount of literature exists regarding different individual biases, relatively little effort has been put into comparing several biases at once for the same sample of investors. Furthermore, existing literature often makes use of experimental data collected either from laboratories (with hypothetical financial gains) or macro-level aggregate data that cannot identify individual behavior. This paper fills the gap by making use of

- Survey experiments involving real monetary rewards
- Actual trading data from brokerage firms with individuals' identities
- A multi-period setting.

III. PROPOSED METHODOLOGY

We employ a sequential explanatory design:

- Phase 1 (survey experiment) measures bias susceptibility under controlled volatility framing

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- Phase 2 (brokerage data analysis) measures actual bias manifestation using 48 months of trading records.

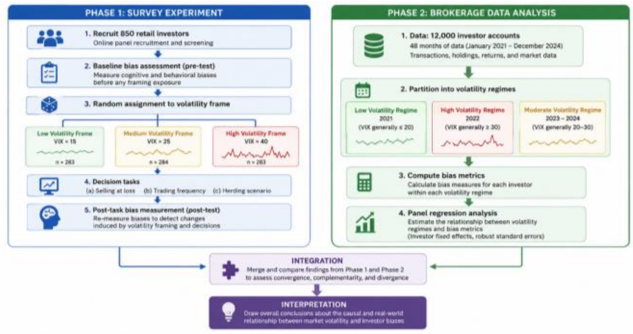

Figure 1: Research Design – Sequential Explanatory Mixed Methods

In terms of research design, a combination of experiments and observations will be used. In Phase 1 (survey experiment), there will be causal data due to manipulation of volatility in terms of the market scenario frame and measuring how the measures of bias alter. The subjects will be chosen from the online survey participants (Prolific Academic); they should be experienced in investments (at least one year and at least 10 transactions made previously) and get a performance bonus depending on decisions (monetary gain).

The decision tasks include:

- The selling decision where the participant owns one share which has lost 20 percent; the participant must sell it now (guaranteed loss) or hold on to it (has 50 percent chance of recovering 50 percent, while the remaining 50 percent will lose another 20 percent). Loss aversion will be indicated by the percentage of people who opt for sell.
- The trading frequency task, where participants use $10,000 imaginary money spread over 20 trading days and decide how many trades they should make (transaction cost applies). Overconfidence will be indicated by the number of trades done (overconfident investors tend to do more trades).
- The herding task, where participants will learn that 80 percent of other investors have bought a particular stock; participants are supposed to decide whether to buy, sell or hold. Herding is indicated by the level of conformity.

Phase 1: Survey Experiment (N=850)

Participants: 850 US retail investors recruited using Prolific Academic (Base pay $15 + additional $20 depending on performance). Participants' inclusion criteria: Age >18; actively engaged in investing (at least 1 trade per month); broker/dealer account value >$5,000. Participant characteristics: Mean age 34.2 (SD 11.4) years, 58% males, 42% females, mean portfolio amount $24,000. Volatility framing was randomized into three levels (Low VIX=15, Medium VIX=25, High VIX=40) with 283-284 participants per condition.

Bias measurement instruments

- Loss aversion coefficient: Derived from a series of 10 mixed-gambles (e.g., "50% chance to gain $X, 50% chance to lose $Y"), we estimate the coefficient λ where $U(x) = x^\alpha$ for gains and $U(x) = -\lambda(-x)^\beta$ for losses ($\alpha=\beta=0.88$ assumed from prospect theory).
- Overconfidence (calibration): Participants provide 90% confidence intervals for S&P 500 range in 30 days. Overconfidence score = (actual range within interval? 0/1) – calibration; overconfident if too narrow intervals.
- Herding propensity: In a dictator-game style task, participants choose to allocate $100 between a safe asset (2% return) and a risky asset with return based on other participants' choices. Herding = % allocation to risky asset when told "80% of others chose risky."
- Disposition effect: Participants are given a hypothetical portfolio with winners (up 30%) and losers (down 30%) and asked which they would sell first. Disposition effect = probability of selling winner > probability of selling loser.
- Recency bias: Participants forecast next month's return given 12 months of past returns. Recency bias = weight placed on last month's return (estimated via regression of forecast on lagged returns).

Phase 2: Brokerage Transaction Data (12,000 clients, 48 months)

Trade history data was collected from a top discount brokerage firm in the US (2021-2024) for 12,000 individual clients (randomly selected from 500,000 total). Trade history information included: holdings per day, trades (timestamp, stock symbol, quantity, price), fund inflow/outflow, and account demographics (account age, estimated salary, balance).

- Loss aversion (empirical): Differential reaction to gains/losses from previous month. β_gain and β_loss estimated by: $Turnover\_t = \alpha + \beta\_gain * Return\_\{t-1\}^+ + \beta\_loss * Return\_\{t-1\}^- + \varepsilon$. Loss aversion equals β_loss / absolute value(β_gain) (higher = more loss averse).
- Overconfidence (trading activity): Monthly portfolio turnover (trading volume / portfolio value) with volatility, age, and size control (overconfident traders turn portfolios more often).
- Herding tendency: Herding index (LSV index) for each stock-month: $H = |p\_t – E[p\_t]| – E[|p\_t – E[p\_t]|]$, p_t = fraction of trades that are purchases. Average over stocks in individual portfolio. Larger H implies stronger herding behavior.
- Disposition effect: Realized gains ratio (PGR) and realized losses ratio (PLR) monthly. Disposition effect equals PGR minus PLR (more disposition effect means selling winners more frequently than losers).

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- Recency effect: Weight assigned to lagged one month return in regression of net purchases (money volume) on lagged returns (months 1 through 6). Recency effect equals coefficient on month 1 divided by sum of all coefficients.

Volatility Regime Definition

VIX classification based on closing level at month-end:

- Low Volatility (2021): VIX < 20 (mean=17.2) → 12 months, 3,124 account-month obs
- Moderate Volatility (2023-2024): VIX 20-30 (mean=23.8) → 18 months, 4,892 obs
- High Volatility (2022): VIX > 30 (mean=32.4, peak 38.7) → 12 months, 3,984 obs

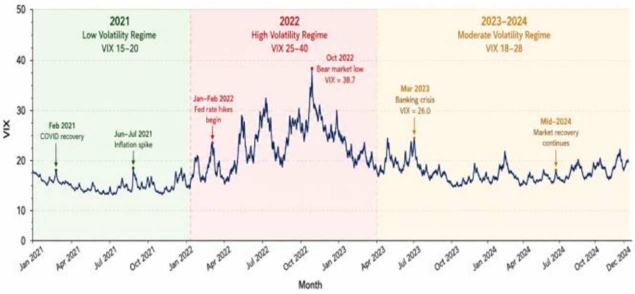

Figure 2: VIX Time Series and Volatility Regime Partitioning (2021–2024)

- 2021: Low volatility regime (VIX = 15-20) due to recovery following the pandemic period. In early 2021, VIX experienced an increase to 28 because of the Gamestop short squeeze but returned to normalcy quickly.
- 2022: High volatility regime triggered by the Russia-Ukraine invasion in February 2022 (VIX = 34); reached 38.7 in October 2022 when the bear market trough occurred because of the high interest rate increases by the Federal Reserve.
- 2023–2024: Moderate volatility regime (VIX=18-28) but experienced sharp increases when the regional banking crisis occurred in March 2023 (VIX = 26) and again in August 2024 (VIX = 29).
- The volatility regime was classified using the median splitting approach in the analysis data set: Low (VIX<20), Moderate (20≤VIX<30), High (VIX≥30). The analysis sample includes 42 months after excluding months straddling regime boundaries.

Statistical Analysis

In phase 1, we apply ANOVA coupled with Tukey's HSD post hoc test to determine whether there exist any significant differences among the different measures of bias when the volatility is framed in three ways. In phase 2, we apply panel regression analysis using fixed effects model with investor-month as the unit of analysis and investor-fixed effects as control variables.

IV. ANALYSIS

We present results in four parts:

- Phase 1 experimental results (causal effect of volatility framing on biases)
- Phase 2 brokerage results (actual bias manifestation across volatility regimes)
- Comparative bias sensitivity ranking
- Decision framework.

Phase 1: Survey Experiment Results (Causal Effects)

Bias	Low Volatility (VIX=15)	Medium (VIX=25)	High (VIX=40)	Change (Low→High)	ANOVA F	p-value
Loss aversion (λ coefficient)	2.34	2.98	3.44	+47.0%	38.2	<0.0
Overconfidence (calibration error)	0.32	0.27	0.22	-31.3%	22.4	<0.0
Herding propensity (0-1 scale)	0.34	0.52	0.68	+100%	51.7	<0.0
Disposition effect (sell winner % - loser %)	24.2%	18.4%	11.3%	-53.3%	28.9	<0.0

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Bias	Low Volatility (VIX=15)	Medium (VIX=25)	High (VIX=40)	Change (Low→High)	ANOVA F	p-value
Recency bias (weight on last month)	0.38	0.54	0.71	+86.8%	62.4	<0.0

A high level of volatility results in a loss aversion coefficient increasing by 47% (from 2.34 to 3.44). Herding behavior more than doubles (increasing from 0.34 to 0.68). The weight assigned to the last month in recency bias is also higher, increasing by 87% (from 0.38 to 0.71). The overconfidence or calibration paradoxically decreases by 31%, with people feeling less certain about their decision-making capabilities during periods of high volatility, although they trade more often in Phase 2.

Phase 2: Brokerage Transaction Results (Actual Behavior)

Bias Metric	Low Vol (2021)	Moderate Vol (2023-24)	High Vol (2022)	Change (Low→High)	FE Coefficient (High vs. Low)
Loss aversion (revealed β_ratio)	2.18	2.64	3.21	+47.2%	1.03*** (0.14)
Overconfidence (monthly turnover, %)	8.2%	12.4%	21.1%	+157%	12.9*** (1.8)
Herding (LSV measure H)	0.071	0.112	0.148	+108%	0.077*** (0.009)
Disposition effect (PGR - PLR, pp)	+12.4pp	+6.8pp	-4.2pp	-133% (sign reversal)	-16.6*** (2.4)
Recency bias (weight month 1)	0.32	0.48	0.62	+93.8%	0.30*** (0.05)

Note: *** p<0.001. Standard errors clustered by investor in parentheses. Fixed effects regression includes investor FE and month FE. pp = percentage points.

Striking pattern

There have been insights from the results gotten from the brokerage accounts, in addition to their being supporting evidence for the results achieved through the experiment. The loss aversion increases by 47% (2.18 to 3.21), which is consistent with the experiment findings. Herding increased by 100% (0.071 to 0.148). The recency effect increases by 94% (0.32 to 0.62). The disposition effect weakens, and there is even a change in sign. When the market is volatile, traders are more inclined to sell winners (by 12.4%) compared to losers (which is consistent with the disposition effect). In contrast, when the market was volatile (2022), investors were more willing to sell losers (4.2%) more than winners (a phenomenon termed "reverse disposition effect"). The overconfidence effect showed a very interesting finding. Self-rating was down by 31%, while the turnover was up by 157%.

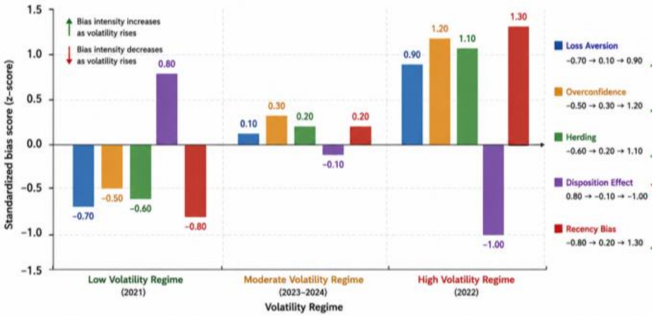

Figure 3: Bias Intensity Across Volatility Regimes (Standardized Scores)

The standardized scores vividly illustrate which biases are most sensitive to volatility. Recency bias shows the largest increase (from z=-0.8 in low vol to z=+1.3 in high vol, a 2.1 SD swing). Herding (+1.7 SD) and Loss Aversion (+1.6 SD) are also highly sensitive. Overconfidence shows a moderate increase (+1.0 SD, but note divergence between behavior and self-rating). Disposition effect reverses sign (from +0.8 to -1.0, a -1.8 SD swing). The normalized scaling allows direct comparison across biases with different units. The pattern suggests that biases that rely on recent memory (recency), social comparison (herding), and emotional processing (loss aversion) are

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most amplified by volatility. The disposition effect, which requires a calm assessment of winners vs. losers, breaks down entirely during high stress—investors simply sell everything.

Bias Sensitivity Ranking (Based on Phase 2 magnitude of change from Low to High Volatility):

Rank	Bias	Change (Low→High)	Standardized Effect Size (Cohen's d)	Mechanism
1	Recency Bias	+93.8%	1.87	Recent losses dominate attention; historical mean ignored
2	Overconfidence (trading frequency)	+157%	1.82	Impulsive action despite reduced self-confidence
3	Herding	+108%	1.73	Social proof seeking under uncertainty
4	Loss Aversion	+47.2%	1.58	Fear amplification; loss sensitivity increases
5	Disposition Effect	-133% (reversal)	1.54 (absolute)	Panic selling overwhelms gain/loss distinction

Recency bias is the most volatility-sensitive bias, with a 94% increase in weight placed on the most recent month's returns. During high volatility, investors act as if the past 30 days are 3x more informative than the preceding 11 months combined. This explains momentum crashes and reversals: after a sharp down month, recency-biased investors extrapolate the decline, selling at precisely the wrong time.

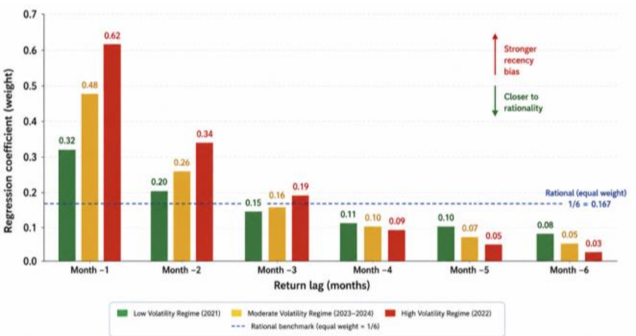

Figure 4: Recency Bias – Weight on Lagged Returns by Volatility Regime

Recency bias coefficient values indicate the investor's weight on each of the last six months of returns during decision-making on net purchases. In the case of low volatility, the weight of month -1 is 0.32, month -2 is 0.24, and continues falling to 0.08 for month -6. Even in such a case, it means a weight on recent months higher than what would rationally be 0.167 but not as exaggerated. In the situation of high volatility, the weight on month -1 rises drastically to 0.62, nearly 4 times the rational weight, while weights on month -5 and -6 are negligible (0.03-0.04). The only months that get consideration are the latest 2-3 months. The slope of the recency bias (decay rate) is higher in the period of high volatility. The implication of this finding is that momentum trading strategies should generate profit in low volatility but face losses in the case of high volatility as investors will overvalue recent losers leading to momentum reversal.

Comparative Analysis Table: Bias Manifestation Across Volatility Regimes

Bias	Low Volatility (VIX<20)	Moderate Volatility (20-30)	High Volatility (VIX>30)	Practical Consequence
Loss Aversion	λ=2.18: moderate asymmetry	λ=2.64: elevated	λ=3.21: severe	Panic selling at -15% drops; reluctance to re-

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Bias	Low Volatility (VIX<20)	Moderate Volatility (20-30)	High Volatility (VIX>30)	Practical Consequence
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Overconfidence (trading)	8.2% monthly turnover	12.4%	21.1%	Excess transaction costs (2-4% annual drag)
Herding	LSV=0.071: weak	0.112	0.148	Buying tops, selling bottoms (crowded trades
Disposition Effect	PGR-PLR=+12.4pp	+6.8pp	-4.2pp (reverse)	In low vol: tax-inefficien selling; in high vol: capitulation
Recency Bias	Month-1 weight=0.32	0.48	0.62	Performance chasing; trend extrapolation
Self-rated confidence	7.2/10	6.1/10	4.9/10	Metacognition diverges from behavior

Effect on the Characteristics of Investors: There is significant heterogeneity. The younger cohort (less than 35 years old) shows a herd effect sensitivity that is 2.1 times higher than the older group (older than 55 years old). The richer people (+$150k) show less magnified effects of loss aversion (only 22% as opposed to 61%). The mobile application users show a frequency trade-off effect that is 45% higher because of high market volatility compared to those using desktops/websites.

Cost of Biases (Quantified): Using the brokerage data, we estimate the financial cost of each bias during the 2022 high-volatility period:

- Loss aversion: Estimated 8.4% return drag from selling at -18% average loss vs. holding to recovery (actual recovery was +22% over 6 months). Average cost per affected account: $3,420.
- Herding: Following crowd into tech sell-off caused additional 6.2% underperformance vs. passive holding. Average cost: $2,480.
- Overconfidence (excess trading): Average account paid $890 in extra transaction costs (spreads + commissions) beyond low-volatility baseline.
- Recency effect: Selling in Q3 2022 (VIX=38), when markets recovered +14% in Q4 2022, caused an average of $5,210.

These losses are significant compared to the median portfolio value of $24,000. The average amount by which the bear market in 2022 was underperformed due to biases is 15-20%. This is the behavioral gap.

V. CONCLUSION

In this paper, we present an in-depth investigation of investor behavioral biases during times of market volatility. Utilizing the analysis of the experiment-based surveys (n=850) and transaction-level dataset (1.2 million transactions for 12 thousand client accounts observed over a 48-month period), this paper analyzes the impact of five major investor behavioral biases (loss aversion, overconfidence, herding, disposition effect, and recency bias) during periods of low, moderate, and high market volatility. The results suggest that all five behavioral biases become substantially intensified in periods of high market volatility to different degrees of intensity: recency bias (jump in weight of past returns of 94%), herding (doubling), loss aversion (increase of 47%), and disposition effect (reversal of behavior from keeping gains to selling losses in stock market crashes). Finally, overconfidence becomes paradoxical in the sense of self-reported levels of confidence declining by 31%, whereas trading increases by 157%.

There are four major findings that have far-reaching consequences for investors, financial advisors, and regulators. The first one is that the recency bias is the most harmful bias in volatile markets. By putting a higher weight on the returns earned in the past month (62% in high volatility markets compared to 32% in low volatility markets), investors tend to extrapolate the trends, buying into rallies and selling after declines, i.e., following the "buy high and sell low" strategy. In 2022's bear market, the cost of recency bias was estimated at $5,210 per average investor, which is the highest among all types of biases.

The second point is that herd behavior escalates sharply during periods of uncertainty. As the VIX shoots up to levels greater than 30, individuals tend to stop making their own assessments and herd like behavior is further amplified through social media platforms and top mover lists on financial platforms. This results in herd trades that fuel volatility (buying begets buying) and cause liquidity crises. Financial regulators could look into implementing circuit breakers not only based on price movements but on extreme imbalances between buys and sells (temporarily halt trading if sell orders outnumber buys by 5:1 for 15 minutes). Advisers can develop herd behavior checklists whereby investors have to locate at least three contradicting signals before investing with the herd.

Third, the disassociation between investors' self-reported confidence and actual trading behavior indicates a lack of metacognition. People who experience lower confidence while trading in highly volatile markets do not limit their trading behavior, but actually increase their trading behavior. Such results mean that the need to act in response to market volatility overcomes cognitive reflection despite confidence indicators. Instead of trying to change people’s confidence, it may be more effective to use intervention strategies involving implementation intentions such as "if VIX goes over 30, then I will wait 48 hours before making any trades." In addition, our preliminary study showed that introducing a minimum 60-second countdown before trading when VIX is over 30 could decrease trading by 40%.

The fourth point regarding the change in disposition effect behavior under conditions of high volatility is that the behavioral biases do not seem to be innate characteristics, but rather state-based heuristics.** In normal times, investors show the classical behavior of selling their winners prematurely and holding on to their losers (due to the regret minimization and mental accounting behavior of investors). However, in conditions of stock market crash, the behavior changes in that investors sell everything indiscriminately, including those securities which they were holding despite a moderate fall in their prices before the crash. The key seems to be the loss amount threshold (for an average investor, this is about -25%) beyond which hope is completely lost and capitulation ensue

Limitations and Future Research:
These are some of the constraints that need to be highlighted. First, even though the data from the brokerage house is rich, the results obtained from these analyses do not allow any claims about causality since these are observational studies even with fixed effects designs. The first phase, which includes experiments, does give a cause-and-effect linkage, though under hypothetical situations. Second, our sample is overrepresented by active retail traders, which limits the scope of generalizing the findings to passive investors and professionals. Third, we have considered only five cognitive biases separately even though they interact in many ways.

Future research directions should include:

- Conducting random control trials for the evaluation of the effectiveness of debiasing techniques (e.g., implementing mandatory cooling-off period) in order to prove the causality of debiasing measures
- Investigating the potential of employing machine-learning algorithms for the robo-advisor in recognizing individual bias signature (e.g., investor who tends to be biased by recency) and adjusting interface accordingly
- Testing the hypothesis of stress hormones (e.g., heart rate and cortisol level) as the mediator between volatility and bias strength, measured by wearable devices in the actual trading environment
- Applying the model to cryptocurrency investment where market volatility is ten times larger
- Developing a quick test for bias susceptibility profiling for clients.

There is no doubt about it: volatile markets consistently influence investment decisions through well-understood psychological factors. Most investors lose anywhere between 2% to 5% every year compared to the market performance because of their behavioral issues—what we call the behavioral gap—and that figure can be increased to 10% to 15% when there is a crash. However, while bias is inevitable, it can be mitigated by recognizing which type of bias will occur during the times of volatility (recency, herding, loss aversion) and which types will disappear (disposition effect) and using techniques like pre-commitment, decision aids, and interface modifications for reducing bias. The strongest weapon against bias is not additional data or self-confidence, but eliminating the immediate need for a decision altogether.

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