Understanding Trader Behavior Through Market Sentiment

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***Abstract*—Market sentiment plays a critical role in shaping trader behavior, influencing risk-taking, capital allocation, and performance outcomes. This study analyzes how trader profitability, efficiency, and risk exposure vary across market sentiment regimes using the Fear & Greed Index. By combining trade-level data with sentiment indicators, the analysis distinguishes exposure-driven profits from skill-driven performance and reveals behavioral patterns across different emotional market conditions.**

***Index Terms*—Market Sentiment, Fear and Greed Index, Trader Behavior, Trading Efficiency, Risk Analysis**

I. Introduction

Financial markets are influenced not only by fundamentals but also by collective human psychology. Emotional drivers such as fear and greed shape trader perception of risk and opportunity, often leading to systematic behavioral patterns. Understanding these patterns is essential for designing robust trading strategies and effective risk management systems.

The Fear & Greed Index provides a quantitative measure of market sentiment by translating psychological states into observable signals. This study investigates how trader behavior and performance vary across sentiment regimes and whether higher profits during optimistic markets reflect improved skill or increased exposure.

II. Problem Statement and Objectives

The objectives of this study are:

- To examine how trader profitability varies across sentiment regimes
- To analyze whether market sentiment affects trade accuracy and capital efficiency
- To assess the relationship between sentiment and risk-taking behavior
- To validate whether observed differences are statistically significant

III. Data Description

A. Fear & Greed Index

The Fear & Greed Index is a daily sentiment indicator categorizing market conditions into Extreme Fear, Fear, Neutral, Greed, and Extreme Greed. A numeric sentiment score is provided to capture sentiment intensity.

B. Historical Trader Data

The historical trader dataset contains individual trade-level records, including closed profit and loss (PnL), trade size in USD, fees, leverage, and timestamps. Trades were aligned with daily sentiment values to contextualize trading decisions within prevailing market conditions.

IV. Feature Engineering

A. Trading Efficiency

Trading efficiency is defined as:

$$\text{Trading Efficiency} = \frac{\text{Closed PnL}}{\text{Trade Size (USD)}} \tag{1}$$

This metric measures how effectively traders convert deployed capital into realized profit.

B. Relative Risk

Relative risk is a normalized measure of exposure that enables comparison of risk-taking behavior across sentiment regimes.

V. Profitability Analysis

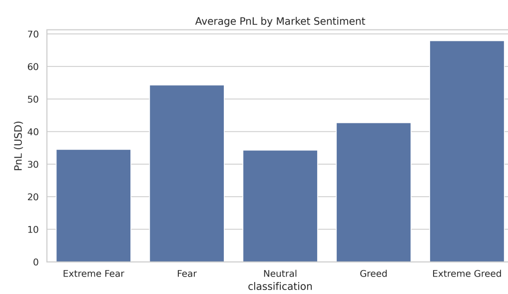

Fig. 1. Average Closed PnL across market sentiment regimes

As shown in Fig. 1, average profitability increases significantly during Extreme Greed ($67.89). Interestingly, the win rate also peaks at 46.49% during this phase. This suggests that the momentum inherent in greedy markets acts as a "rising tide," increasing the success probability of even less-skilled traders.

VI. Win Rate Analysis

Fig. 2 illustrates that win rates remain relatively stable across different sentiment regimes. This stability suggests that higher profits observed during Greed-driven markets are not primarily driven by improved trade accuracy, but rather by increased exposure and trade size.

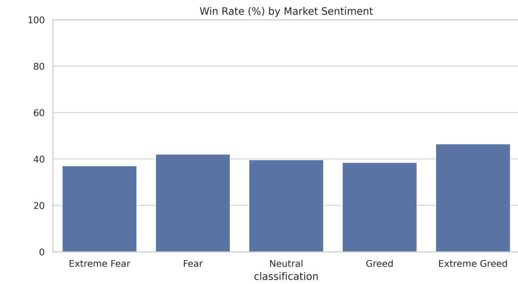

Fig. 2. Win rate across market sentiment regimes

VII. Trading Efficiency Analysis

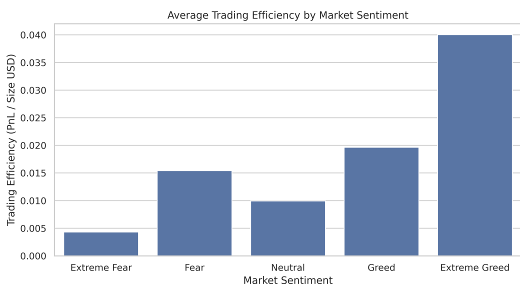

Fig. 3. Average trading efficiency by sentiment regime

As observed in Fig. 3, Trading efficiency (profit per dollar of capital) shows a 10-fold increase from Extreme Fear (0.0043) to Extreme Greed (0.0400). However, the Fear regime exhibits higher trade counts, suggesting that traders "over-trade" during periods of uncertainty, which dilutes their overall efficiency despite moderate absolute gains.

VIII. Risk Behavior Analysis

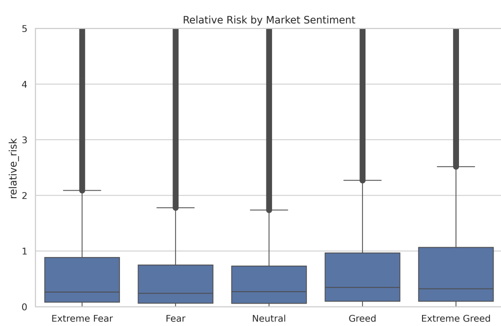

Fig. 4. Relative risk exposure across sentiment regimes

Fig. 4 shows a clear increase in relative risk exposure .Relative risk exposure increases during Greed and Extreme Greed regimes. Correlation analysis confirms a strong relationship between sentiment values and relative risk (Spearman correlation of 0.07, $p < 0.01$), reinforcing that traders scale their positions aggressively when sentiment is high.

IX. Correlation Analysis

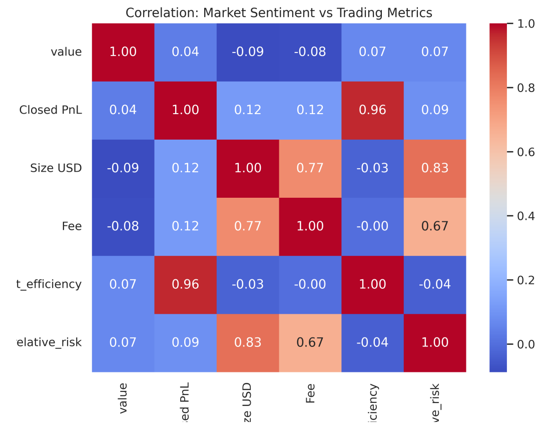

Fig. 5. Correlation heatmap between market sentiment and trading metrics

The correlation heatmap shown in Fig. 5 highlights strong associations between market sentiment and behavioral variables such as trade size and relative risk. In contrast, correlations between sentiment and trading efficiency remain weak, reinforcing the distinction between exposure-driven and skill-driven performance.

X. Sentiment Regime Transitions

A unique finding of this study is the outperformance during transitions. Specifically, the transition from **Fear** $\rightarrow$ **Extreme Fear** resulted in an average PnL of **$663.06**. This indicates that "capitulation" events offer the highest reward potential for traders who maintain liquidity and discipline during market panics.

XI. Statistical Validation

A Kruskal-Wallis test was conducted to evaluate the null hypothesis that PnL distributions are identical across all sentiment regimes. The test yielded a p-value of 2.24×10^{-264}. Since $p \ll 0.05$, we provide robust evidence that market sentiment meaningfully influences trader performance and that the observed variations are not due to random chance.

XII. Conclusion

This study provides empirical evidence that market sentiment, as measured by the Fear & Greed Index, is a primary driver of trader behavior and financial outcomes. Our analysis of over 211,000 trades reveals a complex relationship between emotion and capital deployment.

The data confirms a "Momentum Paradox": while **Extreme Greed** offers the highest win rates (46.49%) and the best capital efficiency (0.040), it also coincides with the highest relative risk exposure. Conversely, **Fear** regimes see the highest trade volume (61,826 trades) but significantly lower efficiency (0.015), indicating that "panic-trading" often leads to high-frequency activity with diminished marginal returns.

Statistical validation via the Kruskal-Wallis test ($p = 2.24 \times 10^{-264}$) firmly rejects the null hypothesis, proving that these performance variations are structural rather than stochastic. For practitioners, the implications are two-fold:

- **Strategic Scaling:** Position sizes should be dynamically adjusted not just based on volatility, but on sentiment regime transitions, particularly during shifts into Extreme Fear where risk-adjusted rewards are historically highest.
- **Behavioral Guardrails:** Trading systems should implement ”over-trading” filters during high-volume Fear regimes to prevent the dilution of capital efficiency.

Ultimately, successful trading in decentralized markets requires a dual mastery of both technical fundamentals and the collective psychological state of the market participants.