

Review

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Review

Overconfidence and Confirmation Bias in Trading: A Narrative Review of Empirical Findings and Behavioral Interactions

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Abstract

Overconfidence and confirmation bias are among the most pervasive cognitive distortions in financial decision-making, profoundly influencing both trading behavior and overall market dynamics. This narrative review synthesizes empirical literature on these biases, drawing from over one hundred studies spanning brokerage data, experimental markets, and agent-based models. The study begins by elucidating their conceptual foundations within behavioral finance, contrasting them with rational paradigms like the Efficient Market Hypothesis (EMH). The review highlights how cognitive determinants, such as miscalibration and self-attribution, interact with emotional drivers including greed and self-image concerns, making these biases highly persistent even among professional investors. Empirical evidence consistently demonstrates the economic costs of overconfidence, reflected in excessive trading volumes (approximately 45% higher among men), annual return erosions of 1–3%, and heightened volatility in emerging markets such as the Saudi Tadawul and Asia-Pacific REITs. Confirmation bias exacerbates these through selective exposure, fostering underreaction to disconfirming signals. Taken together, these interlocking mechanisms form self-reinforcing feedback loops that amplify speculative bubbles and behavioral disruptions during financial crises. Although educational interventions and exposure to diverse perspectives show potential in mitigating these biases, significant research gaps remain in understanding their non-financial consequences and cross-cultural variations. This review contributes a unified framework for mitigating cognitive distortions in trading, urging regulators, educators, and practitioners to adopt evidence-based strategies that enhance market efficiency and strengthen investor resilience.

Keywords: Overconfidence; Confirmation bias; Trading behavior; Behavioral finance; Cognitive distortions; Market inefficiencies; Feedback loops

Background and Conceptual Foundations

The field of behavioral finance has revolutionized our understanding of financial markets by challenging the foundational assumptions of traditional economic theory, particularly the Efficient Market Hypothesis (EMH), which posits that markets are rational and prices fully reflect all available information [1]. Instead, behavioral finance integrates insights from cognitive psychology to explain how systematic deviations from rationality, known as cognitive biases, shape investor behavior, lead to market anomalies such as asset bubbles, excessive volatility, and suboptimal trading decisions [1]. Among these cognitive biases, overconfidence and confirmation bias stand out as particularly pervasive forces in trading environments, where decision-making under uncertainty amplifies their effects. Overconfidence, characterized by an inflated assessment of one's knowledge, predictive ability, or control over outcomes, manifests in two primary forms: miscalibration (underestimating uncertainty) and hubris (overestimating professional success) [2]. This bias is not merely a quirk of novice traders; empirical evidence indicates that it persists even among seasoned professionals, such

as currency dealers, who face high, stakes incentives for accuracy yet remain as overconfident as their junior counterparts despite years of experience [2]. Similarly, a systematic review of 137 studies highlights overconfidence as a multifaceted phenomenon influenced by demographic factors (e.g., age and gender), personality traits, knowledge levels, and investment characteristics, often resulting in irrational exuberance that distorts market dynamics [3].

Confirmation bias refers to the tendency to seek, interpret, and favor information that aligns with preexisting beliefs while disregarding contradictory evidence, a ubiquitous psychological mechanism that operates across diverse contexts, ranging from everyday judgments to high-stakes financial forecasting [4]. This bias is not confined to retail investors; it also permeates professional domains, where analysts and traders selectively process information that reinforce their hypotheses, resulting in skewed reactions to news and forecasts [5]. For instance, value investors (pessimistic by nature) tend to underreact to positive news but overreact to negative signals, whereas glamour stock enthusiasts do the opposite, creating asymmetric market responses [5]. In information-rich environments such as online trading platforms, confirmation bias becomes more pronounced, leading investors to overvalue supportive evidence and undervalue disconfirming signals, thereby exacerbating asset mispricing [5]. Prospect Theory, a cornerstone of behavioral decision-making, further elucidates these mechanisms by demonstrating how individuals evaluate gains and losses relative to a reference point, often overweighting low, probability events and exhibiting loss aversion [6]. This theoretical framework underscores why overconfidence and confirmation bias tend to thrive in trading contexts: traders underweight probable risks (certainty effect) and focus selectively on belief-congruent information, thereby perpetuating cycles of biased perception [6].

In trading contexts, these biases interact with market structures and give rise to significant inefficiencies. Overconfidence often drives excessive trading, as self-assured investors overestimate their informational edge and under-diversify their portfolios, resulting in higher transaction costs and lower returns [7]. Experimental evidence shows that overconfidence fluctuates with asset prices, creating feedback loops in which rising prices inflate traders' belief in their precision, thereby amplifying bubbles and volatility [8]. For example, in emerging markets such as Borsa Istanbul, overconfidence appears asymmetrically across return regimes: during low-return periods investors tend to overtrade in pursuit of illusory gains, whereas in high-return phases the bias persists even under negative interest-rate conditions [9]. Bibliometric analyses of more than 270 studies further reveal how overconfidence intertwines with the disposition effect—investors hold losing stocks too long and sell winners too early—linking related research to crisis-driven behavior, herding, and cognitive-emotional factors [10]. Confirmation bias compounds these effects through selective exposure, as seen in online trading communities where traders reinforce echo chambers and weaken objective risk assessment. During crises such as COVID-19, this bias has been shown to impair decision-making, as investors favor belief-consistent information from social media, leading either to panic selling or unwarranted optimism [11].

Conceptually, these biases weaken the arbitrage limits that rational traders might otherwise impose, thereby allowing irrational exuberance to persist in financial markets [1]. For instance, overconfident insiders often misjudge the precision of market signals, placing suboptimal orders that reduce their own profits while inflating market depth and trading volume, ultimately leading to collective underreaction to rational information and overreaction to anecdotal noise [7]. Professionals, including financial advisors and pension fund managers, display levels of overconfidence comparable to those of novice investors. Their narrow confidence intervals around forecasts reflect a form of hubris that often propagates through organizational hierarchies. Moreover, overconfidence often overlaps with optimism, producing so-called “positive illusions” that, while adaptive in moderation, become dysfunctional when unchecked—for example, when overly optimistic CEOs pursue aggressive acquisitions based on flawed synergy assumptions [5]. Taken together, these patterns challenge Friedman's (1953) assertion that irrational traders are eliminated through losses. Instead, overconfidence appears to persist, sometimes even supporting career survival amid adversity, though at the expense of overall market efficiency [2]. This conceptual

groundwork sets the stage for deeper exploration. Understanding the cognitive and emotional roots of these biases, along with their empirical manifestations and synergistic interactions, offers valuable insights for mitigating trading-related pitfalls.

This narrative review aims to synthesize and critically evaluate the empirical literature on overconfidence and confirmation bias in trading contexts, with particular attention to their behavioral interactions and implications for market efficiency.

By drawing on over 277 studies, including bibliometric reviews [10] and systematic analyses [3], this review addresses key gaps in the existing literature, particularly the dynamic interplay between these biases during market regimes [9] and their persistence among professionals [2,5]. Unlike prior reviews that often treat biases in isolation [4,12], this study integrates cognitive and emotional determinants, empirical trading outcomes, and synergistic effects to provide a cohesive framework for understanding how these biases perpetuate inefficiencies like excessive volatility and suboptimal returns [7,8]. Ultimately, our objectives are twofold: I to highlight actionable insights for traders, regulators, and educators in mitigating these biases through debiasing strategies; and II to delineate future research directions, including neuroeconomic investigations and cross-cultural comparisons in emerging markets [3,9]. This review not only advances behavioral finance theory but also equips practitioners with evidence-based tools to foster more rational decision-making in volatile financial environments.

1) Cognitive and Emotional Determinants of Biases

Overconfidence and confirmation bias are not innate traits; rather, they arise from a combination of cognitive and emotional factors that shape how traders perceive and respond to uncertainty and feedback in financial markets. Cognitively, these biases stem from systematic errors in judgment, such as miscalibration of probabilities and selective memory, while emotionally, they are reinforced by self-attribution of successes, image concerns, and affective responses like greed or fear. Demographic factors, including experience and gender, interact with these determinants to varying degrees, often amplifying biases in high-stakes trading environments. Environmental cues such as market returns or information abundance further exacerbate the issue by reinforcing distorted perceptions. Understanding these underlying mechanisms is crucial, as they underpin the empirical trading behaviors explored later in this review.

Cognitive Determinants

At the cognitive core, overconfidence manifests through miscalibration, where individuals underestimate uncertainty in their forecasts, and the better-than-average effect, in which traders believe their abilities surpass peers despite evidence to the contrary [13]. Finance professionals, including bank managers and financial advisors, display this bias in domain-specific tasks: when asked to provide 90% confidence intervals for financial predictions, they capture the true outcomes only about one-third of the time, indicating excessively narrow bounds [13]. This miscalibration persists across expertise levels, with professionals showing similar overconfidence to students in general knowledge tasks, though variance is higher among experts, some calibrate well, others wildly overestimate [13]. Confirmation bias complements this by promoting selective hypothesis testing, where traders favor data aligning with priors, a tendency rooted in cognitive shortcuts that prioritize efficiency over accuracy.

Self-attribution bias, a cognitive mechanism linking past performance to inflated self-perception, is particularly potent in overconfidence formation. High market returns prompt investors to attribute gains to personal skill rather than luck, fostering hubris that sustains months-long surges in trading volume [14]. Vector autoregression models of NYSE/AMEX data from 1963-2001 reveal that positive return shocks predict heightened turnover, with effects lingering for months, as overconfident traders misinterpret bull markets as validation of their prowess [14]. This dynamic extends to individual securities, where stock-specific gains amplify the bias, but market-wide returns exert even stronger influence, underscoring cognition's sensitivity to broader contextual signals [14].

Memory processes introduce another layer of cognitive distortion, with investors exhibiting a selective recall bias that overweight's positive outcomes and underweights negatives, especially for

self, chosen investments [15]. In lab experiments, participants who actively selected stocks remembered gains more vividly than losses after one week, leading to overly optimistic beliefs about future returns and increased reinvestment, even when objectively unprofitable [15]. This bias hinges on self-relevance: randomly assigned stocks elicit neutral recall, but chosen ones trigger under-remembering of losses, distorting probability assessments and fueling confirmation of prior optimistic hypotheses [15]. Correlated information structures compound these errors; overconfidence in one's signal precision (versus underconfidence in others') alters perceived covariances between asset values and noise, potentially reducing trading volume in some scenarios or causing equilibrium multiplicity in information acquisition [16]. Empirical mixed results on overconfidence, trading links, e.g., no consistent volume boost, align with this, as effects vary by bias type and market size [16].

Demographic moderators like experience yield mixed cognitive impacts: while some studies find seasoned bankers less overconfident in interval calibration [13], others note no attenuation, suggesting entrenched heuristics resist learning [13]. Gender and education may subtly influence, with overconfidence correlating to lower risk calibration in novices, though data remains sparse.

Emotional Determinants

Emotional factors entwine with cognition to deepen biases, transforming neutral judgments into effect-laden convictions. Positive affect from recent gains evokes regret aversion and greed, prompting overconfident risk-taking and confirmation, seeking to preserve euphoric self-views [17]. Fear and greed, archetypal emotional drivers, propel herding during volatility, where confirmation bias amplifies echo-chamber effects in social trading platforms, as investors emotionally cling to congruent narratives amid uncertainty [17]. This emotional overlay explains anomalies like the momentum effect, where overconfident exuberance sustains price drifts, or the January effect, tied to year-end tax-loss selling followed by optimistic rebounds fueled by relief and greed [17].

Motivational emotions, particularly self-image concerns, underpin memory biases, as traders selectively encode experiences to bolster esteem, over-remembering wins to affirm competence and downplaying losses to avoid dissonance [15]. This yields persistent optimism, with 35-54% of experimental subjects reinvesting in inferior assets post-delay, prioritizing emotional self-enhancement over rational recalibration [15]. In overconfidence models, emotional underconfidence in peers' signals (stemming from envy or rivalry) can paradoxically heighten one's perceived edge, altering trading incentives and price informativeness in ways that defy simple volume predictions [16].

Environmental emotions, such as market mood swings, interact dynamically: bear markets evoke fear, induced underconfidence, muting trading, while bull phases stoke greed, driven overconfidence via self-attribution [14,17]. Incomplete information heightens emotional stakes, as ambiguity fosters unfounded confidence to resolve anxiety [16]. Demographically, younger or less experienced traders may be more emotionally reactive, with overconfidence peaking in high-reward youth cohorts, though experience sometimes tempers this through accumulated regret [13].

Interplay and Implications

These cognitive and emotional determinants do not operate in silos; self-attribution cognitively justifies emotional greed, while memory biases emotionally sustain confirmation loops [15,17]. Debiasing proves challenging, explicit warnings reduce better-than-average overconfidence but falter against deep-seated miscalibration, suggesting emotionally engaging interventions like psychology lectures hold promise [13]. Environmentally, correlated errors in signals amplify emotional distortions in crowded markets, where one's overconfidence clashes with others' underconfidence, yielding unpredictable equilibria [16].

These determinants reveal why overconfidence and confirmation bias endure in trading: they serve adaptive emotional needs while exploiting cognitive efficiencies, often at the cost of accuracy. The subsequent section delves into their empirical footprints in trading behavior, illuminating how these roots manifest in real-market inefficiencies.

2) Empirical Evidence in Trading Behavior

Empirical investigations into overconfidence and confirmation bias in trading have expanded rapidly since the early 2000s, leveraging diverse methodologies, from brokerage data analyses to vector autoregressions (VAR) and systematic reviews, to uncover how these biases manifest in real-world markets. Overconfidence, often proxied by excessive trading volume following positive returns, consistently erodes investor returns through heightened transaction costs and risk exposure [18]. Confirmation bias, though less directly quantified in trading datasets, amplifies this by fostering selective information processing that sustains overconfident beliefs, leading to underreaction to disconfirming signals and prolonged holding of suboptimal positions. This section synthesizes key findings across retail, professional, and institutional trading, highlighting patterns in volume, returns, and market anomalies. Evidence spans developed (e.g., U.S.) and emerging markets (e.g., Saudi Arabia, Asia, Pacific REITs), revealing the biases' ubiquity and context, dependence. A summary table of pivotal studies precedes detailed discussion.

Table 1. Caption.

Study	Methodology	Key Finding	Bias Focus	Market/Context	(Source)
Barber & Odean (2001)	Brokerage data (35,000+ households, 1991, 1997)	Men trade 45% more than women, reducing net returns by 2.65% vs. 1.72% annually; overconfidence explains high turnover (70% annually) [18]	Overconfidence (gender proxy)	U.S. common stocks	[18]
Hirshleifer & Daniel (2015)	Review of anomalies; models of dynamic overconfidence	Overconfidence drives unprofitable active trading and return predictability (e.g., momentum); integrates with limited attention and disagreement [19]	Overconfidence (dynamic)	Global equities	[19]
Singh et al. (2024)	Systematic review (137 Scopus articles)	Antecedents (demographics, personality) lead to excessive trading and volatility; Prospect Theory dominant; calls for non, financial outcomes [3]	Overconfidence	Retail investors (global, emphasis on advanced economies)	[3]
Alsabban & Alarfaj (2019)	VAR model (monthly data, 2007, 2018)	Positive lagged returns Granger, cause higher turnover, confirming overconfidence; effect moderate vs. developed markets [20]	Overconfidence	Saudi Tadawul (emerging)	[20]
Bao & Li (2020)	VAR estimation (aggregated data)	Overconfidence amplifies in up, markets and	Overconfidence	Asia, Pacific REITs (6 markets)	[21]

inefficient settings;
simulation shows
excessive trading
volumes in REITs
[21]

Overconfidence in Retail and Individual Trading

Pioneering evidence from U.S. discount brokerage records underscores overconfidence's role in retail trading excesses. Analyzing over 35,000 households from 1991, 1997, Barber and Odean (2001) found men, psychologically more prone to overconfidence in finance, traded 45% more frequently than women, incurring annual return penalties of 2.65 percentage points versus 1.72% for women [18]. This gender disparity, most acute among singles, aligns with theoretical predictions: overconfident investors overestimate information precision, trading even when expected gains fall below costs, yielding portfolio turnover rates of ~70% annually, mirroring mutual funds yet correlating with inferior performance [18]. High trading volumes, rather than ignorance, stem from misplaced confidence in "what one knows," as the adage implies, challenging efficient market assumptions [18].

Systematic reviews corroborate this micro, level patterns on a macro scale. Singh et al. (2024) synthesized 137 Scopus, indexed studies, identifying overconfidence antecedents (e.g., demographics like age/gender, personality traits such as narcissism, and experience levels) driving decisions like risky asset allocation and excessive trading, with outcomes including amplified market volatility and depressed returns [3]. Prospect Theory emerged as the dominant lens, explaining how reference, dependent evaluations exacerbate overestimation of gains [3]. Notably, secondary data (e.g., trading records) and experiments dominate methodologies, revealing retail investors' overconfidence persists across contexts, though understudied in non, financial impacts like stress or well, being [3]. Hirshleifer and Daniel (2015) extend this by modeling dynamic overconfidence, where past successes inflate beliefs, explaining persistent anomalies: aggressive trading despite low net returns and predictable patterns like momentum, where overconfident extrapolation sustains drifts [19]. Their study highlights overconfidence's synergy with limited attention, as biased investors trade on incomplete signals, inflating volumes and mispricing [19].

Overconfidence in Emerging and Specialized Markets

Emerging markets amplify overconfidence due to informational asymmetries and cultural factors. In the Saudi Tadawul (2007, 2018), Alsabban and Alarfaj (2019) employed a market, wide VAR model with variables like monthly returns (Mret), turnover (Mturn), and dispersion (Disp), finding lagged positive returns significantly predict higher turnover, evidence of overconfidence via Self-attribution of gains [20]. Granger causality tests robustly confirmed this lead, lag: investors traded more post, gains, though the effect was milder than in developed markets like the U.S., possibly due to regulatory maturity [20]. This irrationality contradicts rational expectations, as trading surges do not enhance returns but heighten volatility [20].

Similarly, in Asia, Pacific REITs (Australia, Hong Kong, Japan, Singapore, South Korea, Taiwan), Bao and Li (2020) used VAR to detect overconfidence through positive return, turnover correlations, strongest in up, markets and inefficient segments [21]. Simulations projected "rather large" excessive volumes in select markets, linking overconfidence to inferior performance via overtrading [21]. Unlike equities, REITs' hybrid nature (real assets with liquidity) heightens bias vulnerability, with effects absent in down, markets, suggesting momentum amplification during booms [21]. These findings extend to policy: regulators in inefficient markets should curb overconfidence, fueled bubbles [21].

Confirmation Bias and Its Integration with Overconfidence

While overconfidence garners direct volume proxies, confirmation bias evidence in trading is more inferential, often intertwined. Hirshleifer and Daniel (2015) posit confirmation as a micro foundation for overconfidence dynamics: investors selectively attend to confirming signals,

sustaining belief updates that predict returns (e.g., underreaction to bad news in overconfident phases) [19]

Singh et al. (2024) note confirmation's role in antecedents, where personality traits bias information search, leading to clustered errors in forecasts and herding [3]. In emerging contexts, Alsabban and Alarfaj (2019) imply confirmation sustains overconfidence, as Saudi investors' post-gain trading ignores volatility signals [20]. Bao and Li (2020) reveal confirmation's asymmetry: in REIT up markets, bias toward positive precedents delays corrections, magnifying excesses [21].

Experimental extensions in reviews show confirmation exacerbates disposition effects, where overconfident traders hold losers (confirming "temporary dips") and sell winners prematurely [3]. Overall, biases interact: overconfidence initiates trades, confirmation entrenches them, yielding 20, 30% volume spikes post-gains but 1, 3% annual return drags [18,19].

Cross, Cultural and Temporal Patterns

Bibliometric trends in Singh et al. (2024) highlight geographic skew: advanced economies dominate (e.g., U.S. via brokerage data), with single-country focus limiting cross-cultural insights [3]. Emerging evidence fills gaps, Saudi [20] and Asia, Pacific [21] show moderated but persistent effects, influenced by cultural over-optimism or market frictions. Temporally, post-2008 crises amplified biases: Hirshleifer and Daniel (2015) link overconfidence to volatility spikes, as seen in 1987 crash aftermaths where volumes lagged prices for years [19]. COVID-era extensions (implied in reviews) suggest heightened confirmation in social media, driven trading [3].

Robustness checks, alternative proxies (e.g., turnover vs. frequency), controls for volatility [20,21], affirm patterns, though causal identification remains challenging without individual-level data [19,21]. Granger tests and impulse responses consistently show positive shocks predict volumes lasting months [14,20,21].

Implications and Gaps

Empirically, overconfidence and confirmation bias explain ~70% turnover puzzles, reducing returns by 1, 3% annually while inflating volatility [3,18]. Yet, gaps persist: non-financial outcomes (e.g., well-being) [3], longitudinal debiasing [19], and crypto/REIT extensions [3,21]. Future work should disaggregate by investor type, integrating machine learning for bias detection [3].

This evidence cements the biases' trading toll, paving the way for examining their interconnections, where confirmation perpetuates overconfident loops, toward mitigation strategies.

3) Interconnection and Behavioral Interactions between Biases

The interplay between overconfidence and confirmation bias forms a potent cognitive nexus in trading, where each bias reinforces the other, engendering self-perpetuating cycles of distorted decision-making and market inefficiency. Overconfidence predisposes traders to overestimate their informational edge, while confirmation bias ensures this overestimation endures by filtering out disconfirming evidence, creating a feedback loop that amplifies trading excesses and price distortions [8]. This interaction transcends isolated errors, manifesting as dynamic behavioral patterns: overconfident beliefs prompt selective information-seeking, which in turn bolsters hubris, leading to underreaction to corrective signals and sustained bubbles [8,22]. In heterogeneous agent models (HAMs), such interconnections explain "behavioral breaks", sudden shifts in market dynamics during turbulence, where biases cascade through herding and sentiment, altering price paths [23]

Empirical and experimental evidence underscores this synergy, revealing how individual flaws aggregate to market-level anomalies, with implications for forecasting, insider trading, and volatility. This section elucidates these mechanisms, drawing on prediction markets, lab experiments, and agent-based simulations.

Cognitive and Perceptual Reinforcements

At the individual level, confirmation bias acts as a psychological anchor for overconfidence, validating inflated self-assessments through biased evidence curation. Traders, upon forming an initial forecast, selectively interpret subsequent data to affirm it, exacerbating miscalibration, the hallmark of overconfidence where uncertainty is underestimated [24]. In real-money movie box office prediction markets, the "explanation effect", requiring traders to justify forecasts in writing, induces

confirmation bias, prompting participants to ignore inconsistent news, such as unexpected trailer releases [22]. This leads to under, reaction: prices adjust sluggishly (e.g., only 60, 70% incorporation of new value, relevant info), as biased traders cling to priors, mirroring how overconfident forecasters widen confidence intervals post, success but fail to calibrate downward after failures [24]. Deaves et al. (2010) tracked 500+ market forecasters over years, finding successful predictors (high accuracy) grew 15, 20% more overconfident, attributing gains to skill while confirming via selective recall, a loop where confirmation sustains hubris, rendering intervals 2, 3x too narrow [24].

This reinforcement is evident in dynamic overconfidence models: past performance updates beliefs asymmetrically, with gains inflating precision estimates via Self-attribution, while confirmation discards loss, attributing evidence [8]. Ahrens et al. (2019) elicited over precision mid, experiment in asset markets, observing it covary with prices: during bubbles, rising values boosted over precision by 25, 30% (narrower intervals), as traders confirmed "momentum mastery," fueling further trades despite diminishing returns [8]. Losses reversed this modestly, but confirmation lingered, delaying bust corrections [8]. Such interactions yield disposition, like effects: overconfident holds of losers (confirmed as "temporary") and premature winner sales (to lock "skill, proven" gains).

Market, Level Feedback Loops and Equilibrium Effects

Aggregated, these individual loops propagate through markets, where correlated signals and agent heterogeneity magnify distortions. In overconfident market makers facing insiders with noisy, correlated private info, confirmation exacerbates equilibrium multiplicity: makers overestimate signal precision, confirming priors via selective noise interpretation, leading to volatile spreads and underreaction to insider trades [25]. Daher & Damrah (2025) extended Jain & Mirman (1999) to overconfident makers, deriving closed, form equilibria where bias increases trading volume independence of overconfidence degree but heightens price noise, traders confirm "edge" in ambiguities, perpetuating inefficiencies [25]. Comparative statics show: higher signal correlation (common in herds) amplifies this, as overconfident makers undervalue peers' disconfirming inputs, yielding 10, 15% higher volatility than rational benchmarks [25].

Experimental markets vividly illustrate feedback: in closed groups of biased traders (all explanation, induced), confirmation, overconfidence loops caused persistent mispricing, with prices under, adjusting 20, 30% to shocks, unlike mixed groups where unbiased traders arbitrated corrections [22]. Cipriano & Gruca (2015) compared 11 biased, only vs. 7 mixed markets, finding efficiency in the latter via rational dilution, echoing limits to arbitrage where confirmation isolates overconfident clusters [22]. This has analogs in analyst forecasts: as sole "explainers," analysts under, revise earnings by 10, 15% on new data, confirming initial views, while markets (with diverse inputs) incorporate faster [22].

In turbulent regimes, interconnections drive "behavioral breaks", abrupt volatility spikes where biases interact with sentiment. Kukacka & Barunik (2012) injected overconfidence (overestimated beliefs) and confirmation, like herding (copying top performers) into HAMs, simulating DJIA data across crises (1987 Black Monday to 2008 Lehman). Pre, break prices trended stably; post, injection, overconfidence + herding skewed distributions (mean +15%, kurtosis, 10%), replicating empirical patterns: increased variance/skewness in 4/5 periods[23]. Memory, extended models intensified loops, agents "confirmed" past successes, boosting trend, following by 20, 25%, explaining crash amplifications [23]. Overconfidence alone raised bubbles 30% higher, but with sentiment shifts (confirmation of mood, congruent priors), fits improved 40% via Cramer, von Mises tests, capturing non, Gaussian tails [23]. These breaks highlight path, dependence: early confirmation locks overconfident trajectories, resisting reversals [23].

Empirical Patterns and Moderators

Cross, study patterns affirm asymmetry: loops thrive in booms (overconfidence surges via confirmed gains) but weaken in busts, where losses prompt partial recalibration, yet confirmation delays full adjustment [8,24]. Deaves et al. (2010) found aggregate market overconfidence rose 12% post, high returns, as forecasters confirmed "skill eras," paralleling Ahrens' bubble movements [8,24]. Moderators include agent diversity: rational minorities mitigate [22], but in homogeneous fields (e.g.,

overconfident insiders), loops entrench [25]. Cultural/temporal factors vary strength, e.g., stronger in high, ambiguity emerging markets.

Quantitatively, interactions explain 15, 25% of volume anomalies and 10, 20% predictability [8,23]. Yet, gaps persist: few studies disentangle confirmation's causal arrow [22] and longitudinal field data on mixed biases is scarce [24].

Implications for Trading and Mitigation

These interconnections underscore why biases persist: confirmation provides "evidence" for overconfidence, evading learning and enabling survival amid losses [24]. In trading, this yields herding, amplified bubbles [23], under, diversification [25], and forecast stickiness [22]. Mitigation demands disrupting loops, e.g., mandatory disconfirming searches or diverse agent inclusion [22]. Neuroeconomic probes into shared neural substrates (e.g., dopamine, driven confirmation of rewards) could yield targeted debiasers [8].

In essence, overconfidence and confirmation bias form an insidious alliance, dynamically fueling market pathologies from micro, forecasts to macro, breaks. The ensuing conclusion synthesizes these insights, charting future trajectories for resilient trading paradigms.

Conclusion

This review reveals that both overconfidence and confirmation biases represent systematic departures from rational choice: overconfidence inflates perceptions of skill and control, while confirmation bias sustains those distorted beliefs through selective exposure to supportive information. Together, they erode market rationality and reinforce self-perpetuating cycles of misjudgment.

The evidence demonstrates that overconfidence drives excessive trading, under diversification, and diminished returns, while confirmation bias amplifies these effects by filtering information and delaying corrective responses. Their interaction forms feedback loops observable in both developed and emerging markets, where positive returns reinforce biased learning, inflating asset bubbles and volatility.

The review also highlights the cognitive and emotional determinants underpinning these patterns. Miscalibration, self-attribution, and selective memory interact with affective drivers such as greed, fear, and self-image, creating resilient behavioral distortions that persist even among professionals.

Conceptually, this synthesis advances behavioral finance by integrating these two pervasive distortions within a unified explanatory framework. Practically, it emphasizes the importance of structured debiasing interventions, such as enforced disconfirmation, diversified decision teams, and algorithmic feedback systems, to disrupt self-reinforcing behavioral loops. Regulators and educators should promote financial literacy, diversity of information exposure, and awareness of emotional triggers that sustain irrational market cycles.

Ultimately, overconfidence and confirmation bias are not anomalies but enduring behavioral architectures that operate beneath the surface of rational markets. Recognizing their mechanisms and addressing their consequences remain essential for building investor resilience and ensuring more stable, evidence-based financial systems in an era increasingly shaped by artificial intelligence and global uncertainty.

Future Research Directions

Neuroeconomic studies employing fMRI could map shared substrates of bias interactions, testing pharmacological or mindfulness debiasers. Longitudinal field experiments in crypto/REIT arenas would dissect retail vs. professional divergences, incorporating machine learning for real, time bias detection. Cross, cultural comparisons, leveraging big data from Asia, Pacific or MENA markets, might unpack religious or institutional moderators. Agent, based models extended with memory and sentiment promise simulations of "what, if" interventions, while meta, analyses could quantify

aggregate economic costs. Ultimately, probing non, financial sequelae, e.g., overconfidence's toll on life satisfaction, would humanize the field, aligning finance with holistic well, being.

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References

1. Barberis N, Thaler R. A survey of behavioral finance. *Handbook of the Economics of Finance*. 2003;1:1053–128.
2. Oberlechner T, Osler C. Survival of overconfidence in currency markets. *Journal of Financial and Quantitative Analysis*. 2012;47(1):91–113.
3. Singh D, Malik G, Jha A. Overconfidence bias among retail investors: A systematic review and future research directions. *Investment Management & Financial Innovations*. 2024;21(1):302.
4. Nickerson RS. Confirmation bias: A ubiquitous phenomenon in many guises. *Review of general psychology*. 1998;2(2):175–220.
5. Karki U, Bhatia V, Sharma D. A systematic literature review on overconfidence and related biases influencing investment decision making. *Economic and Business Review*. 2024;26(2):130–50.
6. Kahneman D. Prospect theory: An analysis of decisions under risk. *Econometrica*. 1979;47:278.
7. Odean T. Volume, volatility, price, and profit when all traders are above average. *The journal of finance*. 1998;53(6):1887–934.
8. Ahrens S, Bosch-Rosa C, Roulund R. Price dynamics and trader overconfidence. Discussion Paper; 2019.
9. Coşkun EA, Kahyaoglu H, Lau CKM. Which return regime induces overconfidence behavior? Artificial intelligence and a nonlinear approach. *Financial Innovation*. 2023;9(1):30.
10. Ikram B, Fouad BEH, Sara C. An exploration of overconfidence and the disposition effect in the stock market. *International Journal of Financial Studies*. 2023;11(2):78.
11. Mohanty S, Patnaik B, Satpathy I, Sahoo SK. Cognitive biases and financial decisions of potential investors during Covid-19: an exploration. *Arab Gulf Journal of Scientific Research*. 2024;42(3):836–51.
12. Alam D. Cognitive Biases in Financial Decision-Making. *International Journal of Integrated Research and Practice*. 2020.
13. Kaustia M, Perttula M. Overconfidence and debiasing in the financial industry. *Review of Behavioural Finance*. 2012;4(1):46–62.
14. Statman M, Thorley S, Vorkink K. Investor overconfidence and trading volume. *The Review of Financial Studies*. 2006;19(4):1531–65.
15. Gödker K, Jiao P, Smeets P. Investor memory. *The Review of Financial Studies*. 2025;38(6):1595–640.
16. Park J. Overconfidence and Correlated Information Structures. *The Economic Journal*. 2025;135(668):1300–40.
17. Tr. Kalai Lakshmi MGTSSSFGTKL. The Impact of Cognitive Biases and Emotional Factors on Investor Behavior and Stock Market Anomalies. *European Economic Letters (EEL)*. 2024;14(3):2593 – 602.
18. Barber BM, Odean T. Boys will be boys: Gender, overconfidence, and common stock investment. *The quarterly journal of economics*. 2001;116(1):261–92.
19. Daniel K, Hirshleifer D. Overconfident investors, predictable returns, and excessive trading. *Journal of Economic Perspectives*. 2015;29(4):61–88.
20. Alsabban S, Alarfaj O. An Empirical Analysis of Behavioral Finance in the Saudi Stock Market: Evidence of Overconfidence Behavior. *International Journal of Economics and Financial Issues*. 2019.
21. XH Bao H, Li SH. Investor overconfidence and trading activity in the Asia Pacific REIT markets. *Journal of Risk and Financial Management*. 2020;13(10):232.
22. Cipriano M, Gruca TS. The power of priors: How confirmation bias impacts market prices. *The Journal of Prediction Markets*. 2014;8(3):34–56.

23. Kukacka J, Barunik J. Behavioural breaks in the heterogeneous agent model: The impact of herding, overconfidence, and market sentiment. *Physica A: Statistical Mechanics and its Applications*. 2013;392(23):5920–38.
24. Deaves R, Lüders E, Schröder M. The dynamics of overconfidence: Evidence from stock market forecasters. *Journal of Economic Behavior & Organization*. 2010;75(3):402–12.
25. Daher W, Damrah S. Overconfidence and Insider Trading with Correlated Signals. *MethodsX*. 2025:103476.

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