Comprehensive Technical Report: Correlation Between Trader PnL and External Market Sentiment

Introduction and Project Mandate

1.1 Project Objective

The primary objective of this quantitative study is to investigate and quantify the relationship between a single algorithmic or high-frequency trader's realized daily Profit and Loss (PnL) and the contemporaneous state of the broader market, as measured by a quantitative Market Sentiment Index (specifically, the Fear & Greed Index).

1.2 Core Hypothesis

The analysis operates under the hypothesis that a trader's performance, risk-taking behavior (e.g., leverage utilization and trade size), and overall trading efficiency are systematically influenced by the prevailing market sentiment. Specifically, we aim to answer:

1. Are periods of extreme market sentiment (Fear or Greed) correlated with statistically different PnL outcomes?
2. Does the trader become more or less risk-averse (by adjusting leverage or capital size) in response to high market euphoria (Greed)?
3. Can we identify a specific sentiment state where the trader’s risk-adjusted performance (efficiency) is maximized?

1.3 Scope and Limitations

This report documents the methodology and structure of the analysis pipeline. While the current merged dataset contains only **N=4 daily observations**, the methodology is designed to scale with a larger, continuous dataset. Conclusions regarding statistical significance (Section 3.3) and long-term correlations (Section 4.5) are currently limited by this small sample size. Furthermore, the reliance on a synthetic leverage value (5.0x) due to missing raw data means conclusions regarding the trader’s active risk-taking behavior (Section 4.2) are preliminary.

2. Data Acquisition and Engineering

The analysis relies on two distinct datasets, each requiring bespoke cleaning and standardization to ensure a successful daily merge. The process is fully automated within the Python script (`trader_sentiment_analysis.py`, Sections 1 and 2).

2.1 Data Source Standardization (Section 1.2)

To ensure the pipeline is robust against varying data schemas, the script employs aggressive column normalization.

- **Trader Data:** Raw trade files may use column headers such as `timestampst`, `closedpnl`, or `size(USD)`. These are cleaned using regular expressions and mapped to internal, standardized keys: `time`, `closedpnl`, `size`, and `leverage`. The `time` column, typically a Unix millisecond timestamp, is converted to a standard `datetime` object.
- **Sentiment Data:** Files often use `score`, `value`, `index_number`, or `Classification`. These are mapped to `sentiment_index_value` (numerical score) and `classification` (textual label, e.g., 'Fear').

2.2 Date Aggregation and Synchronization (Section 2)

The primary challenge is synchronizing high-frequency trade data with daily sentiment data.

1. **Trader Data Processing:** The precise time of each trade is converted to a common date key (`date`). This allows all individual trades within a 24-hour period to be grouped together.
2. **Sentiment Data Processing:** The sentiment data, already daily, is standardized to the same `date` format.
3. **Leverage Workaround:** A critical robustness check is implemented: If the `leverage` column is missing from the raw trade data, a constant value of `5.0x` is inserted into a synthetic column. This prevents script failure in risk-related plots but invalidates active risk-taking conclusions.

2.3 The Inner Join and Sample Size

The core of the data engineering occurs in Section 3.2, where an **inner join** is performed between the daily aggregated trading metrics and the daily sentiment index data on the common `date` key.

$$DF_{\text{Merged}} = DF_{\text{Trader Metrics}}^{\text{Daily}} \cap DF_{\text{Sentiment}}^{\text{Daily}}$$

The result is the final `df_merged` dataset, which contains N rows, where N is the number of days that possess **both** trading activity and a corresponding market sentiment score. The current analysis has $N=4$.

3. Feature Engineering and Trading Metrics

The analysis requires moving beyond simple PnL and engineering advanced metrics that characterize the quality and efficiency of the trader's decisions (Section 3.1).

3.1 Core Daily Aggregation

For every day in the merged dataset, the following core metrics are calculated from the high-frequency trade data:

- **Total Daily PnL (**$\sum \text{PnL}$**):** The sum of all closed PnL for that day.
- **Total Trades (**Count**):** The total number of transactions executed.
- **Total Volume (**$\sum \text{Size}$**):** The total capital committed (size) across all trades.
- **Average Leverage (**$\overline{\text{Leverage}}$**):** The mean leverage used across all trades on that day.

3.2 Engineered Metrics for Performance Evaluation

Two crucial engineered features are derived to provide deeper insight into the trader's discipline:

3.2.1 Trading Quality: Win Rate (%)

Win Rate measures the percentage of trades that closed profitably, acting as a proxy for the *quality* and *consistency* of the entry/exit points chosen by the trader.

$$\text{Win Rate} = \frac{\text{Total Wins}}{\text{Total Trades}} \times 100$$

3.2.2 Trading Efficiency: Risk-Adjusted PnL Score

Risk-Adjusted PnL is a critical metric designed to mimic the **Sharpe Ratio** or **Sortino Ratio**. It measures the return achieved relative to the volatility of that return (risk). A higher score indicates a superior performance, where high returns were generated without excessive day-to-day PnL variance.

$$\text{Risk-Adjusted PnL Score} = \frac{\text{Average Daily Closed PnL}}{\text{Standard Deviation of Daily PnL}}$$

Where the denominator, σ_{PnL}, is the standard deviation of all individual closed PnL values *within that specific day*.

4. Quantitative Results and Discussion (The 8-Step EDA)

This section details the expected outputs and interpretations for the eight exploratory data analysis (EDA) steps defined in Section 4 of the Python script.

4.1 Daily PnL Distribution by Market Sentiment (Boxplot)

Plot: Boxplot of `total_closed_pnl` grouped by the five textual sentiment categories (Extreme Fear to Extreme Greed).

Interpretation: This visualization is key for assessing the trader's median and volatility across market states.

- **Median Return:** The black horizontal line inside each box reveals the typical return. If the median is highest in the 'Fear' box, it indicates a successful contrarian tendency.
- **Risk/Volatility:** The height of the box (Interquartile Range) and the length of the whiskers indicate the volatility of PnL. A tall box on 'Greed' days suggests that while returns *can* be high, the risk of a significant loss is also elevated during euphoria.

4.2 Average Leverage Used by Sentiment (Bar Plot)

Plot: Bar plot of `average_leverage` grouped by the five sentiment categories.

Interpretation: This is an analysis of the trader's risk appetite.

- **Expected Finding:** If real leverage data were used, we would typically look for a trend where the bar height increases as sentiment moves towards 'Extreme Greed.' This would confirm a **pro-cyclical risk profile**, where the trader increases exposure when the market feels safest (euphoria).
- **Current Limitation:** Since $\overline{\text{Leverage}}$ is currently synthetic (5.0x), all bars will be uniform, rendering the plot non-conclusive regarding active risk-taking.

4.3 Statistical T-Test: Pessimism vs. Optimism PnL (Bar Chart)

Plot: Bar chart comparing the mean PnL of two aggregate groups: Pessimism (Extreme Fear/Fear) and Optimism (Extreme Greed/Greed).

Interpretation: This attempts to provide a binary answer to the core hypothesis: which extreme market state is more profitable on average?

- **T-Test Role:** The statistical t-test determines if the difference between the two mean PnL values is likely due to chance.
- **Current Status:** Due to $N=4$, the T-Test is currently **skipped**. For the test to be statistically robust, we require $N > 30$ and non-zero PnL variance in both groups. When $P < 0.05$, the difference is confirmed as statistically significant.

4.4 PnL vs. Trade Count, Colored by Numerical Sentiment Index (Scatter Plot)

Plot: Scatter plot where X-axis is `total_trades`, Y-axis is `total_closed_pnl`, and the bubble color is the numerical `sentiment_index_value`. Bubble size represents `total_volume`.

Interpretation: This reveals the conviction and activity level relative to PnL.

- **High-Conviction Clusters:** Look for large bubbles (high volume) clustered high on the Y-axis (high PnL). The color of these bubbles indicates the sentiment state that rewarded high capital commitment.
- **High-Frequency Noise:** Days clustered low on the Y-axis (near zero PnL) but far to the right (high trade count) suggest days where the trader was highly active but effectively netted out, perhaps using a scalping or hedging strategy that was not influenced by sentiment.

4.5 Rolling 30-Day Correlation: PnL vs. Sentiment Index Value (Line Plot)

Plot: A line plot tracking the 30-day rolling Pearson correlation coefficient between daily PnL and the numerical Sentiment Index over time.

Interpretation: This analysis moves beyond static averages to understand strategic evolution.

- **Dynamic Strategy:** If the line crosses from positive territory (Pro-Cyclical) to negative territory (Contrarian) over several months, it indicates the trader changed their effective strategy or the strategy's effectiveness changed with market regimes.

- **Current Status:** With limited data, this line is likely flat or highly noisy and provides minimal actionable insight. This feature is intended for long-term historical analysis.

4.6 Individual Trade Size Distribution by Sentiment (Boxplot)

Plot: Boxplot of the distribution of **individual** trade sizes (`size`) across the five sentiment states (using the micro-merged dataset from Section 3.3).

Interpretation: This is a crucial check for **Herd Mentality** and emotional trading.

- **Emotional Escalation:** If the median trade size significantly increases on 'Greed' or 'Extreme Greed' days, it suggests the trader is becoming overconfident and committing more capital per single transaction during periods of euphoria. This capital expansion often precedes major losses.
- Conversely, a sharp drop in size on 'Extreme Fear' days suggests the trader panics and pulls back capital, potentially missing strong bounce opportunities.

4.7 Trading Efficiency vs. Quality (Scatter Plot)

Plot: Scatter plot where X-axis is `Win Rate` (Quality) and Y-axis is `Risk-Adjusted PnL` (Efficiency). Points are colored by the textual sentiment classification.

Interpretation: This is arguably the most valuable plot for prescriptive strategy.

- **Optimal Performance Quadrant (Top Right):** Days clustered in the top-right quadrant (High Efficiency, High Quality) represent the sentiment states where the trader is at their best—achieving high returns with high consistency and low internal volatility.
- **High Risk, Low Quality (Bottom Left):** Days clustered in the bottom-left show poor performance, characterized by low win rates and PnL that is highly volatile relative to the average return.

4.8 Linear Relationship: Daily PnL vs. Numerical Sentiment Index (Regression Analysis)

Plot: A regression plot fitting a best-fit line to the relationship between the numerical `sentiment_index_value` and `total_closed_pnl`.

Interpretation: This plot quantifies the fundamental relationship between external market feeling and internal trader performance.

- **Correlation Coefficient:** A positive coefficient (e.g., $r = +0.55$) indicates a **Pro-Cyclical** trader: higher sentiment leads to higher PnL. A negative coefficient (e.g., $r = -0.45$) indicates a **Contrarian** trader: higher PnL occurs when the market is fearful.
- **Current Correlation:** The calculated correlation coefficient based on the current data is **[CALCULATED CORRELATION]**. The sign of this coefficient directly informs the strategic recommendation in Section 5.

5. Strategic Recommendations and Path Forward

5.1 Preliminary Findings (Based on N=4)

Based on the highly limited dataset of $N=4$ daily observations:

- **Core Relationship:** The correlation coefficient is **[INSERT CORRELATION SIGN HERE]**, suggesting a **[Pro-Cyclical/Contrarian]** relationship.
- **Efficiency Peak:** Preliminary clustering in Section 4.7 suggests the most optimal days (high Risk-Adjusted PnL and high Win Rate) occurred during the **[INSERT SENTIMENT CLASSIFICATION HERE]** sentiment state.
- **Statistical Caution:** No statistical significance can be claimed due to the insufficient sample size.

5.2 Formalizing the Strategic Recommendation

The goal is to formalize the hidden signal identified in the analysis.

Observed Correlation	Strategic Recommendation	Risk Management Focus
Negative Correlation (Contrarian)	**Maximize Exposure during Extreme Fear:** The trader's methods are most effective when others are panicking. The strategy should mandate a systematic increase in trade size and/or leverage when the Sentiment Index drops below 30.	**Monitor Panic Selling:** Ensure the PnL is not derived from highly volatile liquidation spikes, which introduce execution risk.

Positive Correlation (Pro-Cyclical)	**Restrict Risk during Extreme Greed:** The trader successfully rides momentum. However, high PnL during euphoria often precedes drawdowns. The strategy should impose **fixed maximum leverage and trade size** during the Greed state (Index > 70) to prevent emotional over-leveraging (as suggested in Section 4.6) and preserve capital for the inevitable correction.	**Drawdown Protection:** Implement tighter trailing stop-losses on positions initiated during high Greed to prevent large losses if the momentum abruptly reverses.

5.3 Next Steps for Analysis Improvement

The following three actions are critical to validate the preliminary findings and elevate the analysis to an institutional-grade standard:

1. **Massively Increase Data Volume (N > 30 Days):** The single most important step. A dataset with over 30 days of merged, continuous trading history is required to achieve two primary goals:
    - Enable the **T-Test (Section 4.3)** to determine statistically significant differences in PnL means.
    - Normalize the **Rolling Correlation (Section 4.5)** line, making it a reliable indicator of strategic evolution.
2. **Integrate Real-Time Leverage Data:** The synthetic leverage value must be replaced with the trader's actual recorded leverage per trade. This will allow Section 4.2 to confirm whether the trader exhibits a pro-cyclical risk bias by actively increasing exposure during euphoric market phases.
3. **Analyze Directional Bias (Long vs. Short):** A future analysis should segment PnL by the trade direction (Long/Short). This will reveal whether the trader is a better **contrarian buyer** (longing during Fear) or a better **momentum seller** (shorting during Greed), providing granular insight into the specific market behavior they exploit.

6. Appendix: Methodology Summary and Code Structure

The technical analysis is underpinned by the modular Python script (`trader_sentiment_analysis.py`).

6.1 Code Modularity Overview

The script is structured into six logical sections, guaranteeing clear separation of concerns and maintainability:

Script Section	Purpose	Dependent Data
Section 1	Setup & Data Loading	External CSVs
Section 2	Data Cleaning & Preprocessing	Raw DataFrames
Section 3	Feature Engineering & Aggregation	Daily & Trade-Level Aggregates
Section 4	Comparative Analysis (8 EDA Steps)	`df_merged` (Daily) & `df_trader_micro_merged` (Trade)
Section 5	Note to User	Console Output

6.2 Key Functions and Robustness

The robustness of the script is maintained by several critical design choices:

- **Robust Column Mapping:** Section 1.2 employs dictionary mapping after aggressive string cleaning (`.str.lower().str.replace(r'[\s\(\)_]', '', regex=True)`) to find the correct PnL, Time, and Size columns, even if the source files use inconsistent naming conventions.
- **Leverage Defaulting:** The implementation of the synthetic leverage default (Section 2.2) is a mandatory safety feature, preventing KeyErrors that would halt the entire pipeline if the risk metric is absent.
- **Statistical Guardrails:** Section 4.3 contains explicit guard clauses (`if len(group) > 1 and group.var() > 0:`) to prevent the T-Test from

executing on insufficient data, which would otherwise generate a misleading or non-sensical result.

- **Contrarian Signal:** A high or low PnL that consistently occurs when the market sentiment is at the opposite extreme (e.g., high PnL during Extreme Fear) suggests a successful contrarian strategy.
- **Pro-Cyclical Signal:** High PnL consistently aligning with high Greed suggests the trader is successfully riding momentum, but needs strict risk management.