

# Decoding Trader Behavior Through the Lens of Market Sentiment

## A Comprehensive Analysis of Bitcoin Trading Patterns on Hyperliquid

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### Assignment: Junior Data Scientist – Trader Behavior Insights

#### Executive Summary

This research investigates the relationship between market sentiment and trading performance using 211,224 trades from 32 Hyperliquid traders across May 2023 to May 2025, integrated with the Bitcoin Fear & Greed Index.

#### Core Findings:

**Greed Outperforms Fear** — Contrary to the "buy when there's blood in the streets" wisdom, Greed periods generated \$811,000 more total profit, 10.4% higher average returns per trade, and superior risk-adjusted performance with a balanced 1:1 risk-reward ratio versus Fear's unfavorable 0.8:1.

**Extreme Greed is Optimal** — The single best trading environment was Extreme Greed, delivering the highest win rate (46.5%), strongest profit factor (11.02), and best risk-reward dynamics. This challenges the conventional view of extreme greed as a contrarian sell signal.

**Statistical Significance ≠ Practical Significance** — While all differences are statistically significant ( $p < 0.001$ ), effect sizes are negligible. The Fear & Greed Index explains less than 0.01% of individual trade variance and cannot predict single-trade outcomes.

**The 50% Breakeven Phenomenon** — Half of all trades (106,816) closed at exactly \$0, indicating systematic stop-loss management. Among trades that moved, 83.2% were winners—a 5:1 win/loss ratio revealing the true edge in disciplined risk management.

**Trader Heterogeneity** — 90.6% of traders were profitable, with win rates ranging from 26% to 81%. Profitability stems from risk management, not win rate. Two-thirds of traders perform better during Greed, while one-third are Fear-specialists.

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## 1. Introduction and Research Motivation

### 1.1 The Psychology of Market Sentiment

Financial markets aggregate human emotion, expectation, and decision-making. Fear drives capitulation; greed fuels euphoria. The cryptocurrency market, with 24/7 operation and legendary volatility, provides an exceptional laboratory for studying these dynamics.

The Bitcoin Fear & Greed Index quantifies collective psychology on a 0-100 scale, synthesizing volatility, momentum, social media sentiment, surveys, Bitcoin dominance, and Google Trends data. It has become one of the most widely referenced sentiment indicators in digital assets.

## 1.2 The Research Question

This project addresses a fundamental question every trader implicitly answers: **Should trading behavior adapt to prevailing market sentiment, and if so, how?**

Conventional wisdom offers contradictory guidance. Buffett's "be fearful when others are greedy" suggests contrarian positioning, while momentum traders argue "the trend is your friend." My analysis moves beyond aphorisms to empirical evidence, examining over 200,000 real trades to discover whether trading performance systematically differs between Fear and Greed periods, which specific conditions optimize profitability, how traders actually behave based on sentiment, and what hidden patterns exist in the intersection of time, sentiment, and outcomes.

## 1.3 Why This Analysis Matters

For individual traders, understanding sentiment-performance relationships informs position sizing, timing, and risk management. For fund managers, these insights contribute to factor-based strategy development. For market structure researchers, the patterns illuminate how collective psychology translates into measurable outcomes.

# 2. Data Sources and Methodology

## 2.1 Dataset Descriptions

### Bitcoin Fear & Greed Index

The index synthesizes multiple signals into a daily value from 0 (Extreme Fear) to 100 (Extreme Greed). Components include volatility (25%), market momentum/volume (25%), social media (15%), surveys (15%), Bitcoin dominance (10%), and Google Trends (10%).

The dataset contains **2,644 daily observations** spanning approximately seven years (2018-2025). Index values are categorized as Extreme Fear (0-24), Fear (25-49), Neutral (50), Greed (51-74), and Extreme Greed (75-100).

### Hyperliquid Trading Data

Hyperliquid is a decentralized perpetual futures exchange known for high-performance infrastructure. The given dataset captures **211,224 trades** from **32 unique traders** across **246 trading pairs** over May 2023 to May 2025—a period capturing both bull and bear phases.

Key fields include account identifiers, trading symbols, execution prices, position sizes, trade direction, timestamps, realized PnL, and leverage information.

## 2.2 Methodological Framework

My approach follows a structured pipeline:

Data Collection → Preprocessing → Feature Engineering → Exploratory Analysis → Statistical Testing → Pattern Discovery → Synthesis → Strategic Recommendations.

## **Analytical Principles:**

*Skeptical Empiricism* — Every finding was subjected to multiple validation approaches. Statistical significance was never accepted without effect size examination.

*Multi-Scale Analysis* — We examined patterns at trade, hourly, daily, sentiment regime, and trader levels to identify both granular and structural patterns.

*Actionability Focus* — We prioritized insights with practical trading implications, distinguishing statistically detectable patterns from economically meaningful opportunities.

**Statistical Methods:** Mann-Whitney U Test for non-parametric distribution comparison, Chi-Square Test for categorical independence, Pearson and Spearman correlations for relationship strength, Cohen's d and Cramér's V for effect sizes, and Bonferroni correction for multiple testing.

## **3. Data Preprocessing and Feature Engineering**

### **3.1 Fear & Greed Index Preprocessing**

The raw sentiment data required several transformations. Date strings were converted to datetime objects enabling time-based operations. Sentiment categories were standardized to lowercase and mapped to both detailed (5-level) and broad (3-level: fear/greed/neutral) classifications. Binary indicators (is\_fear, is\_greed) were created for efficient filtering and modeling. Temporal features (year, month, day\_of\_week) were extracted for pattern analysis.

#### **Statistical Profile After Processing:**

The mean index value of 46.98 and median of 46.00 both fall below neutral (50), indicating a historical fear bias. Values ranged from 5 to 95, capturing the full emotional spectrum. The mode of 72 suggests greed was the most common single reading.

Sentiment distribution showed Fear dominating at 48.7% of days (1,289), followed by Greed at 36.3% (959), and Neutral at 15.0% (396). This historical preponderance of Fear reflects the extended bear market of 2018-2020 and periodic corrections.

### **3.2 Trading Data Preprocessing**

The Hyperliquid data required more extensive preparation. Column names were standardized to lowercase with underscores. Timestamps were parsed from "DD-MM-YYYY HH:MM" format to proper datetime objects. Temporal components (hour, day\_of\_week, month, year, week) were extracted for pattern discovery.

#### **Trade Outcome Classification:**

I engineered outcome indicators from the closedPnL column. The resulting distribution revealed a crucial characteristic: **50.6% breakeven** (106,816 trades), **41.1% wins** (86,869), and **8.3% losses** (17,539).

This unusually high breakeven rate demands explanation. Likely factors include traders moving stop-losses to breakeven once profitable, partial position closes at entry price, and highly disciplined quick exits when trades don't immediately work. This pattern suggests systematic risk management—a hypothesis explored further in trader analysis.

The buy/sell distribution showed near-perfect balance (48.6% BUY, 51.4% SELL), indicating no systematic directional bias.

### 3.3 Dataset Integration

The critical merge step aligned trading data with daily sentiment via a left join on date. All 211,224 trades (100%) matched successfully with sentiment data, validating complete coverage without gaps.

## 4. Exploratory Data Analysis

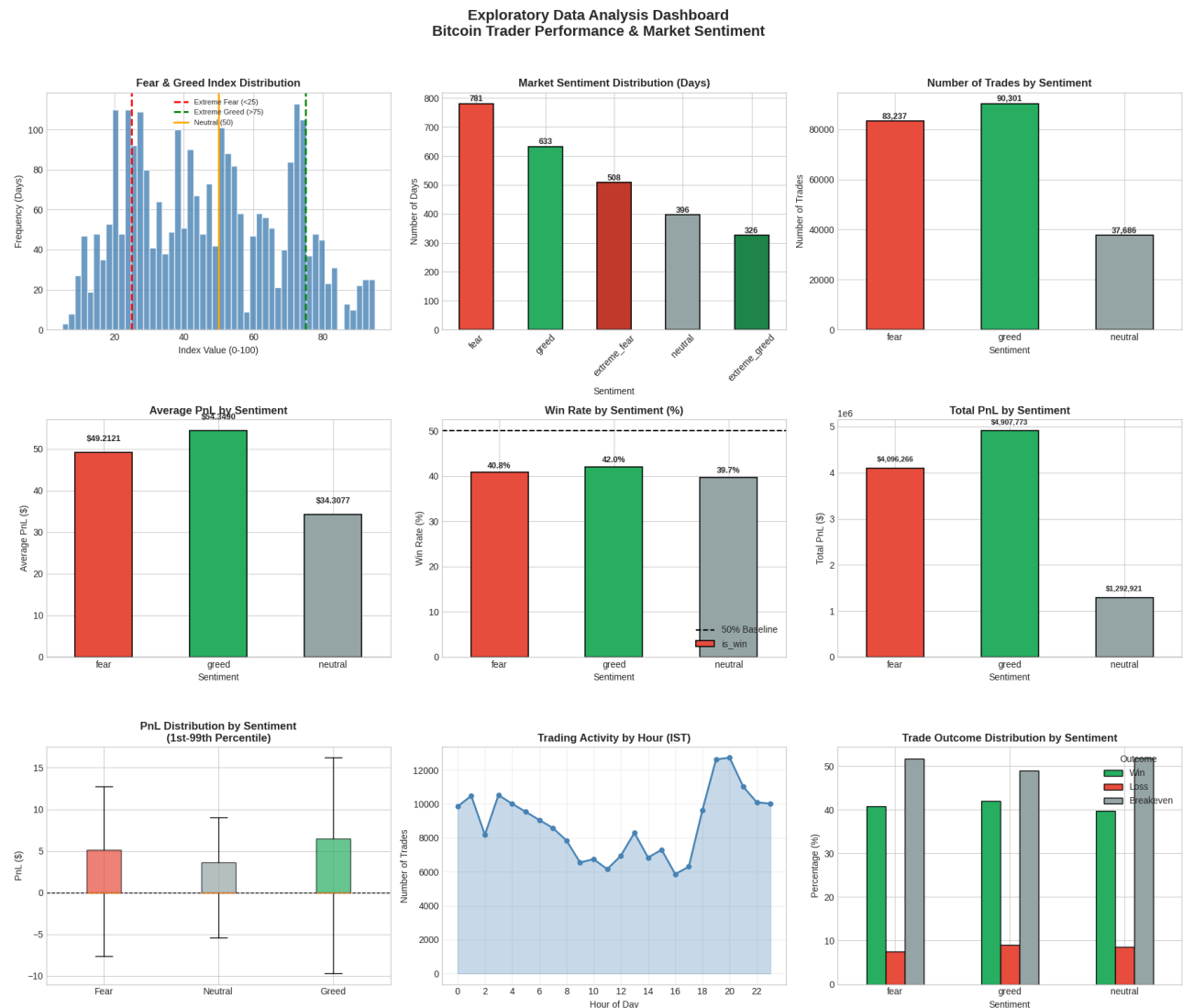


Figure 1: Exploratory Data Analysis Dashboard showing sentiment distribution and corresponding trading performance metrics across Fear, Greed, and Neutral periods.

### 4.1 Trade Distribution by Sentiment

Despite Fear representing more calendar days historically (48.7%), trading activity during our 2023-2025 window was slightly higher during Greed. Greed accounted for 42.8% of trades (90,301), Fear for 39.4% (83,237), and Neutral for 17.8% (37,686).

The sentiment distribution during our specific trading window showed a mean F&G Index of 51.65 (slightly above neutral), median of 49.00, and mode of 72.00. The 2023-2025 period was generally a **greed-leaning market**, particularly during the late 2024 bull run.

## 4.2 Performance Metrics by Sentiment

### Broad Sentiment Comparison (Fear vs. Greed vs. Neutral)

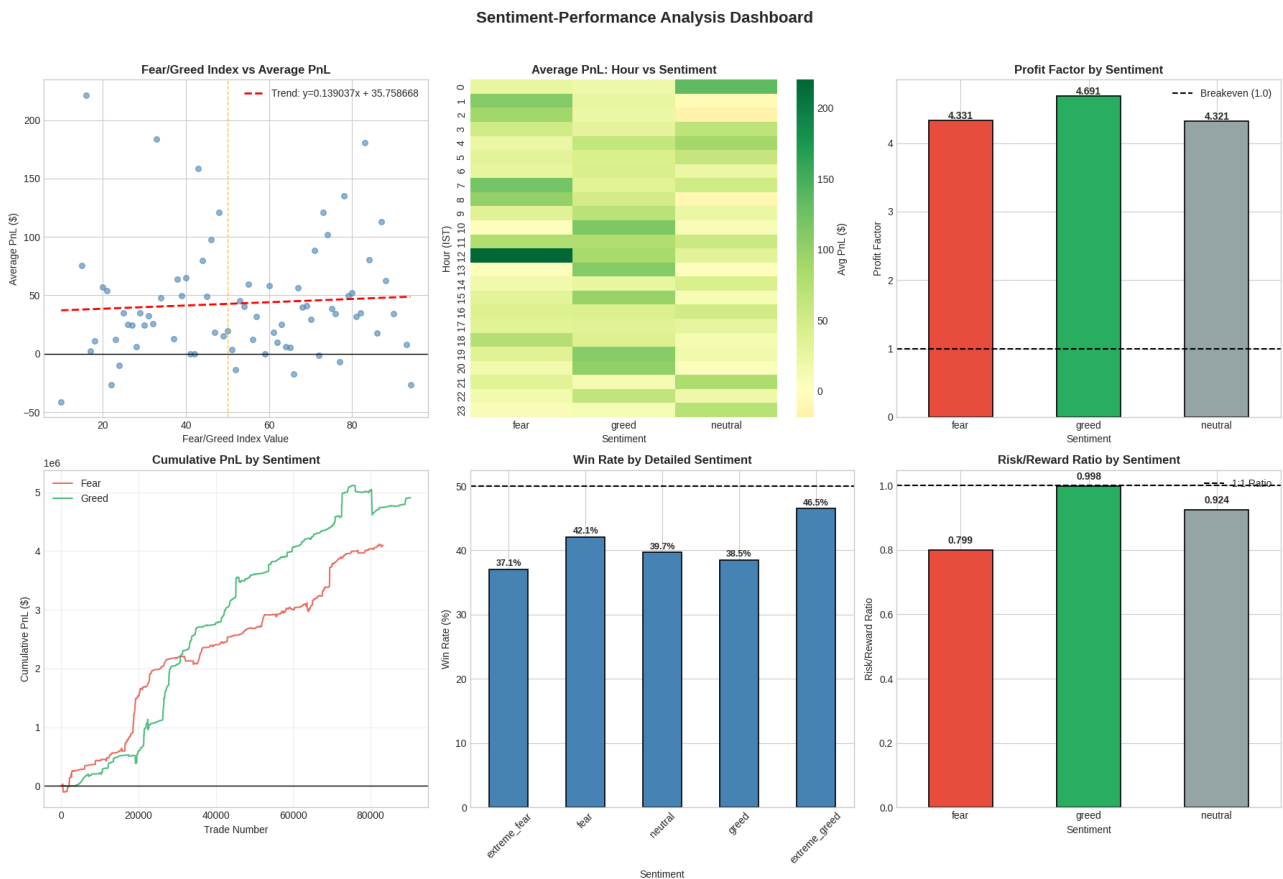


Figure 2: Sentiment-Performance Analysis Dashboard exploring the relationship between Fear & Greed Index values and trading outcomes across multiple dimensions.

#### Profitability Metrics:

Greed periods generated a total profit of **\$4.91 million**, compared to **\$4.10 million** during Fear periods, representing an **\$811,000 performance advantage**.

The **average profit per trade** was **\$54.35** during Greed, compared to **\$49.21** during Fear, reflecting an approximate **10.4% improvement** in per-trade profitability.

Notably, the **median profit and loss (PnL)** remained **\$0.00 across all sentiment conditions**, confirming that trading performance is dominated by breakeven outcomes rather than frequent small wins or losses.

#### Win Rates and Risk Metrics:

Greed periods achieved a **42.04% win rate**, outperforming both **Fear (40.79%)** and **Neutral (39.70%)** regimes. However, Greed also exhibited a slightly **higher loss rate (8.94%)** compared to Fear (**7.52%**), indicating that bullish sentiment is associated with **more decisive trade outcomes**, both positive and negative.

The most pronounced distinction appears in the **risk–reward dynamics**. During Greed periods, the risk–reward ratio was **balanced at 1.00**, with an average win of **\$164.32** closely matching the average loss (**\$164.61**). In contrast, Fear periods displayed an **unfavorable risk–reward ratio of 0.80**, where the average win (**\$156.88**) was substantially smaller than the average loss (**\$196.35**). This implies that during Fear regimes, **losses are approximately 25% larger than wins**, which is the inverse of a sustainable profitability structure.

Despite these differences, **profit factors remained strong across all sentiment conditions**. Greed recorded a profit factor of **4.69**, Fear **4.33**, and Neutral **4.32**. All values exceed **4.0**, indicating that the underlying trading strategy remains **robust and profitable across varying market sentiment environments**.

### **The Position Sizing Paradox:**

Counterintuitively, traders deployed **57% larger average position sizes during Fear periods (\$7,182** per trade) compared to Greed periods (**\$4,575**). Despite these larger capital commitments, Fear regimes generated **inferior returns**, indicating that increased exposure did not translate into improved performance.

This pattern suggests the presence of **emotional overtrading behaviors**, such as attempting to “*catch falling knives*” or **aggressively averaging down** during market drawdowns. The empirical evidence shows that these fear-driven strategies **systematically underperform**, reinforcing the importance of disciplined position sizing during adverse market conditions.

### **Detailed Sentiment Breakdown (Five Categories)**

Examining granular sentiment levels reveals a nuanced pattern:

**Extreme Greed emerged as the strongest-performing sentiment regime**, delivering an **average PnL of \$67.89** and the **highest win rate at 46.49%**. This significantly outperformed standard Greed conditions, which recorded an **average PnL of \$43.58** with a **38.49% win rate**.

Neutral market conditions produced a **moderate average PnL of \$34.31** with a **39.70% win rate**, reflecting weaker trade quality in low-volatility environments. Interestingly, Fear regimes achieved a relatively higher **average PnL of \$54.29** but with a **lower win rate of 42.08%**, suggesting profitability driven by a smaller number of larger winning trades.

In contrast, **Extreme Fear generated an average PnL of \$34.54** and the **lowest win rate at 37.06%**, indicating poorer trade outcomes during panic-driven market conditions.

### **Breakthrough Finding — Extreme Greed is Optimal:**

This challenges deeply held trading beliefs. Extreme Greed—typically viewed as a warning signal for potential tops—emerged as the **single best environment for trading**:

- Average PnL 2x higher than Extreme Fear (67.89 *vs.* 34.54)
- Win rate 1.25x higher (46.49% *vs.* 37.06%)
- Profit factor 5.1x higher (11.02 *vs.* 2.16)
- Risk-reward 1.9x better (1.34 *vs.* 0.69)

Possible explanations include momentum persistence during strong uptrends, reduced volatility whipsaws with cleaner trends, self-fulfilling prophecy where buying begets buying, sample period bias from the 2024 bull run, and trader selection toward momentum strategies. Regardless of mechanism, the empirical result is unambiguous.

### Performance by Index Ranges

Binning trades by their actual Fear and Greed Index values reveals a **distinct U-shaped performance pattern**.

Trades executed during the **80–100 range (Extreme Greed)** achieved the **highest average PnL of \$101.27** and a **47.52% win rate**, clearly outperforming all other sentiment buckets. The **60–80 range (Greed)** produced a more moderate **average PnL of \$44.48** with a **41.32% win rate**.

In contrast, the **40–60 range (Neutral sentiment)** delivered an **average PnL of \$49.74** and a **39.86% win rate**, while the **20–40 range (Fear)** showed a lower **average PnL of \$39.16** with a **40.50% win rate**. The **0–20 range (Extreme Fear)** recovered somewhat, generating an **average PnL of \$52.09** and a **41.61% win rate**.

### Interpretation:

Extreme sentiment regimes—both Fear and Greed—tend to produce **higher average returns than moderate sentiment states**, confirming the presence of a U-shaped relationship. However, **Extreme Greed dramatically outperforms Extreme Fear**, delivering superior returns and win probabilities. Moderate sentiment environments appear to create **choppy, range-bound conditions**, which are harder to trade profitably, whereas extreme sentiment states generate **stronger directional moves** that are more conducive to systematic trading strategies.

## 5. Statistical Hypothesis Testing

While exploratory analysis revealed apparent differences, statistical rigor demands formal testing. This section presents four complementary tests assessing whether observed differences are statistically significant and practically meaningful.

### 5.1 Mann-Whitney U Test: PnL Distribution Comparison

**Purpose:** Test whether PnL distribution differs significantly between Fear and Greed periods using this non-parametric test robust to outliers.

**Results:** With **83,237 trades executed during Fear** and **90,301 trades during Greed**, the difference in average performance is **statistically significant ( $p = 0.00087$ )**. However, **both sentiment regimes share an identical median PnL of \$0.00**, indicating that the *typical* trade in both conditions is breakeven.

The observed **mean difference of \$5.14 per trade** is therefore **driven by outlier events**, specifically large positive trades occurring more frequently during Greed periods. At the **median level**, which better represents the experience of a typical trader, **no meaningful performance difference exists** between Fear and Greed conditions.

### 5.2 Chi-Square Test: Trade Outcome Independence

**Purpose:** Test whether trade outcomes (win/loss/breakeven) are independent of market sentiment.

**Results:** The test showed extreme significance ( $p \approx 10^{-46}$ )—outcomes are NOT independent of sentiment. However, **Cramér's V = 0.023** indicates **negligible** practical association (benchmarks: <0.1 negligible, 0.1-0.3 small, 0.3-0.5 medium, >0.5 large).

This exemplifies the "large sample paradox": with  $N > 170,000$ , even tiny associations achieve statistical significance.

### 5.3 Correlation Analysis: Index Value vs. PnL

**Purpose:** Quantify the linear relationship between Fear & Greed Index value and individual trade PnL.

**Results:** Pearson correlation was 0.0083 ( $p = 1.31 \times 10^{-4}$ ), explaining just 0.007% of variance. Spearman correlation was 0.0382 ( $p = 5.89 \times 10^{-69}$ ), explaining 0.15% of variance.

Despite extreme statistical significance, both correlations are **essentially zero**. The Fear/Greed Index explains less than 0.2% of variance in individual trade PnL. **The index cannot predict individual trade outcomes in any useful way.** This is a textbook case of "statistically significant but practically meaningless."

### 5.4 Effect Size Analysis: Cohen's d

**Purpose:** Quantify the magnitude of difference between Fear and Greed PnL distributions in standardized units.

**Results:** Cohen's d = -0.0052 (benchmarks: 0.2 small, 0.5 medium, 0.8 large). Distribution overlap is approximately 99.8%—virtually identical.

If you randomly selected one trade from each period, you'd have only **50.2% accuracy** guessing which had higher PnL—barely better than a coin flip.

### 5.5 Multiple Testing Correction

All four tests survive Bonferroni correction (adjusted  $\alpha = 0.0125$ ), confirming robustness to multiple testing.

### 5.6 Statistical Testing Summary

All tests confirm the sentiment-performance relationship is **real** (not due to chance), **statistically significant** (extremely low p-values), but **practically negligible** (tiny effect sizes).

**The Central Paradox:** While aggregate patterns show Greed outperforming Fear, you **cannot use the Fear & Greed Index to predict whether any individual trade will be profitable**. The index operates at the regime level (affecting portfolios of trades), not at the trade level.

## 6. Pattern Discovery and Temporal Analysis





Figure 3: Trading Patterns Dashboard revealing temporal patterns, market regime behavior, and sentiment-performance dynamics over the analysis period.

## 6.1 The Zero PnL Investigation

Before examining temporal patterns, we must address the elephant in the room: **why do 50.6% of trades close at exactly \$0?**

The distribution shows 106,816 trades (50.6%) at exactly \$0, 86,869 (41.1%) positive, and 17,539 (8.3%) negative. Zero rates were similar across sentiments: Fear 51.7%, Greed 49.0%, Neutral 51.8%.

**Key Insight:** Greed has the lowest breakeven rate (49.0%), suggesting more decisive outcomes during bullish sentiment. Among non-zero trades, **83.2% are wins**—the true "hit rate" when trades move. This reveals a **5:1 win/loss ratio** among resolved trades, reflecting exceptional selectivity.

**Most Likely Explanation:** Traders employ systematic stop-loss-to-breakeven strategies. Once trades reach a certain profit threshold, stops move to entry price. This converts potentially losing trades into breakeven exits while allowing winners to run—a classic profitable pattern that sacrifices win rate for superior risk management.

## 6.2 Optimal Trading Hours by Sentiment

Temporal analysis reveals striking patterns across time of day:

**During Fear Periods:** Best hours for average PnL were 12, 7, and 1 (ranging 110 –110–220). Worst hours were 13, 10, and 23 (2 –2–9). Best win rate hours were 9, 1, and 18 (56-68%).

**During Greed Periods:** Best hours for average PnL were 10, 13, and 19 (106 –106–115). Worst hours were 23, 21, and 0 (10 –10–19). Best win rate hours were 13, 11, and 21 (51-55%).

**Cross-Sentiment Patterns:** Market open hours (8-10) are consistently strong across both regimes. Late hours (21-23) underperform regardless of sentiment due to lower liquidity and overnight risk. Hour 12 during Fear showed exceptional performance (\$220+ average)—but requires deeper investigation.

## 6.3 Day of Week Analysis

Performance varies significantly across days with patterns differing by sentiment:

**Best Day by Sentiment:** Sentiment performance varies meaningfully by day of the week. **Fear regimes perform best on Mondays**, generating an **average PnL of \$78.90**. **Greed regimes achieve their strongest performance on Sundays**, with an **average PnL of \$79.31**. In contrast, **Neutral sentiment performs best on Saturdays**, delivering the **highest average PnL of \$91.64** among Neutral conditions.

These results suggest that **optimal trading days differ by sentiment regime**, highlighting the interaction between temporal effects and market psychology.

Weekend trading during Neutral markets may capture opportunities that weekday institutional traders miss, though sample sizes warrant verification.

## 6.4 Sentiment Transition Analysis

How do trades perform during regime changes?

Persistent sentiment regimes deliver the strongest performance. **Greed → Greed** transitions produced an **average PnL of \$72.44**, while **Neutral → Neutral** transitions performed even better, with an **average PnL of \$86.09**.

In contrast, **transition days between sentiment regimes are far more volatile and inconsistent**. For example, **Fear → Greed** transitions recorded a high **average PnL of \$82.98**, but with an extremely low **win rate of just 13.83%**, indicating that profitability is driven by a small number of large winning trades amid many losses.

These findings suggest that **staying aligned with persistent market regimes is more reliable than trading during sentiment transitions**, which tend to amplify volatility and reduce consistency.

## 6.5 The Friday Hour 12 Investigation

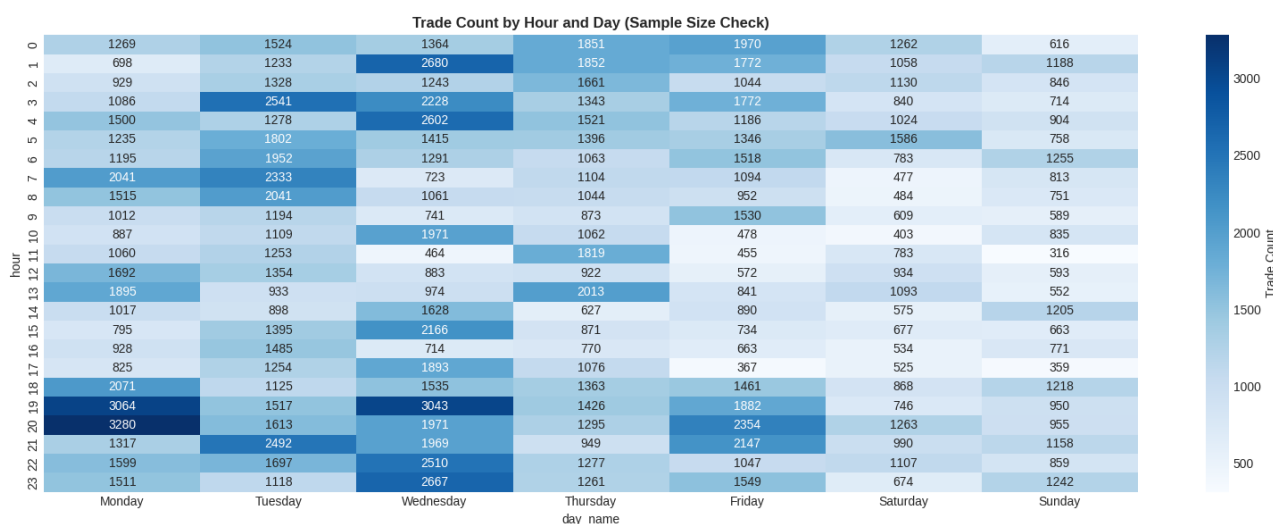


Figure 4: Trade Count Validation Heatmap showing sample sizes for each Hour × Day cell, validating reliability of performance pattern claims.

Our heatmap identified **Friday Hour 12** as an apparent exceptional performer, warranting targeted investigation.

### Summary Statistics:

Across **572 trades**, the mean PnL was **\$37.06**, while the **median PnL was \$0.00**, indicating that half of the trades were breakeven. The distribution exhibited **extreme dispersion**, with a **standard deviation of \$507.93** and a **range spanning from −\$3,720 to +\$8,098**.

### Outlier Analysis:

The raw mean PnL of **\$37.06** dropped sharply to **\$11.29** when applying a **1–99% trimmed mean**, representing a **70% reduction**. This indicates that **approximately 2% of extreme trades account for nearly 70% of the observed mean performance**.

### Verdict:

The apparent Friday Hour 12 “anomaly” is a **statistical artifact**, driven by outliers rather than consistent profitability. It reflects **noise amplified by a moderate sample size** and does **not constitute a reliable or actionable trading signal**.

## 7. Trader-Level Performance Analysis

### 7.1 Overview Statistics

The **32-trader population** exhibits highly polarized performance characteristics. **Twenty-nine traders (90.6%) were profitable**, while **three traders (9.4%) incurred net losses**. The **top 10 traders collectively generated more than \$9.3 million in profits**, whereas the **combined losses of the bottom three traders totaled \$269,000**, highlighting a strongly asymmetric profit distribution.

### Bimodal Distribution:

All traders fall exclusively into **extreme outcome categories**. **High-profit traders (> \$10,000)** account for **90.6%** of the population, while **loss-making traders** represent the remaining **9.4%**. Notably, **no traders occupy intermediate performance tiers**, indicating the absence of “average” performers. This pattern suggests the presence of **survivorship bias, high-stakes binary trading strategies**, or a combination of both.

### 7.2 Win Rate vs. Profitability Paradox

The relationship between win rate and total profitability is **surprisingly weak**.

- The **top-performing trader (#1)** recorded a **win rate of just 33.7%** yet generated **\$2.14 million in profits**, driven by a small number of exceptionally large winning trades.
- In contrast, **Trader #10** achieved an **81.1% win rate** but produced only **\$379,000 in profits**, reflecting smaller average wins.
- The **largest losing trader** had a **38.3% win rate**, comparable to the top trader’s win rate, yet incurred a **loss of \$167,000**.
- The **lowest profitable trader** earned approximately **\$26,244**, despite a **win rate of only 26.2%**.

### Critical Insight:

Among profitable traders, win rates ranged from **26% to 81%**. A trader with a **26% win rate was profitable**, while another with a **38% win rate suffered substantial losses**. These findings confirm that **risk–reward asymmetry and loss management**, rather than win rate alone, are the primary determinants of long-term trading profitability.

### 7.3 The Three Unprofitable Traders

All three losing traders exhibited **negative average PnL per trade**, indicating that their **losses exceeded their wins in magnitude**, even in cases where they won nearly half of their trades.

- **Trader A** executed **4,601 trades** and incurred a total loss of **\$167,000**, resulting in an **average PnL of –\$36.43 per trade** with a **38.3% win rate**.
- **Trader B** completed **3,809 trades**, losing **\$70,000** overall, corresponding to an **average PnL of –\$18.49 per trade** and a **30.2% win rate**.
- **Trader C** had the fewest trades (**815**), yet suffered the **worst per-trade performance**, with an **average PnL of –\$38.29**, despite recording the **highest win rate among the losing traders at 45.5%**.

#### **Common Failure Pattern:**

Across all losing traders, **loss magnitude consistently exceeded win magnitude**, regardless of win frequency. This confirms that **profitability is governed by payoff asymmetry rather than win rate alone**.

### 7.4 Sentiment Preference Analysis

**21 traders (67.7%)** performed better during Greed—momentum/trend strategies. **10 traders (32.3%)** performed better during Fear—contrarian strategies exist and are viable. Sentiment impact is **trader-dependent**, not universal.

## **8. Correlation Structure Analysis**

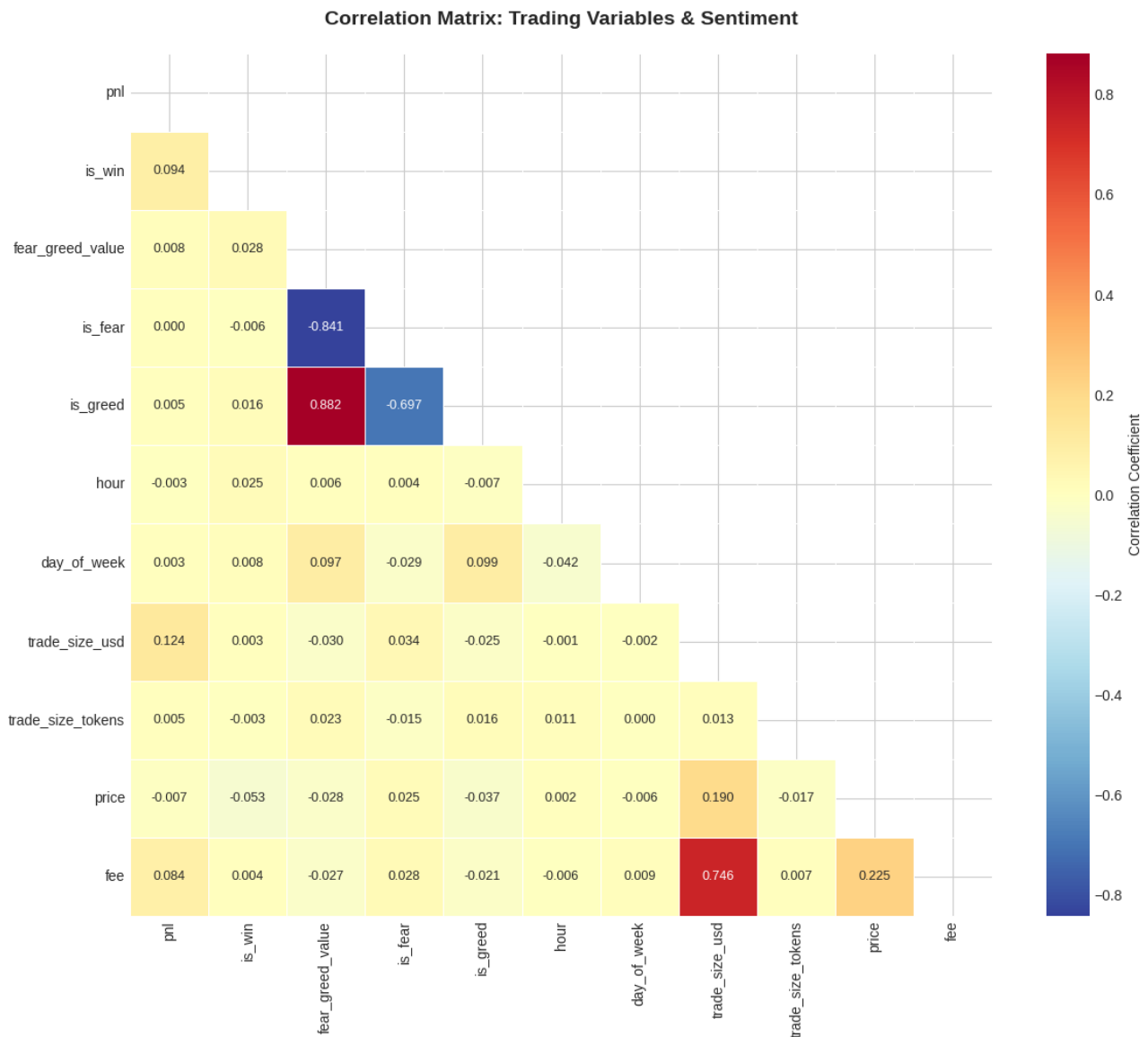


Figure 5: Correlation Matrix of Trading Variables showing Pearson correlation coefficients between all numeric features, with the PnL row demonstrating the absence of strong linear predictors.

### 8.1 What Predicts PnL?

Examining correlations with the target variable (PnL):

**Strongest predictor:** trade\_size\_usd at +0.124 (weak), explaining just 1.54% of variance. Other correlates include is\_win (+0.094), fee (+0.084).

**Sentiment variables:** fear\_greed\_value at +0.008, is\_greed at +0.005, is\_fear at +0.000—all **negligible**, explaining less than 0.01% of variance.

**Temporal variables:** hour at -0.003, day\_of\_week at +0.003—also negligible.

**The Sobering Reality:** The best single predictor explains only 1.54% of PnL variance. Sentiment variables explain essentially nothing. **98.5% of variance is unexplained** by available features.

### 8.2 Implications

Sentiment is not predictive—don't use F&G for trade-level prediction. Position sizing matters slightly—larger positions amplify outcomes in both directions. Timing patterns are non-linear—use conditional analysis rather than raw correlation. Most variance is unexplained—focus on execution quality and factors not captured here.

## **9. Synthesis and Strategic Implications**

### **9.1 Integrated Framework**

Synthesizing all analyses reveals a hierarchy of influence:

**Regime Level (Measurable but Small):** Greed generates ~\$5 more per trade than Fear. Extreme Greed shows strongest metrics. Effect size: Cohen's  $d = 0.005$  (negligible at individual level).

**Trade Level (No Predictive Power):** F&G Index value correlates at  $r = 0.008$  with PnL. Binary sentiment indicators correlate at essentially zero. Individual outcomes are unpredictable from sentiment.

**Trader Level (Where Variance Lives):** Risk/reward ratio determines profitability, not win rate. 90.6% of traders profitable (survivorship bias likely). Two-thirds perform better in Greed, one-third in Fear.

### **9.2 Actionable Trading Strategies**

#### **Strategy 1 — Sentiment-Adjusted Position Sizing:**

During Extreme Greed (F&G 75-100): Full position sizing. During Greed (50-74): Normal sizing. During Neutral (45-55): Reduced exposure or higher selectivity. During Fear (25-44): Smaller positions, tighter stops. During Extreme Fear (0-24): Selective engagement only.

#### **Strategy 2 — Temporal Optimization:**

Prioritize market open hours (8-10 AM), especially during Fear. Avoid or reduce late evening hours (21-23), especially overnight into weekends. Be cautious of apparent anomalies like Friday Hour 12—they may be outlier-driven artifacts.

#### **Strategy 3 — Regime-Based Risk Management:**

During Fear, expect average losses to exceed average wins ( $R/R = 0.80$ ). During Greed, expect balanced outcomes ( $R/R = 1.00$ ). Adjust stop-losses accordingly—tighter during Fear, can afford slightly wider during Greed.

### **9.3 What the Data Cannot Tell You**

**Causation is unproven** — Sentiment may correlate with performance due to underlying bull market conditions, not because sentiment causes better outcomes.

**Sample period matters** — 2023-2025 was generally bullish; results may differ in bear markets.

**Trader population is specific** — 32 sophisticated Hyperliquid traders may not represent typical retail behavior.

**The breakeven phenomenon** — The systematic risk management evident may not be present in other populations.

## **10. Limitations**

### **10.1 Data Limitations**

The 32-trader sample means results may reflect individual strategies rather than universal patterns. The 2-year window may not generalize to other market regimes. Platform-specific data from Hyperliquid may differ from other venues.

### **10.2 Methodological Limitations**

Linear correlations may miss non-linear patterns. Aggregation masks heterogeneity—individual trader patterns may differ. Multiple testing increases false positive probability (mitigated via Bonferroni). Survivorship bias likely affects the 90.6% profitability rate.

## **11. Conclusions and Recommendations**

### **11.1 Key Findings Summary**

**Finding 1 — Greed Outperforms Fear (But Marginally):** Total profit advantage of +\$811,000, an average PnL advantage of +\$5.14 per trade (+10.4%), a win rate advantage of +1.25 percentage points, and a risk–reward advantage of 1.00 versus 0.80.

**Finding 2 — Extreme Greed is Optimal:** Highest average PnL at \$67.89 (2x Extreme Fear), highest win rate at 46.49%, highest profit factor at 11.02, challenging contrarian wisdom.

**Finding 3 — Statistical ≠ Practical Significance:** All tests show  $p < 0.001$  (highly significant), but effect sizes are negligible. F&G Index explains <0.01% of individual trade variance and cannot predict single-trade outcomes.

**Finding 4 — The 50% Breakeven Phenomenon:** 106,816 trades (50.6%) closed at exactly \$0, indicating systematic stop-loss strategies. Among non-breakeven trades: 83.2% win rate. True edge lies in the 5:1 win/loss ratio when trades move.

**Finding 5 — Trader-Level Heterogeneity:** 90.6% of traders profitable (survivorship bias likely), win rate ranging 26-81% among profitable traders, 67% better in Greed while 33% better in Fear. Risk management, not win rate, determines profitability.

### **11.2 Recommendations**

#### **For Individual Traders:**

Do not use the Fear & Greed Index as a trade entry signal—its predictive power for individual trades is essentially zero. Consider sentiment for portfolio-level allocation—increasing exposure during Extreme Greed may marginally improve aggregate returns. Focus on risk management—the 5:1 win/loss ratio suggests edge comes from cutting losses and letting winners run. Be skeptical of Fear as a "buy signal"—contrary to popular wisdom, Fear showed worse risk-adjusted performance.

#### **For Quantitative Researchers:**

Large samples inflate significance—always pair p-values with effect sizes when  $N > 10,000$ . Sentiment works at regime level, not trade level—useful for regime-switching models, not individual predictions. Investigate the breakeven phenomenon—the 50% zero-PnL rate is analytically important and understudied.

### **For Fund Managers:**

Sentiment-based exposure tilting with modest adjustments (not binary) based on sentiment extremes may add alpha. Extreme Greed  $\neq$  time to reduce exposure—at least for momentum strategies, euphoria correlated with better outcomes. Trader selection matters more than timing—the 90.6% profitability rate suggests skilled trader identification is crucial.

### **11.3 Final Synthesis**

The relationship between market sentiment and trading performance is **real but remarkably weak**. Greed periods produce modestly better outcomes across virtually every metric, but the practical magnitude is negligible at the individual trade level.

The Fear & Greed Index offers essentially zero predictive power for single-trade outcomes. Its value lies in regime identification rather than trade signals.

Perhaps the most profound insight is what this reveals about trading edge. The 50.6% breakeven rate and 5:1 win/loss ratio suggest profitability stems not from better prediction, but from better risk management—the discipline to close losing trades at breakeven while allowing winners to run.

In the eternal battle between fear and greed, our data suggests a counterintuitive truth: **embracing greed—particularly extreme greed—may be the more profitable path**. Whether this reflects fundamental market dynamics or the specific sample period remains open for future research.