Overconfidence and Excess Trading: Evidence from Equity and Crypto Markets

Behavioral Economics

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Sworn Statement

"We hereby solemnly declare that we have independently prepared this paper. All quotations in the text have been marked as such, and the paper or considerable parts of it have not previously been subject to any examination or assessment."

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1 Introduction

Neoclassical economics assumes the existence of *homo economicus*, a rational agent dedicated to utility maximization based on stable preferences. Yet, this framework serves largely as a normative ideal of optimal decision-making rather than a reflection of reality. In practice, observed behavior often diverges significantly from these predictions. Behavioral Economics bridges this gap by analyzing the cognitive biases that lead to systematic, predictable departures from rationality.

Within finance, the persistence of massive trading volume remains a puzzle. In 2024, the US equity market averaged $607 billion in daily volume (SIFMA, 2025). This phenomenon has been described as "the single most embarrassing fact to the standard finance paradigm" (Glaser & Weber, 2007). Under the standard "No-Trade Theorem," rational agents should trade rarely, realizing that a willingness to trade implies the counterparty holds superior private information. Since traditional models struggle to explain this volume, behavioral factors provide essential explanations. As noted by De Bondt and Thaler (1995):

> The key behavioral factor needed to understand the trading puzzle is overconfidence. Overconfidence explains why portfolio managers trade so much... and why even financial economists often hold actively managed portfolios - they all think they can pick winners.

Overconfidence, a consequence of fast, automatic System 1 thinking (Kahneman, 2011), typically manifests in three forms: overestimation (thinking you are better than you are), overplacement (the "better-than-average" effect), and overprecision (excessive certainty). While theoretical models often model this as overprecision, empirical work by Glaser and Weber (2007) suggests that the "better-than-average" effect is the stronger predictor of trading volume.

This paper extends the literature by investigating the economic penalty of this behavior across asset classes. While overconfidence in equities is well-documented, the cryptocurrency market, which is characterized by a higher share of retail participation and fewer fundamental valuation anchors, provides a unique setting to test these predictions. This heavy retail presence can exacerbate behavioral effects, leading to higher volatility and larger price deviations from any potential intrinsic value.

Specifically, we address the following research question:

Does excess trading, as a proxy for investor overconfidence, predict lower risk-adjusted returns across equities and cryptocurrencies?

By comparing a diversified bundle of S&P 500 equities with a corresponding bundle of major cryptocurrencies, we aim to determine if the lack of fundamental anchors in crypto markets exacerbates the cost of behavioral bias.

2 Literature Review

2.1 Theoretical Framework: Neoclassical vs. Behavioral Views

The standard neoclassical framework, based on the Efficient Market Hypothesis, hypothesizes that asset prices fully reflect all available information. A central prediction of this model is the *No-Trade Theorem* proposed by Milgrom and Stokey (1982). The theorem argues that in a market of rational agents with common priors, speculative trading should be essentially non-existent. If an investor is willing to buy an asset, they must deduce that the seller possesses superior private information that warrants selling. Consequently, rational agents should refuse to trade solely on differences in information, leading to a market equilibrium with low volume driven only by liquidity needs or life-cycle rebalancing.

Empirical reality, however, contradicts this prediction; volume is consistently high. Behavioral Economics adresses this paradox by relaxing the assumption of rationality. The most prominent explanation is **Overconfidence**. As formally modeled by Odean (1998), overconfidence biases an investor's assessment of their own information precision, causing them to trade aggressively on noise they mistake for signal, ultimately lowering their profits.

2.1.1 The Mechanism of Overconfidence

Overconfidence affects decision-making through two primary factors relevant to trading volume:

1. **Overprecision:** Investors overestimate the accuracy of their private information. This false certainty allows them to overcome the adverse selection problem posed by the No-Trade Theorem; they trade because they mistakenly believe they are the informed party.

2. **Overplacement:** As noted by Glaser and Weber (2007), this instance of overconfidence, where investors believe their skills exceed the median, is a stronger predictor of trading volume than miscalibration. Investors attribute past gains to skill (Self-Attribution Bias) and losses to bad luck, intensifying their desire to trade actively despite negative feedback.

These biases are rooted in *System 1* thinking (Kahneman, 2011), where intuitive, fast, and emotional judgments override the statistical reasoning required to assess the probability of being on the wrong side of a trade.

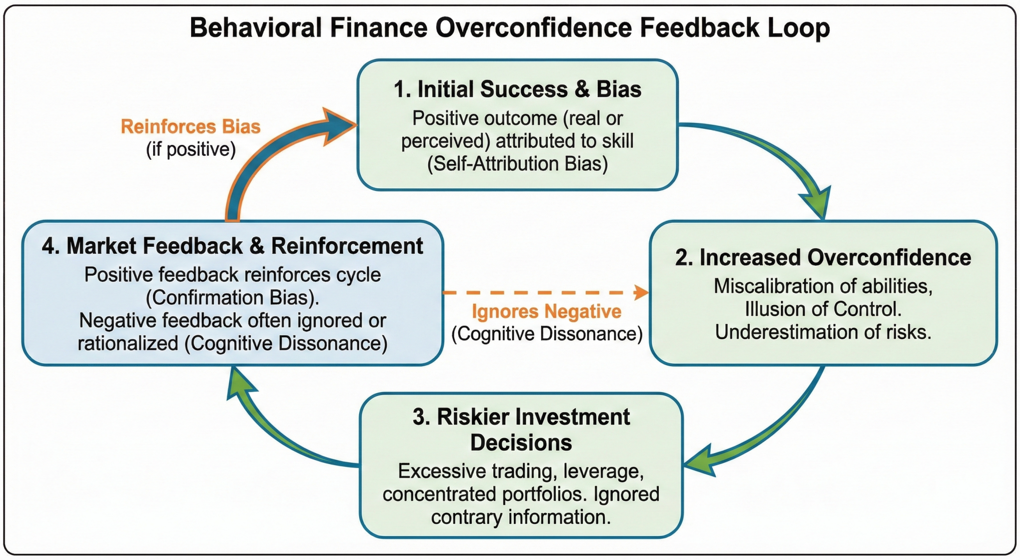

Figure 1: Conceptual framework of the Overconfidence Feedback Loop.

2.2 Empirical Evidence

2.2.1 Overconfidence in Equity Markets

The link between overconfidence and excessive trading is well-documented in equity markets. Barber and Odean (2000) conducted a study of 66,000 household accounts at a large discount brokerage. Their findings were clear: the households that traded the most earned an annual return of 11.4%, while the market returned 17.9%. They concluded that "trading is hazardous to your wealth", confirming that investors pay a penalty for their overconfidence in the form of transaction costs and counterproductive attempts at timing the market.

Furthermore, Glaser and Weber (2007) provided survey-based evidence distinguishing between types of overconfidence. They found that while investors often hold miscalibrated beliefs about market volatility, it is the belief in superior investment skills that correlates most strongly with monthly turnover. This suggests that high volume is driven by an illusion of control and supports our hypothesis that excess trading stems from investor overplacement.

2.2.2 Retail Presence, Attention, and Speculation in Cryptocurrency

While equity markets have fundamental "anchors" to inherent value (such as earnings reports) that eventually correct price deviations, the cryptocurrency market is characterized by high uncertainty. Baur et al. (2018) provide empirical evidence that Bitcoin behaves distinctly from currencies or gold, acting primarily as a speculative asset.

The distinct nature of these assets means that bubble-like dynamics, align closely with the "Greater

Fool Theory". As Malhotra (2025) argues, this framework characterizes the market as a game of beliefs, where demand is driven primarily by the expectation that a "greater fool" will pay a premium. Essentially, this speculative dynamic creates a fragile environment that disproportionately threatens retail investors.

The significantly higher retail presence in crypto markets, compared to institutional-dominated equities, exposes this asset class to greater volatility and behavioral effects. Kaiser and Stöckl (2020) investigated herding behavior in the cryptocurrency market, finding evidence that investors follow the trend during periods of high market volatility. This aligns with the concept of "attention-driven trading," where retail investors rely on heuristics such as availability and social proof (Da et al., 2011).

Supporting this, Kogan et al. (2024) analyzed detailed transaction-level data from the crypto trading platform eToro and found that, unlike traditional assets, where retail traders typically move against market trends, crypto investors exhibit strong momentum-following behavior. Rising prices strengthen investor overconfidence, triggering higher trading volume that is not grounded in superior information. Their findings provide empirical backing for our central hypothesis: excess trading in cryptocurrencies is more tightly linked to behavioral forces than in equities, and therefore more likely to cause a greater decrease in returns.

2.3 Motivation for Hypotheses

The literature establishes that overconfident investors trade too much and earn too little. However, few studies directly compare this "overconfidence penalty" across asset classes with differing information structures.

Our study bridges this gap. By defining "Excess Trading" ($zVol$) as a behavioral proxy, we test whether the negative relationship between turnover and returns holds universally (H1). Furthermore, by contrasting Equities (anchored by fundamentals) with Cryptocurrencies (driven by speculation and high retail influence), we test the boundary conditions of these behavioral theories (H2).

3 Study Design

3.1 Hypotheses

We test whether high trading volume is driven by genuine information processing or behavioral biases. Under rational expectations, high volume should facilitate price discovery, leading to neutral or positive risk-adjusted returns. Conversely, if high volume predicts *negative* returns, it suggests that traders held miscalibrated beliefs about their information advantage.

- **H1 (The Overconfidence Penalty):** Days of Excess Trading ($ExTrading = 1$) are followed by significantly lower CAPM-adjusted returns (CAR) in the subsequent h-day period. A negative relationship validates the overconfidence mechanism, as it implies a gap between the investor's perceived skill (willingness to trade) and actual skill (realized loss).

- **H2 (The Crypto Effect):** The negative coefficient of excess trading on future returns is larger for cryptocurrencies than for established equities, reflecting the stronger influence of behavioral biases in assets lacking fundamental anchors.

3.2 Data Collection

We utilize a dataset of daily closing prices, trading volumes, and risk factors spanning the period from January 1, 2015, to January 1, 2025.

3.2.1 Asset Selection: The "Fair Bundle" Methodology

To ensure a thorough comparison between the two asset classes, we construct two symmetric portfolios ("Fair Bundles") of 5 assets each. This balanced sample design ($N_{\text{Equity}} = N_{\text{Crypto}} = 5$) prevents sample size imbalances from skewing the statistical significance of our comparative tests.

- **Cryptocurrency Bundle:** We select the top 5 cryptocurrencies by average market capitalization over the sample period, excluding stablecoins to focus strictly on floating-price assets.
  - *Cryptos:* Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), and Cardano (ADA).
  - *Justification:* By limiting the sample to the top 5, we capture the majority of the asset class's liquidity while avoiding low-cap coins where price movements are often driven by manipulation (Liu & Tsyvinski, 2021).

- **Equity Bundle:** To ensure a representative bundle of stocks, we select the single largest constituent by average market capitalization over the sample period from five distinct GICS sectors: Information Technology, Financials, Energy, Health Care, and Consumer Staples.
  - *Equities:* Apple (AAPL), Berkshire Hathaway (BRK.B), ExxonMobil (XOM), Johnson & Johnson (JNJ), and Walmart (WMT).
  - *Justification:* This sector-neutral approach ensures that our equity control group represents a robust baseline of the market.

- **Sources:** Price and volume data are sourced from Yahoo Finance using "Adjusted Close" for equities to account for corporate actions. Risk-free rates and the CBOE Volatility Index (VIX) are retrieved from Federal Reserve Economic Data (FRED), while the CCi30 Index is sourced from the official CCi30 database.

3.3 Variables and Measures

3.3.1 Independent Variable: Excess Trading ($zVol$)

Following Glaser and Weber (2007), we use abnormal trading volume as our primary proxy for overconfidence. To normalize across assets with vastly different liquidity profiles, we compute the standardized volume ($zVol$) for asset i at time t:

$$zVol_{i,t} = \frac{Volume_{i,t} - \mu(Volume_{i,t-60})}{\sigma(Volume_{i,t-60})} \tag{1}$$

where μ and σ represent the rolling mean and standard deviation over the prior 60 trading days. We define our binary treatment variable, $ExTrading_{i,t}$, as:

$$ExTrading_{i,t} = \begin{cases} 1 & \text{if } zVol_{i,t} \geq 1.5 \quad \text{(High Overconfidence)} \\ 0 & \text{otherwise} \end{cases}$$

A threshold of zVol ≥ 1.5 identifies volume observations that are at least 1.5 standard deviations above their 60-day average. This corresponds to the top $\sim 7\%$ of the volume distribution under normality, and is consistent with other literature's use of large or abnormal volume.

3.3.2 Dependent Variable: Risk-Adjusted Returns (CAR)

To ensure that any underperformance is not simply a result of market-wide movements, we calculate Cumulative Abnormal Returns (CAR). The abnormal return (AR) for asset i on day t is derived from the Capital Asset Pricing Model (CAPM):

$$AR_{i,t} = (R_{i,t} - r_{f,t}) - \hat{\beta}_{i,t-1}(R_t^m - r_{f,t}) \tag{2}$$

- R^m (Market Return): For the equity bundle, we use the S&P 500 (SPY). For the cryptocurrency bundle, we use the CCi30 Index.

We then aggregate these residuals to calculate the cumulative abnormal return over the subsequent horizons $h \in \{5, 10, 20\}$ days:

$$CAR_{i,t \to t+h} = \sum_{s=t+1}^{t+h} AR_{i,s} \tag{3}$$

3.3.3 Control Variables

- **Market Volatility ($Vol_{m,t}$):** To control for systematic market distress, we employ a market-specific volatility proxy.
  - For the **Equity Bundle**, we utilize the *CBOE Volatility Index (VIX)*, which captures implied volatility in the S&P 500.
  - For the **Cryptocurrency Bundle**, we utilize the *Realized Volatility of the CCi30 Index*, calculated as the annualized 30-day rolling standard deviation of the index returns.
- **Lagged Returns (R_{t-1}):** Controlled to account for momentum or mean-reversion effects, as past returns are a known theoretical driver of overconfidence-induced volume (Statman et al., 2006).

3.4 Statistical Model

To formally test our hypotheses, we estimate the following predictive regression model separately for the equity and cryptocurrency bundles:

$$CAR_{i,t \to t+h} = \alpha + \beta_1 ExTrading_{i,t} + \beta_2 Vol_{m,t} + \beta_3 R_{i,t-1} + \epsilon_{i,t} \tag{4}$$

Where:

- $CAR_{i,t \to t+h}$ is the cumulative abnormal return for asset i over the future horizon h.
- α is the regression intercept.
- $ExTrading_{i,t}$ is our binary variable of interest.
- $Vol_{m,t}$ represents the specific market volatility proxy (VIX for equities, CCi30 Realized Volatility for crypto).
- $R_{i,t-1}$ represents the asset's lagged return.
- $\epsilon_{i,t}$ is the error term.

- **Test of H1:** We expect $\beta_1 < 0$ and statistically significant. This would indicate that days of excess trading systematically predict negative future returns.
- **Test of H2:** We compare the size of β_1 across asset classes. We expect $|\beta_{1,Crypto}| > |\beta_{1,Equity}|$, indicating a larger penalty in the crypto market.

3.5 Design Justification and Validity

The primary challenge in identifying the effect of overconfidence on asset returns is distinguishing between *behavioral trading* and *rational information processing.* In a neoclassical framework, high trading volume often signifies new fundamental information (e.g., an earnings surprise), which rational agents incorporate into prices. If high volume is merely a proxy for news, any subsequent price movement could be an efficient adjustment to risk rather than a behavioral penalty.

To address this threat to *internal validity*, our design employs a specific identification strategy to isolate the behavioral component of trading volume:

First, for the equity bundle, we exclude all trading days falling within a 3-day window of quarterly earnings announcements and dividend declarations. By removing these periods of scheduled fundamental disclosure, the remaining variance in trading volume ($zVol$) is less likely to be driven by rational portfolio rebalancing in response to fundamental news and more likely to reflect differences of opinion or overconfidence, specifically *overprecision.*

Second, the inclusion of cryptocurrencies serves as a strategic contrast. Unlike equities, cryptocurrencies lack scheduled fundamental disclosures (such as dividend dates) and traditional valuation anchors (such as P/E ratios). To ensure that our proxy for overconfidence is not influenced by major information shocks unique to this market, we exclude all trading days falling within a 3-day window of major crypto-specific events. These include network upgrades or hard forks, Bitcoin halving events, and major exchange outages.

By systematically excluding fundamental news events (earnings, dividends, forks), we isolate discretionary trading activity. In the absence of public information shocks, discretionary trading requires a strong belief in superior private information (Overplacement). If this specific subset of trading volume leads to underperformance, it empirically validates the presence of Overconfidence rather than rational liquidity provision. If $zVol$ predicts negative abnormal returns even after these exclusions, it provides strong evidence against the Efficient Market Hypothesis, as rational liquidity shocks should not systematically lead to subsequent drops.

Validity Concerns We acknowledge certain limitations in this proxy. High volume can occasionally result from exogenous liquidity shocks (e.g., a large fund liquidation) unrelated to overconfidence. To mitigate this confound, we include the VIX index (for equities) and realized volatility (for crypto) as control variables in our regression. This helps ensure that the measured effect of "Excess Trading" captures the *voluntary* betting behavior of investors, rather than a systemic reaction to market-wide distress. Furthermore, we rely on Ben-Rephael et al. (2017), who demonstrate that aggregate trading volume is a distinct proxy for retail attention, whereas institutional attention is reflected primarily through news searching activity. This distinction supports the validity of using $zVol$ to capture retail-driven overconfidence rather than informed institutional flow.

4 Analysis and Expected Results

4.1 Descriptive Statistics and Model Diagnostics

Before estimating the predictive regressions, we examine the summary statistics to contrast the market structures. We anticipate observing distinct volatility regimes:

- **Equity Bundle:** We expect moderate baseline volatility with volume spikes highly correlated to exogenous announcements. By filtering out these announcements, the remaining "Excess Trading" days are expected to provide sufficient data.

- **Crypto Bundle:** We anticipate significantly higher baseline volatility. Crucially, we expect trading volume in cryptocurrencies to exhibit stronger autocorrelation (clustering) than in equities, consistent with the herding behavior described by Kaiser and Stöckl (2020).

4.2 Test of Hypothesis 1: The Overconfidence Penalty

Estimating Equation (4) for the pooled sample, we expect the coefficient for Excess Trading (β_1) to be negative and statistically significant ($p < 0.05$).

- **Statistical Evidence:** A significant negative β_1 confirms that days of abnormal turnover are systematically followed by price reversals ($CAR < 0$).

- **Behavioral Interpretation:** This supports the Barber and Odean (2000) hypothesis that aggregate trading is motivated by overconfidence (noise) rather than genuine information. If investors were rational, high volume would facilitate efficient price discovery, leading to random (non-predictable) future abnormal returns.

4.3 Test of Hypothesis 2: The Crypto-Equity Gap

When splitting the sample by asset class, we hypothesize that the magnitude of the penalty will be distinct:

$$|\beta_{1,Crypto}| > |\beta_{1,Equity}| \tag{5}$$

We expect the coefficient for the cryptocurrency bundle to be significantly more negative. This would indicate that for every unit of "excess" volume, the subsequent price reversal is sharper in digital assets.

5 Discussion

5.1 Theoretical Implications

1. **Validation of the "Better-than-Average" Effect:** If volume predicts losses, it implies investors are trading not because they have private signals, but because they *believe* they have signals. This aligns with Glaser and Weber (2007), suggesting that volume is a metric of investor hubris (overplacement) rather than information processing.

2. **Boundary Conditions of Biases and Retail Influence:** By demonstrating a stronger effect in crypto, we highlight that behavioral biases are context-dependent. In equity markets, fundamental anchors act as a "System 2 brake", limiting how far overconfidence can drive prices away from value. In crypto markets, the combination of a high retail presence and the lack of such anchors allows "System 1 narratives" and the "Greater Fool Theory" to drive volume and prices unchecked, resulting in a more pronounced behavioral penalty.

5.2 Practical and Policy Contributions

Beyond individual portfolio underperformance, overconfidence-driven volume represents a deadweight loss to the economy by reallocating capital based on noise rather than productive capacity. Policy intervention is therefore justified not merely to protect individuals from their own biases, but to enhance overall market efficiency and reduce the systemic risks associated with speculative bubbles:

- **For Retail Investors:** The results advocate for "rules-based" investing (e.g., dollar-cost averaging) to avoid the temptation of overconfidence-driven market timing.

- **For Platform Design (Nudging):** Brokerages could implement a "System 2" nudge. If an investor attempts to trade during a period of high volatility (high $zVol$), the platform could display a warning for unusually high trading activity.

5.3 Limitations and Future Research

We acknowledge specific limitations in our design:

- **Aggregate vs. Individual Data:** We use market-wide volume as a proxy. We cannot definitively prove that the *same* people buying are the ones losing money without account-level data. It is possible that institutional arbitrageurs profit from the high volume at the expense of retail traders.

- **Rational Motivations:** While we control for earnings news, we cannot rule out that some high volume days are driven by other rational factors (e.g., tax-loss harvesting) rather than pure overconfidence.

- **Competing Motivations:** We attribute excess trading primarily to overconfidence. However, we acknowledge the "Sensation Seeking" hypothesis Grinblatt and Keloharju (2009), which suggests "risk-loving" investors trade for utility rather than expected value. While the outcome is identical to the overconfidence penalty, the motivation for the behavior differs.

Future Research Directions: Future studies could employ experimental methods to test if providing "fundamental anchors" (e.g., showing a calculated fair value on screen) reduces trading volume in experimental asset markets, thereby testing our mechanism for the Equity-Crypto gap.

Concluding Remarks: Ultimately, this study aims to empirically demonstrate the tangible cost of overconfidence. By linking excess trading volume to subsequent underperformance across asset classes, we highlight the financial penalty associated with behavioral biases and underscore the need for greater reliance on slow, reflective System-2 reasoning to counteract impulsive, bias-driven behaviour.

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