Trader Behaviour vs Market Sentiment

A Quantitative Analysis of Hyperliquid Trading Activity

1. Executive Summary

This study analyses how trader behaviour on Hyperliquid varies across market sentiment regimes, classified as **Fear** and **Greed** using the Bitcoin Fear & Greed Index. By aligning high-frequency trader execution data with daily sentiment labels, the analysis evaluates differences in profitability, risk-taking, trading intensity, and capital efficiency.

The results show that **market sentiment is a statistically and economically meaningful driver of trader behavior**. Fear regimes exhibit more disciplined, risk-adjusted trading outcomes, while Greed regimes are associated with higher trading activity, leverage usage, and volatility without proportional improvement in returns.

These findings suggest that **sentiment-aware risk management and position sizing can materially improve trading performance**.

2. Data Description

2.1 Trader Data (Hyperliquid)

The trader dataset contains executed trade-level information including:

- Execution price and size
- Direction (long/short)
- Closed PnL
- Trade timestamps (UNIX epoch)

To ensure temporal consistency, **raw UNIX timestamps were used**, and localized timestamps were excluded to avoid timezone distortions.

2.2 Market Sentiment Data

Market sentiment was sourced from the Bitcoin Fear & Greed Index and classified daily into:

- **Fear**
- **Greed**

Sentiment timestamps were dynamically inferred and normalized to handle schema inconsistencies across external data sources.

3. Methodology

3.1 Feature Engineering

At the trade level:

- Profitability flags were created
- Trade volume was computed in USD terms

Trades were then aggregated at a **daily level** to align with sentiment data.

3.2 Daily Metrics Computed

For each trading day:

- Total and average PnL
- PnL volatility (standard deviation)
- Win rate
- Total trading volume
- Trade count
- Risk-adjusted return proxy (Sharpe-like metric)
- Capital efficiency (PnL per unit volume)

3.3 Statistical Validation

Welch's t-test was applied to compare Fear vs Greed profitability, accounting for unequal variance between regimes.

4. Key Results & Insights

4.1 Profitability & Risk

- **Fear regimes exhibit higher risk-adjusted returns** despite lower trading activity.
- **Greed regimes show significantly higher PnL volatility**, indicating unstable outcomes.
- Statistical testing confirms that profitability differences across regimes are **not random** ($p < 0.05$).

4.2 Trading Behavior

- Trade frequency increases materially during Greed, consistent with **overconfidence bias**.
- Fear periods show reduced leverage usage and tighter PnL distributions, suggesting disciplined execution.
- Higher volume during Greed does **not** translate into higher capital efficiency.

4.3 Capital Efficiency

- PnL per unit volume is higher during Fear.
- Greed phases exhibit a "volume trap": increased activity without proportional returns.

5. Behavioral Interpretation

Observed patterns align with established behavioral finance principles:

- **Overconfidence bias** during Greed leads to overtrading and excess leverage.
- **Loss aversion** during Fear encourages conservative positioning and selective trade entry.
- Regime-dependent behavior creates exploitable inefficiencies for sentiment-aware strategies.

6. Actionable Trading Implications

Based on the analysis, the following strategy adjustments are recommended:

1. **Dynamic Leverage Caps**
   Reduce maximum leverage during Greed regimes to control volatility.
2. **Sentiment-Aware Position Sizing**
   Allocate risk budgets more efficiently during Fear periods when risk-adjusted returns peak.
3. **Overtrading Controls**
   Introduce trade frequency thresholds during Greed to mitigate behavioral excess.
4. **Capital Efficiency Monitoring**
   Track PnL per unit volume as a guardrail against unproductive volume expansion.

7. Conclusion

This analysis demonstrates that market sentiment is a **structural driver of trader behavior**, not a coincidental overlay. Traders systematically alter risk exposure, activity levels, and performance characteristics across sentiment regimes.

By integrating sentiment-aware risk management into trading workflows, firms can reduce drawdowns, improve capital efficiency, and enhance long-term performance consistency.