Decoding Stock Returns: The Role of Earnings, Macro, and Sentiment

Final Recommendation

Prepared and Presented by

Insight Alchemists [Team 1]

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Business Objectives and Traceability

- How do stock price movements before earnings announcements predict post-announcement stock price movement?
- How do key financials released on earnings dates (e.g. earnings surprise, revenue, profit margins) predict post-announcement stock price movement?
- How do macroeconomic conditions before/on earnings announcements predict post-announcement stock price movement or earnings outcomes?
- What role does news sentiment play in stock price movements around earnings announcements?
- Can earnings-related data predict macroeconomic factors (e.g. inflation, GDP) over the next 3, 6, or 12 months?
- How do stock price trends post-earnings relate to long-term performance predictions?

Signposting Our Journey So Far

Data Collection from Jan-2000 to Jan-2025

- FMP
- FRED
- Y-Finance

Data Wrangling and Preprocessing

- News Sentiment Analysis
- Pre-Announcement Stock Price Momentum
- Post Announcement Stock Price Momentum
- Consolidated Financial Ratios - BS, IS and CF
- Macros Seasonally Adjusted Rate of Changes

Exploratory Data Analysis and Sentiment Analysis using NLP

- Multiple Linear Regression
- TextBlob and FinBert for Sentiment Analysis using NLP
- Logistic Regression
- Correlation Heatmaps

Feature Engineering and Predictive Modelling

- Labelling and Classification
- Random Forest Classifier
- Hyperparameter RandomisedSearchCV
- Classification Reports

Signal Generation and Evaluation

- Signal Generation - Buy/Hold/Sell
- Signal Evaluation – Confusion Matrices

Trading Strategy Simulation

- Long & Short Position Classification using Predicted Signals
- Generate Trade Returns, Drawdowns, Cumulative Returns

Phase 1 - Lead Up to Initial Pitch and Recommendation

Phase 2 – Scope for Final Pitch and Presentation

EDA Insights Summary

Stock Price Momentum

Weak correlation exists between price returns in the 2-5 days windows before and after Earnings Announcements.

No significant correlation detected for price movements beyond the 5-days window

Earnings Data

EPS Surprise and Revenue Surprise have significant Impact on 2 days / 5 days Returns post announcement

Macroeconomic Indicators

Real GDP Growth, UST Yield changes had a stronger correlation amongst macroeconomic indicators

Sentiment Analysis

News Sentiment has a negative drift on 5 days return post announcement.

Negative news sentiment leads to a drop on 2-3 days return post news publishing, however it neutralises thereafter

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PHASE 2 : TRADING STRATEGY RECOMMENDATION

Trading Strategy and Model Design

GOAL

- Capture >5% stock price moves in 2 or 5 days after earnings
- Based on financial metrics, macro data & sentiment analysis

TRADING SIGNALS

- Buy → Expected returns > +5%
- Sell → Expected returns < -5%
- Hold → Expected returns within ±5%

MODEL SPECIFICATIONS

- **Algorithm: Random Forest Classifier**
- **Data: 2005-2024 historical data**
- **Tuning: RandomizedSearchCV optimization**
- **Features: Pre-earnings indicators**
  - Financial metrics
  - Macro indicators
  - News sentiment scores

EXECUTION RULES

Recommends Position based on Predicted Trading Signals:

Long for Buy Signal

Short for Sell Signal

No Action for Hold Signal

AAPL trading strategy overview

Model performance

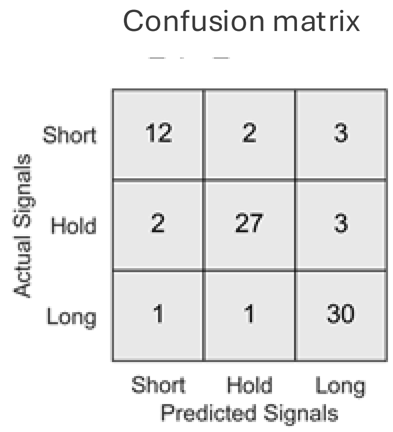
- The dataset covers 81 earnings announcement events
- **Recall:** 49/81 events provide a trading opportunity (manually labelled as Long or Short):

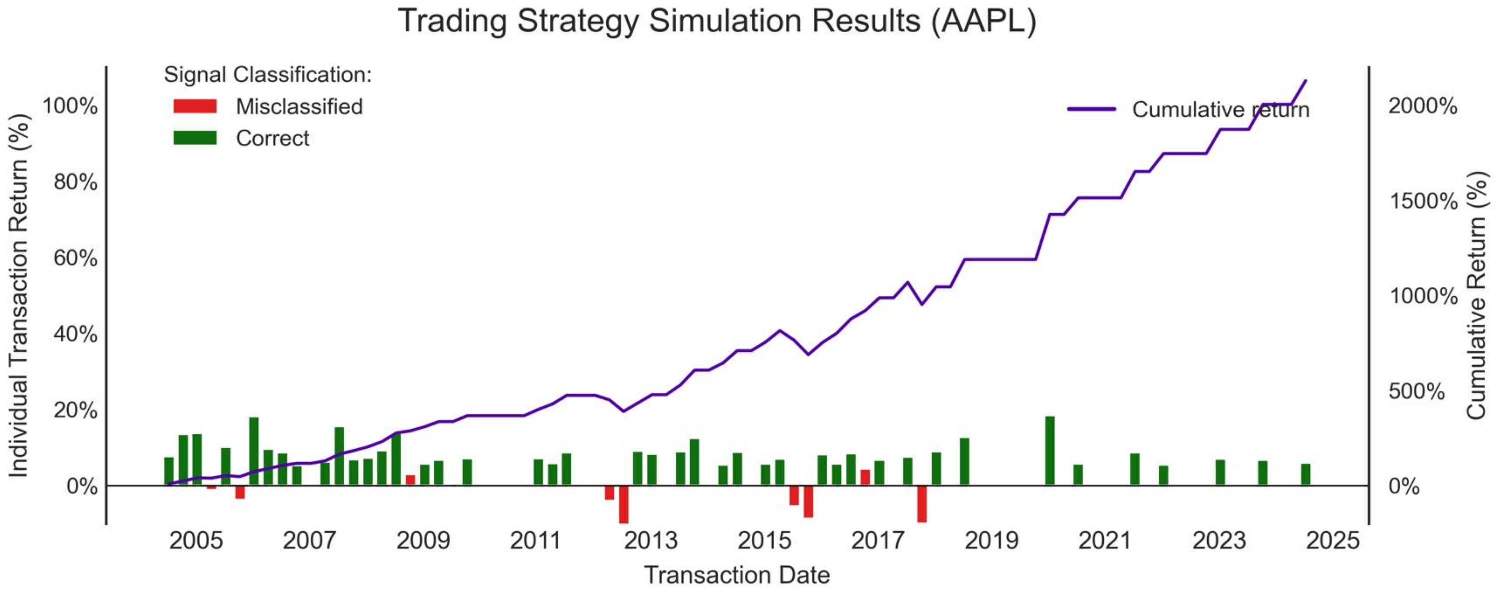
  Long: 30/32 identified

  Short: 12/17 identified
- **Precision** : The model generates **51** signals:

  Long: 30/36 are correct

  Short: 12/15 are correct





Strategy evaluation:

Metrics:

- Average Return per Deal: 6.5%
- Maximum Drawdown: -14.8%
- Total Cumulative Return: >20x (over 51 five-day periods)

Methodology:

Return is calculated based on close prices over the analysed time window

No Stock-exchange or intermediary commissions are considered

GOOGL trading strategy overview

Model performance

- The dataset covers 80 earnings announcement events
- **Recall**: 41/80 events provide a trading opportunity (manually labelled as Long or Short):

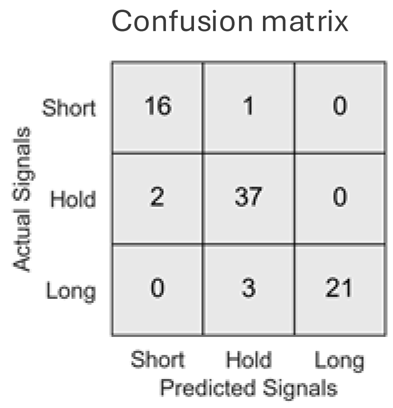
  Long: 21/24 identified

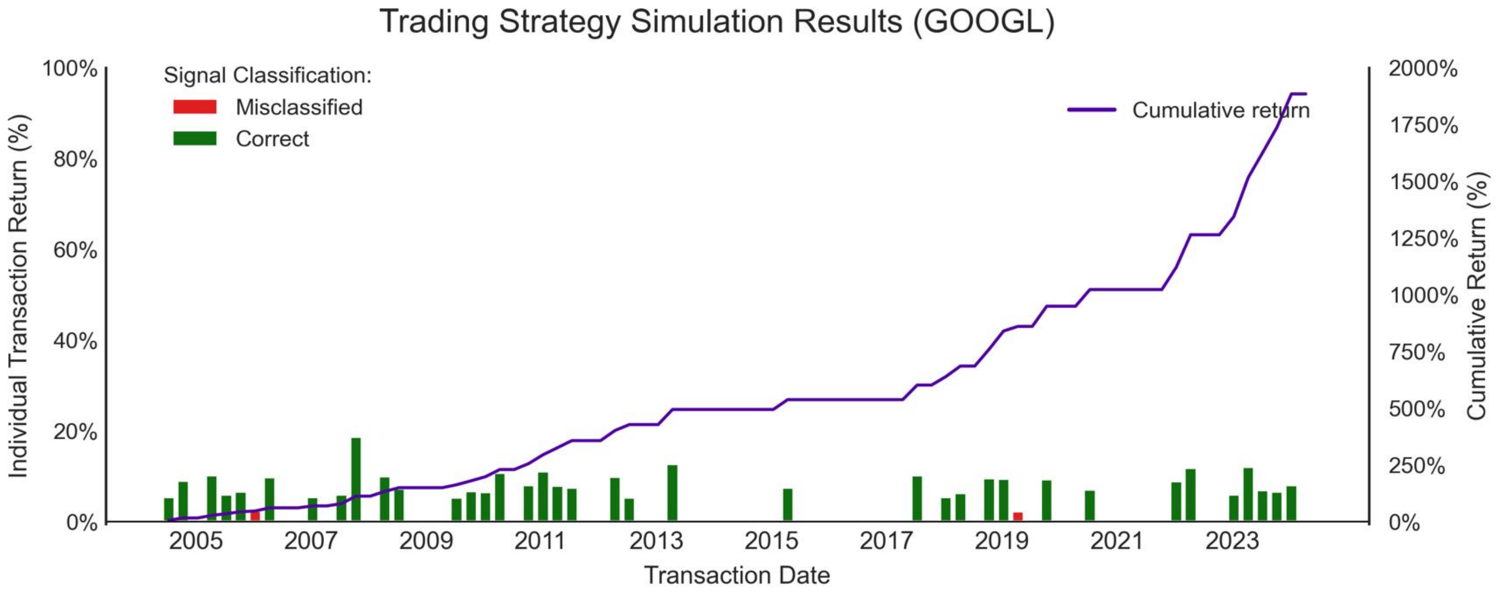
  Short: 16/17 identified

- **Precision**: The model generates **39** signals:

  Long: 21/21 are correct

  Short: 16/18 are correct





Strategy evaluation:

Metrics:

- Average Return per Deal: 8.0%
- Maximum Drawdown: 0.0%
- Total Cumulative Return: >20x (over 39 two-day periods)

Methodology:

Return is calculated based on close prices over the analysed time window

No Stock-exchange or intermediary commissions are considered

NVDA trading strategy overview

Model performance

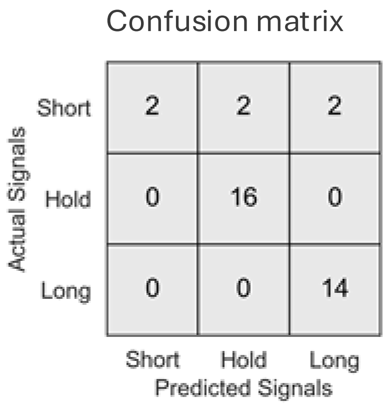
- The dataset covers 36 earnings announcement events
- **Recall:** 20/36 events provide a trading opportunity (manually labelled as Long or Short):

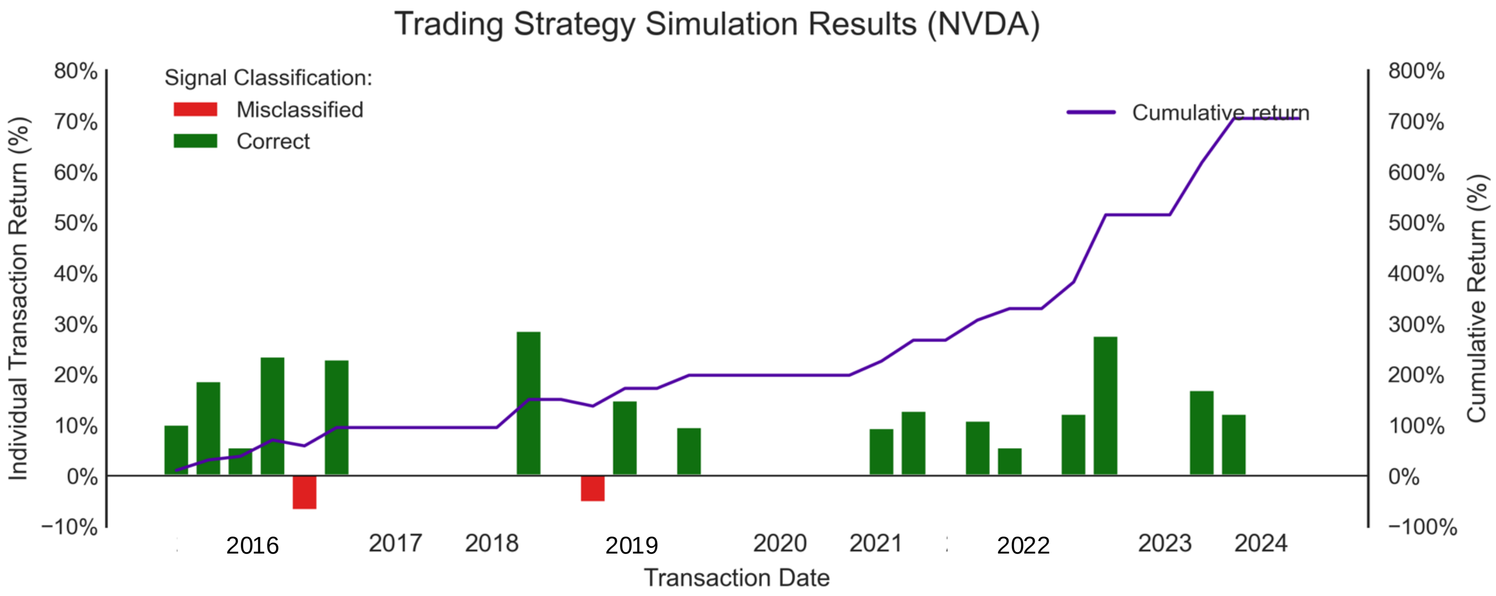
  Long: 14/14 identified

  Short: 2/6 identified
- **Precision:** The model generates **18** signals:

  Long: 14/16 are correct

  Short: 2/2 are correct





Strategy evaluation:

Metrics:

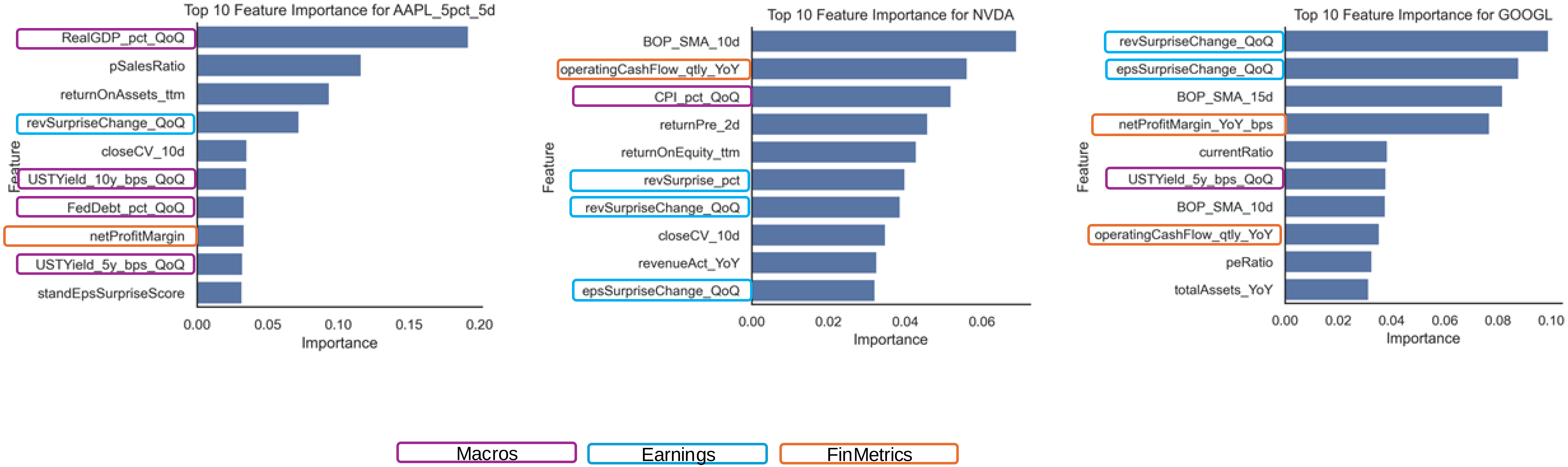
- Average Return per Deal: 12.7%
- Maximum Drawdown: -6.9%
- Total Cumulative Return: c.700% (over 39 two-day periods)

Methodology:

Return is calculated based on close prices over the analysed time window

No Stock-exchange or intermediary commissions are considered

Feature Importance Observations and Insights



Key Observations and Insights

1. Earnings and Revenue Suprises have a consistent predictive power across all 3 Stocks

2. Finmetrics such as profitability and cashflow play a more significant role for B2B stocks such as GOOGL and NVDA than a B2C focused business such as AAPL

3. Macros such as Tr. Yields, FedDebt and Real GDP growth play a more significant role for B2C stock such as AAPL

Note: Spurious Feature importance (coincidental data patterns), commonly observed in high-dimensional, small sample datasets is noticed in the feature importance. The features have been retained to improve predictive power.

Q&A and Feedback

PHASE 1 : EXPLORATORY DATA ANALYTICS

Earnings Announcement – Event Study

Objective: To evaluate whether earnings surprises provide predictive insights into price movements after earnings announcements

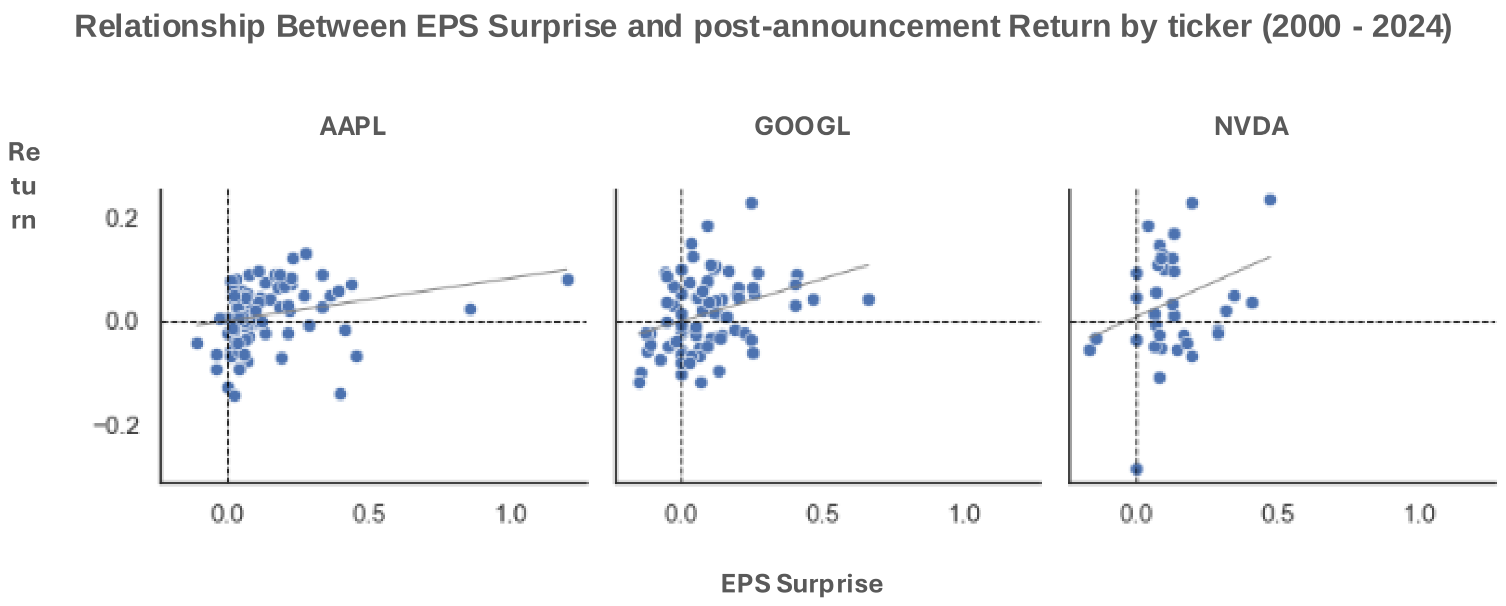
Approach: To examine the relationship over different post-announcement windows, both for individual tickers and in aggregate

Raw data:

- Source: Financial Modelling Prep API (Earnings Surprises)
- Period covered: 2000 - 2024

Pre-processing:

- Extreme outliers
- Negative and small Net Profit Margins (< 5%)

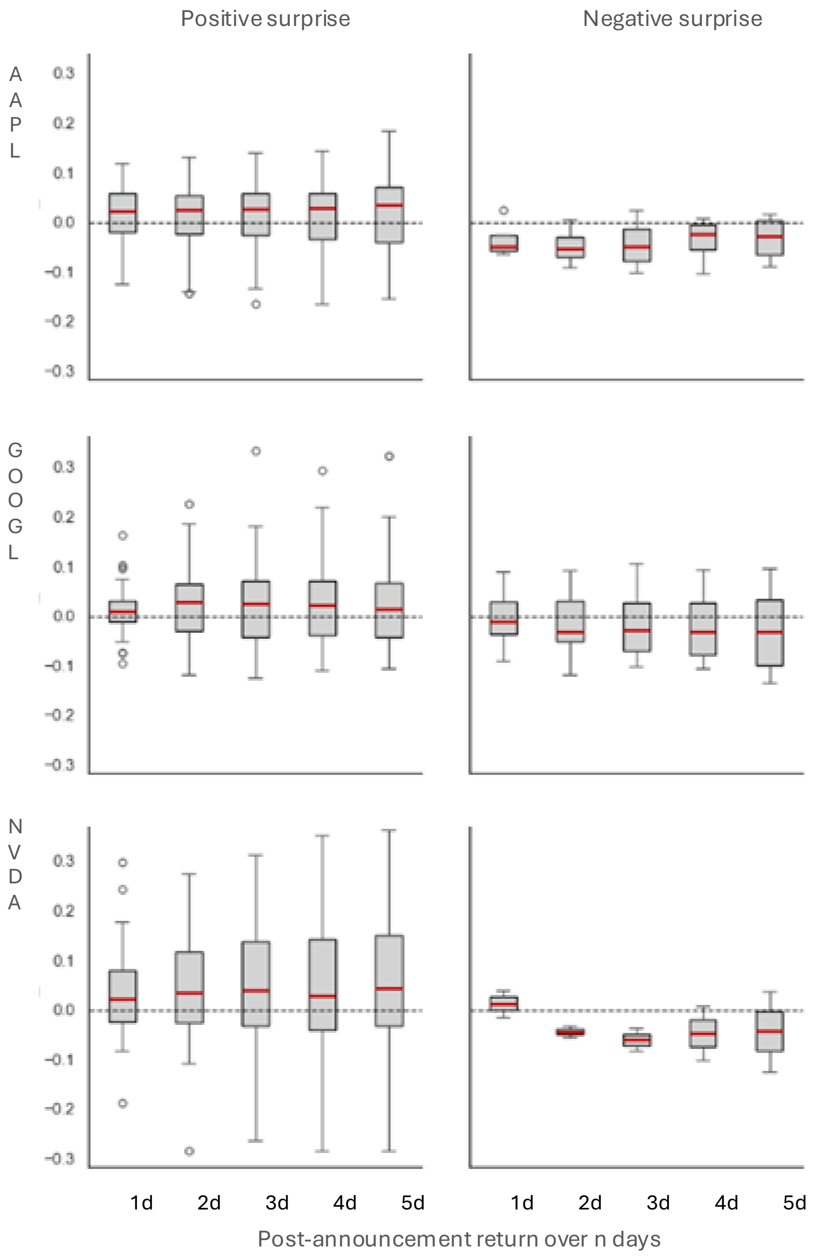


Initial observations:

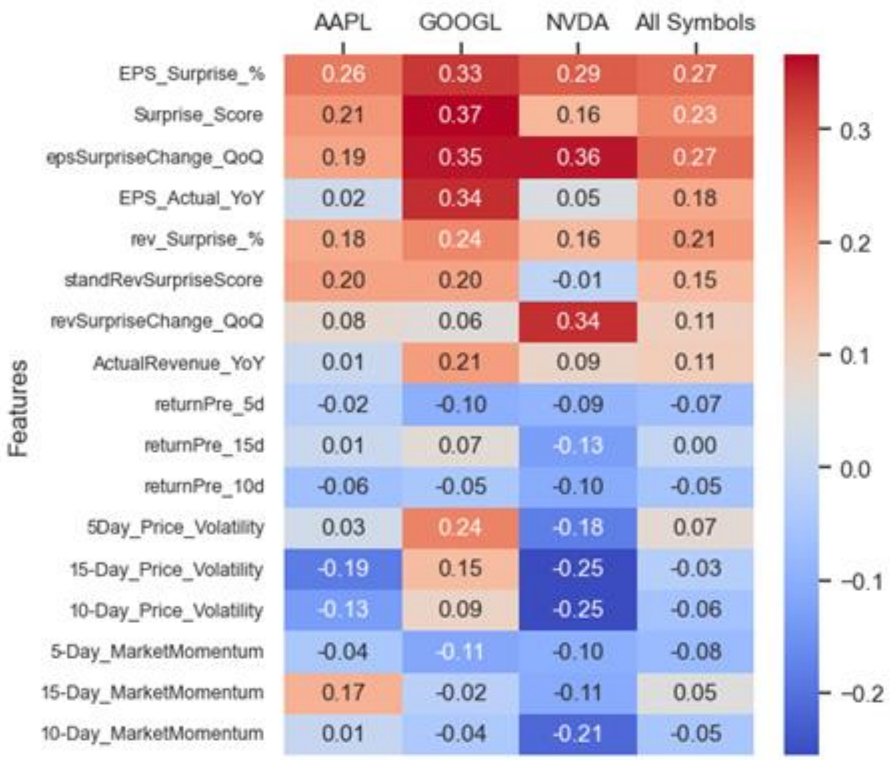
1. Most EPS surprises are positive.
2. Post-earnings announcement returns generally align with the direction of the EPS surprise.

Earnings Announcement – Event Study

Distribution of post-announcement cumulative returns



Pearson correlation analysis: EPS surprise vs. 2-day post-announcement equity return (2000 - 2024)



Derived features:

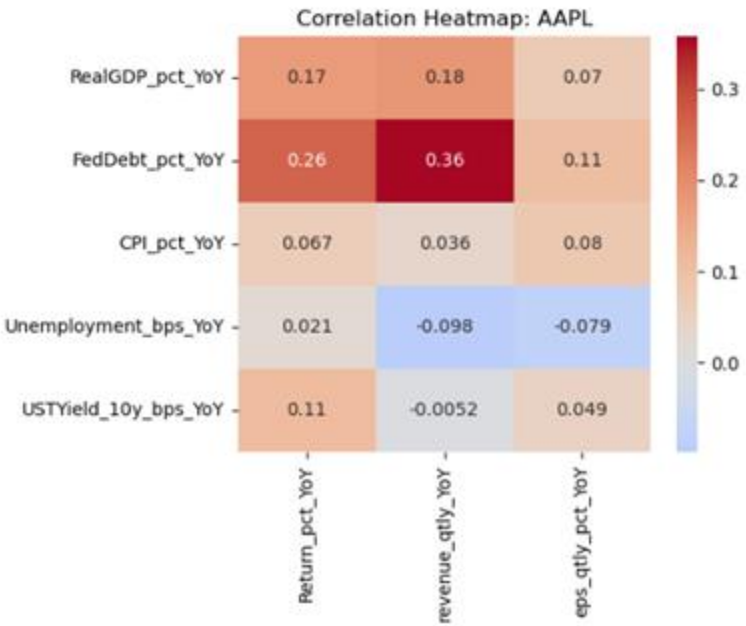
- EPS Surprise Percentage
- Standardised EPS Surprise Score
- QoQ Change in EPS Surprise
- Pre-Earnings Return / ROC
- Coefficient of Variation of Closing Prices

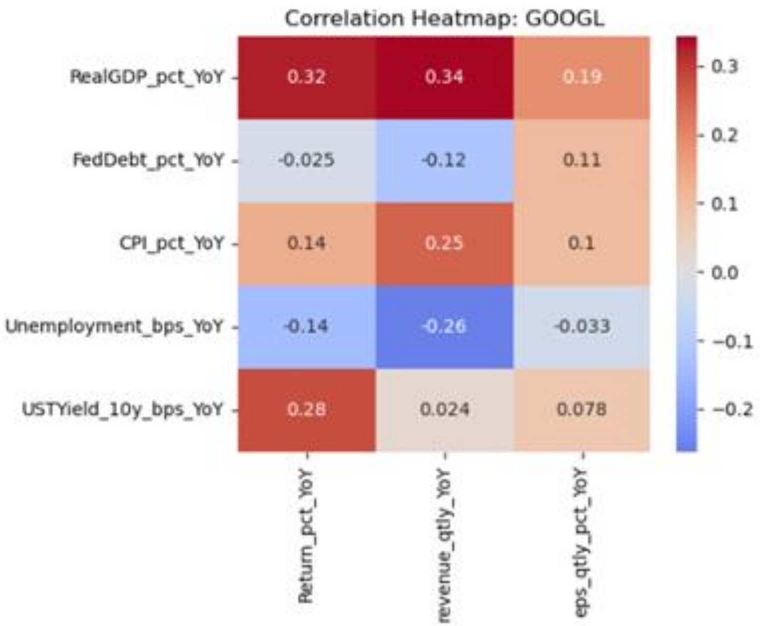
Key Insight:
EPS Surprise and Revenue Surprise have significant Impact on 2 days / 5 days Returns post announcement

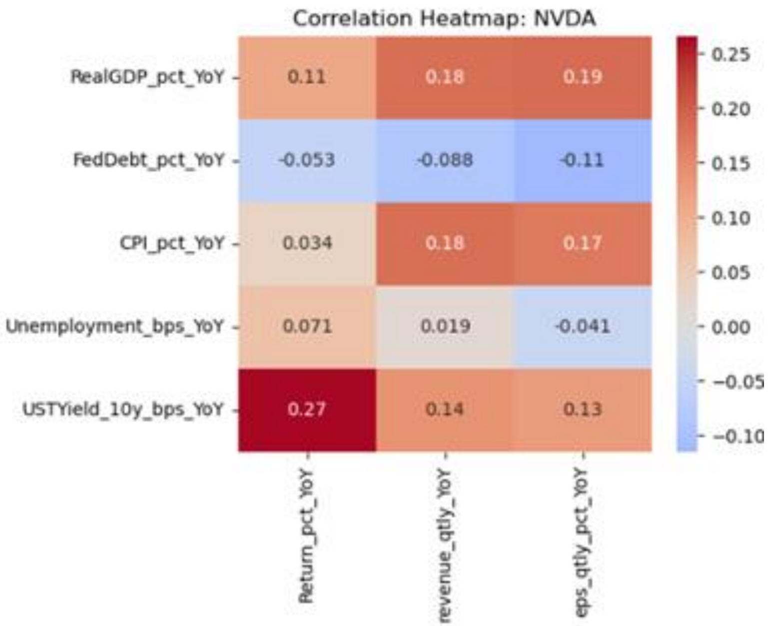
Macro Economic Indicators

Macro Economic Indicators – GDP, Inflation, Unemployment, federal Debt, US Treasury Yield 10Y

Correlation Heatmap between Macro indicators and Stock Returns and Earnings





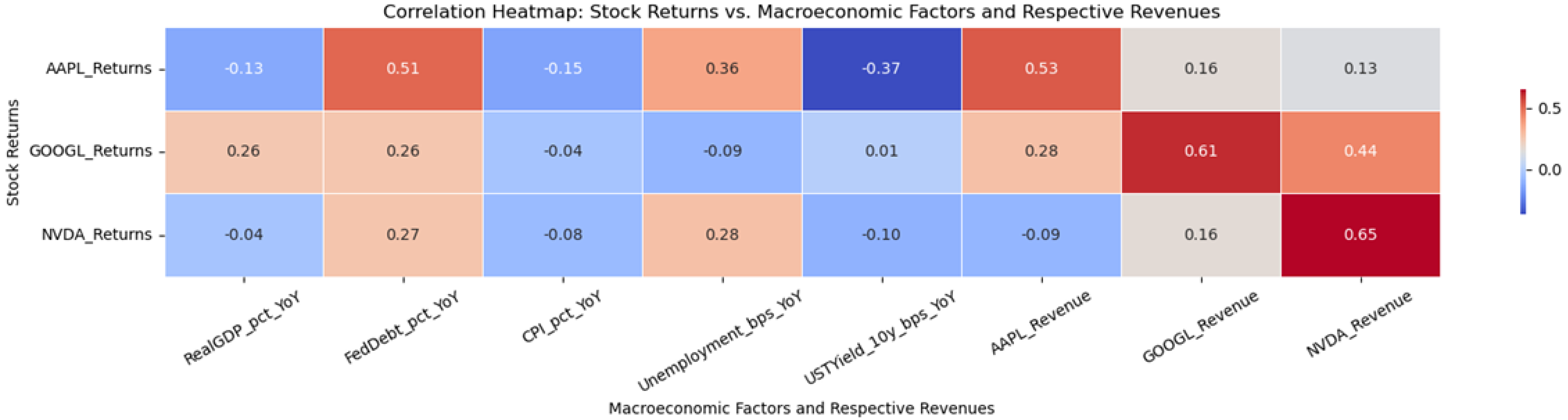


Company	Macro Economic Factor
Apple	Real GDP, Federal Debt
Google	Real GDP, Inflation, UST Yield 10Y
Nvidia	Real GDP, Inflation, UST Yield 10Y

Macro Economic Indicators

Macro Economic Indicators considered: GDP, Inflation, Unemployment, federal Debt, US Treasury Yield 10Y
Analysis Time Period: 2000 - 2024

Correlation Heatmap between Macro indicators, Revenue to Stock Returns



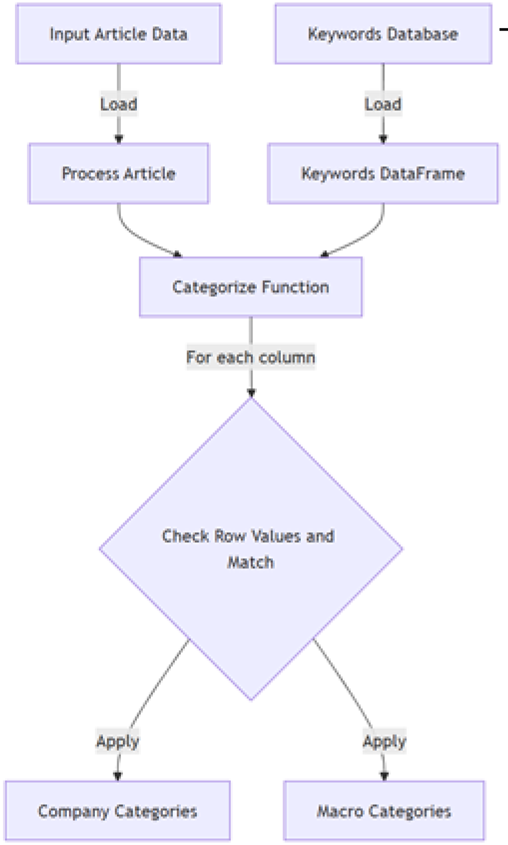
Key Insight:
Revenue has a higher impact on Returns than macro-economic conditions as these are high-growth companies.
Real GDP Growth, UST Yield changes had a stronger correlation amongst macro economic indicators

News Sentiment Analysis Framework

Dataset Overview:

- NY Times Articles : 1474 (provided by Vantage Data)
- Time period: 2019 – 2024
- Post-Initial Cleanup : 1423 Articles [51 removed]

Article Classification Workflow (Rule Based Classification Pipeline):



Keyword	Company_value	Macro_value
Apple Inc	Apple	
Apple TV	Apple	
Google Inc	Google	
Alphabet Inc	Google	
NVIDIA Corporation	Nvidia	
Artificial Intelligence		Tech-AI
ChatGPT		Tech-AI
Cloud Computing		Tech-Macro
Computer Chips		Tech-Macro
Microsoft Corp		Tech-Macro
Coronavirus (2019-nCoV)		Market-Macro
Corporate Taxes		Market-Macro
Economic Conditions and Trends		Market-Macro
Elections		Market-Macro

Pipeline Features:

- Customizable, Easy to maintain/update
- Expandable to dedicated keywords
- Independent of ML / AI limitations

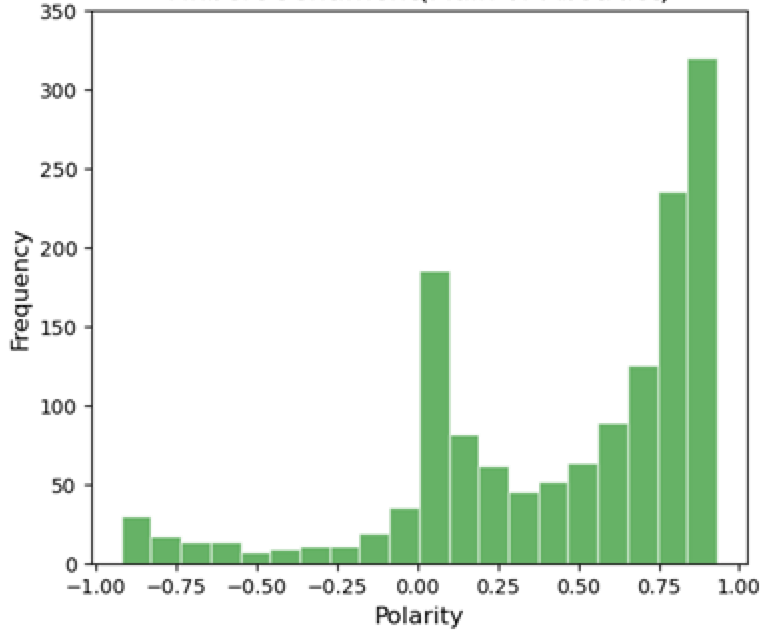
Sentiment Scoring:

- Abstract, Main (extracted from metadata) and Lead Paragraph considered for analysis.
- ProsusAI's FinBERT and TextBlob utilized for sentiment evaluation
- Multiple composite scores evaluated and finalized on:

$$\textit{Sentiment Score}(Article) = F(Main)\ or\ F(Abstract)$$

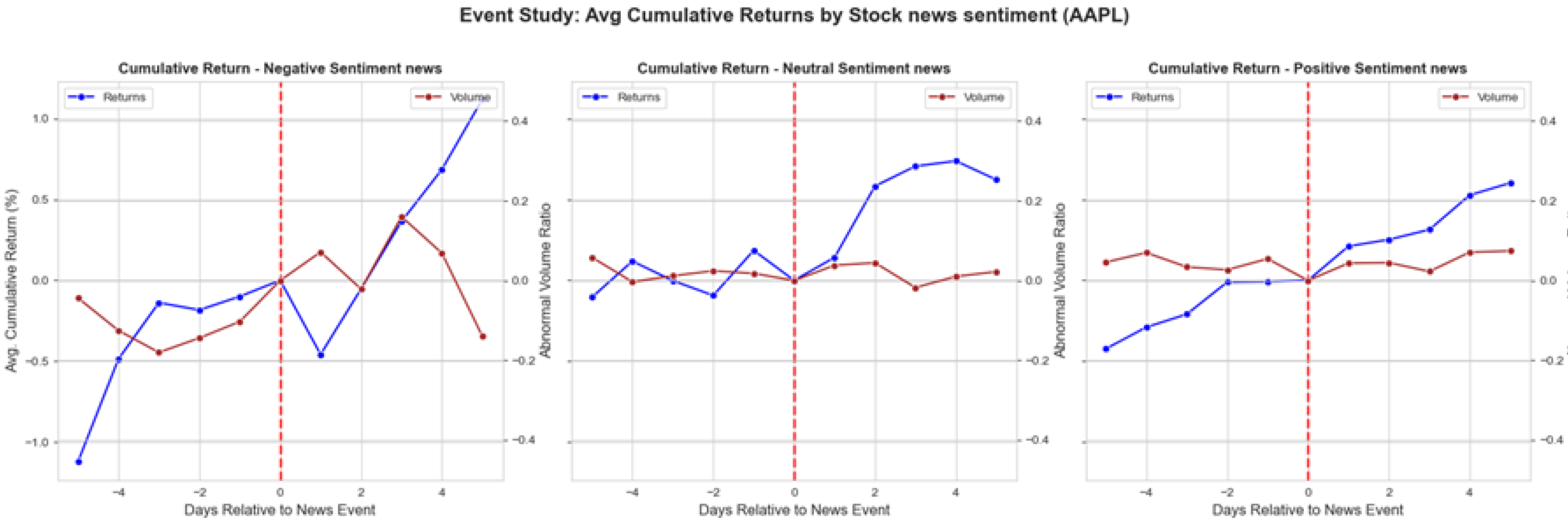
$$^{*}\ F(Text) = Finbert_{positive} - Finbert_{negative}$$

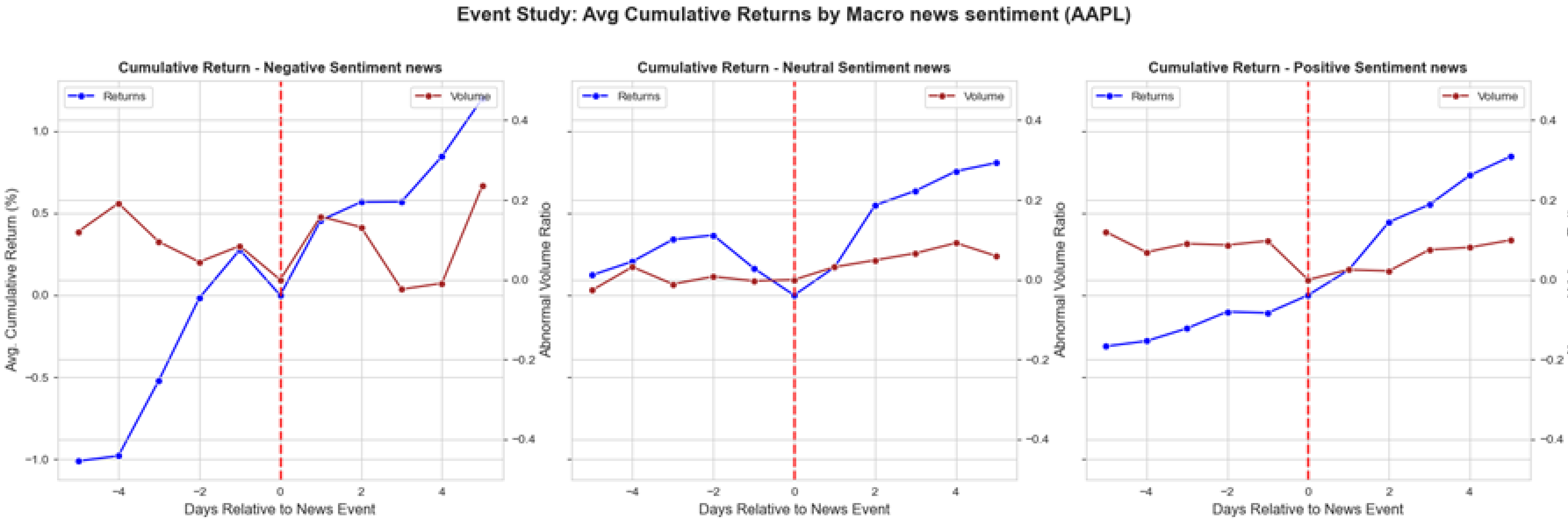
Sentiment Distribution:



News Sentiment Analysis – Event Study

Event Study – What role does news sentiment play in stock price movements?





METHODOLOGY:

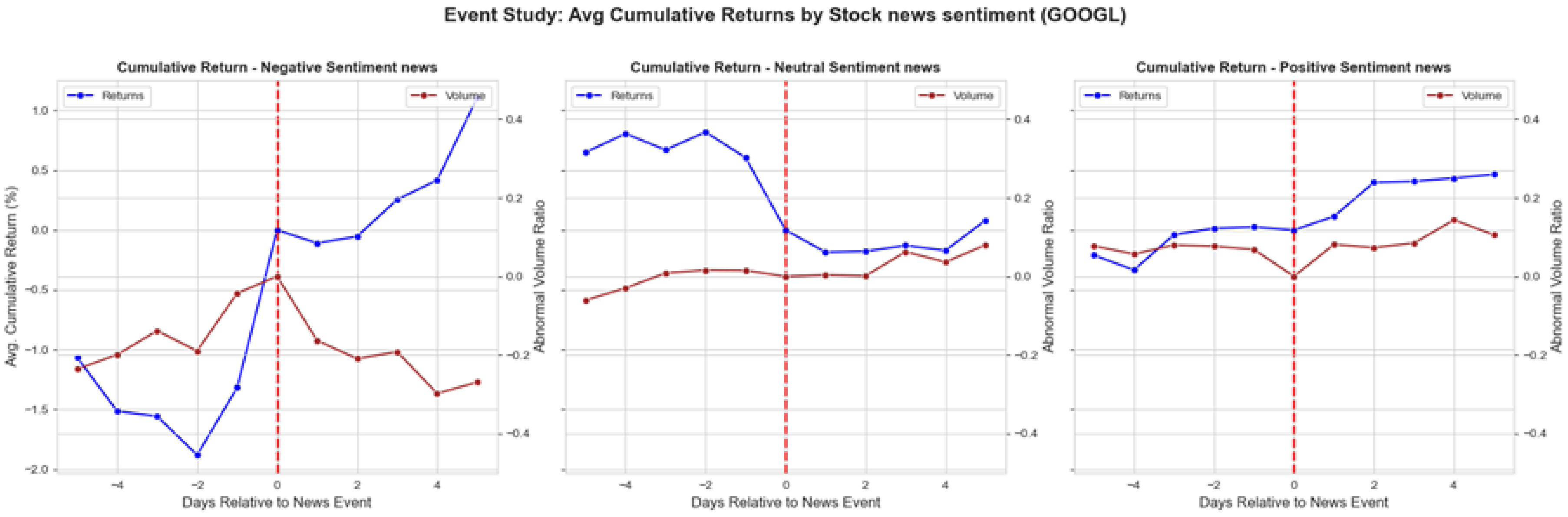
- 5-day pre/post publishing event window analysis (Returns and Trade volume)
- Stock Sentiment: Company-specific news
- Macro Sentiment: Non-Company news

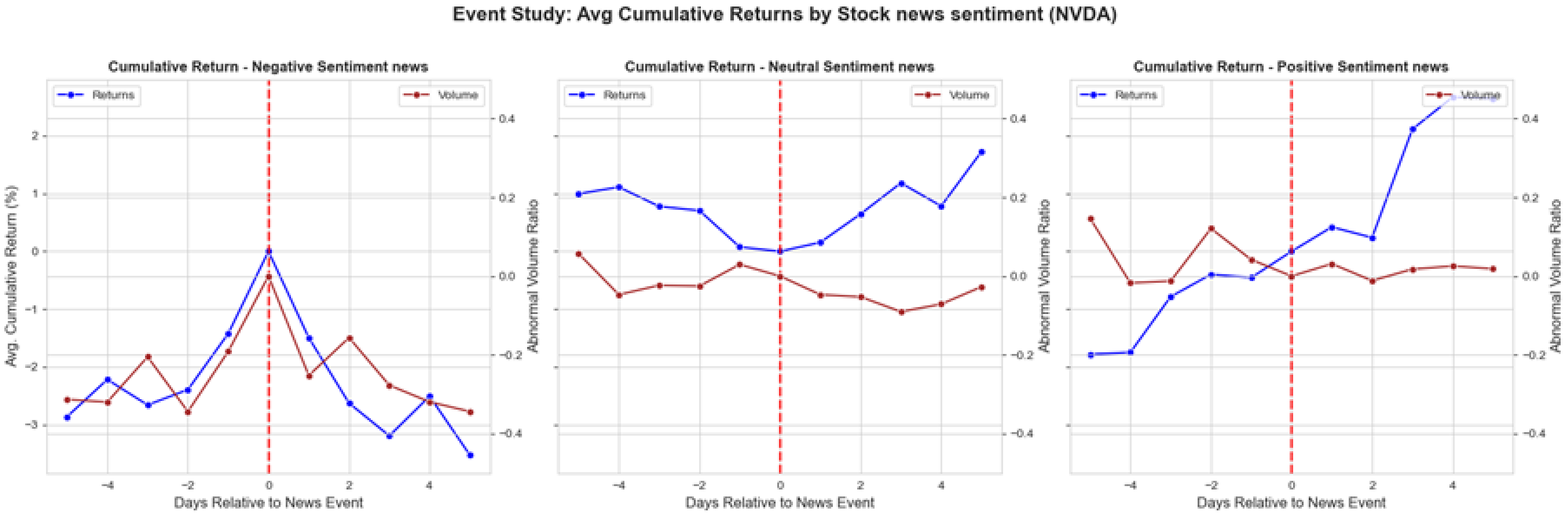
APPLE FINDINGS:

- **Negative news: -0.5% dip, recovers by day 3**
- Positive/Neutral news: +1% drift over 5 days
- Resilient to macro news impact

News Sentiment Analysis – Event Study

Event Study – What role does news sentiment play in stock





GOOGLE FINDINGS:

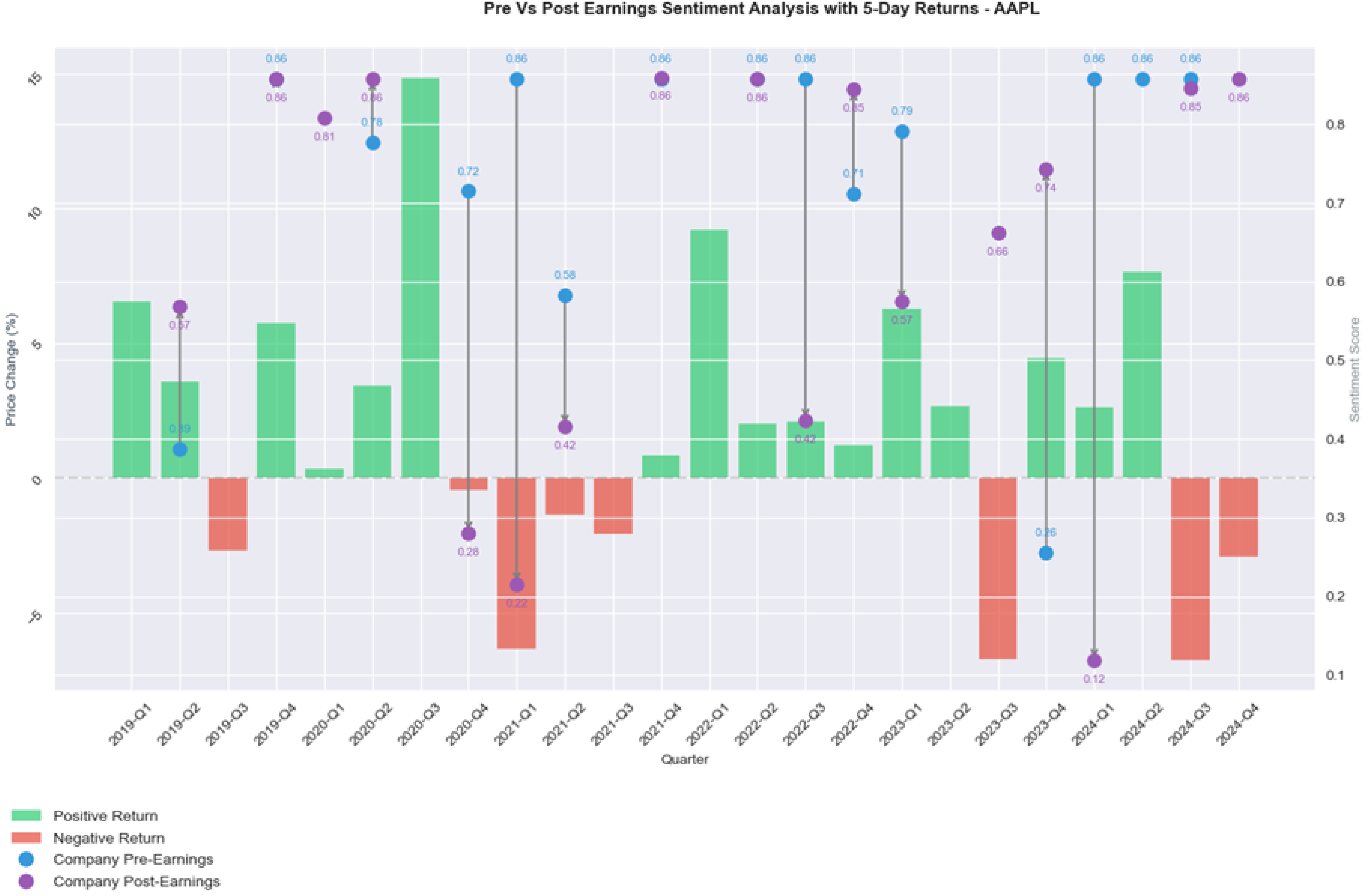
- **Most stable to sentiment among peers.**
- Returns stay within 1% for neutral/ positive news.
- Acts as safe-haven during macro uncertainty (negative news)

NVIDIA FINDINGS:

- Highest sentiment sensitivity
- Impact lasts 2-3 days post-event
- **Larger fluctuations than peers (± 2-3%)**
- Strong positive reaction to macro negativity

Earnings Announcement Event Study and Sentiment Effect

Apple : Stock Returns behaviour around earnings returns with Company and Macro sentiment



Pre-Announcement Sentiment Trends:

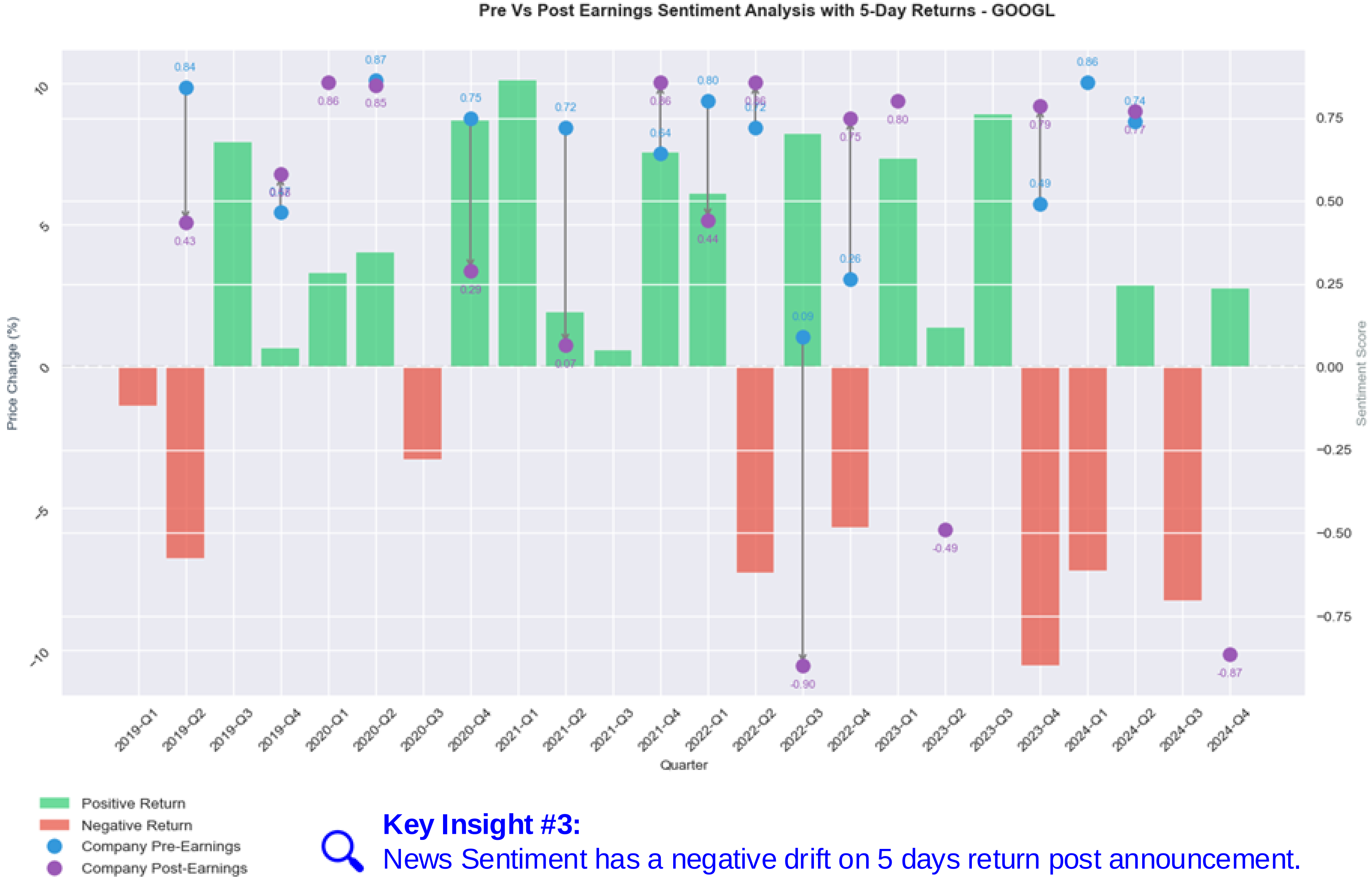
- Pre-earnings company sentiment (blue dots) tends to be optimistically biased and it is very rare to see negative pre-earnings sentiment.
- High pre-earnings sentiment doesn't reliably predict positive returns

Post-Announcement Sentiment Trends:

- Company Sentiment (purple dots) 5 days post earnings announcement is mostly seen to go down compared to pre-earnings sentiment.
- This reinforces the optimistic bias seen in the pre-earnings sentiments.

Earnings Announcement Event Study and Sentiment Effect

Google : Stock Returns behaviour around earnings returns with Company and Macro sentiment



Pre-Announcement Sentiment Trend:

- Consistently optimistic (0.3-0.8)
- Better sentiment data than Apple.

Post-Announcement Sentiment Trends:

- Regular downward sentiment shifts
- Major drops below -0.50 in several quarters
- Notable disappointment in 2022-Q3 (-0.90)

Insight:

- Pattern of high pre-earnings optimism followed by post-earnings disappointment

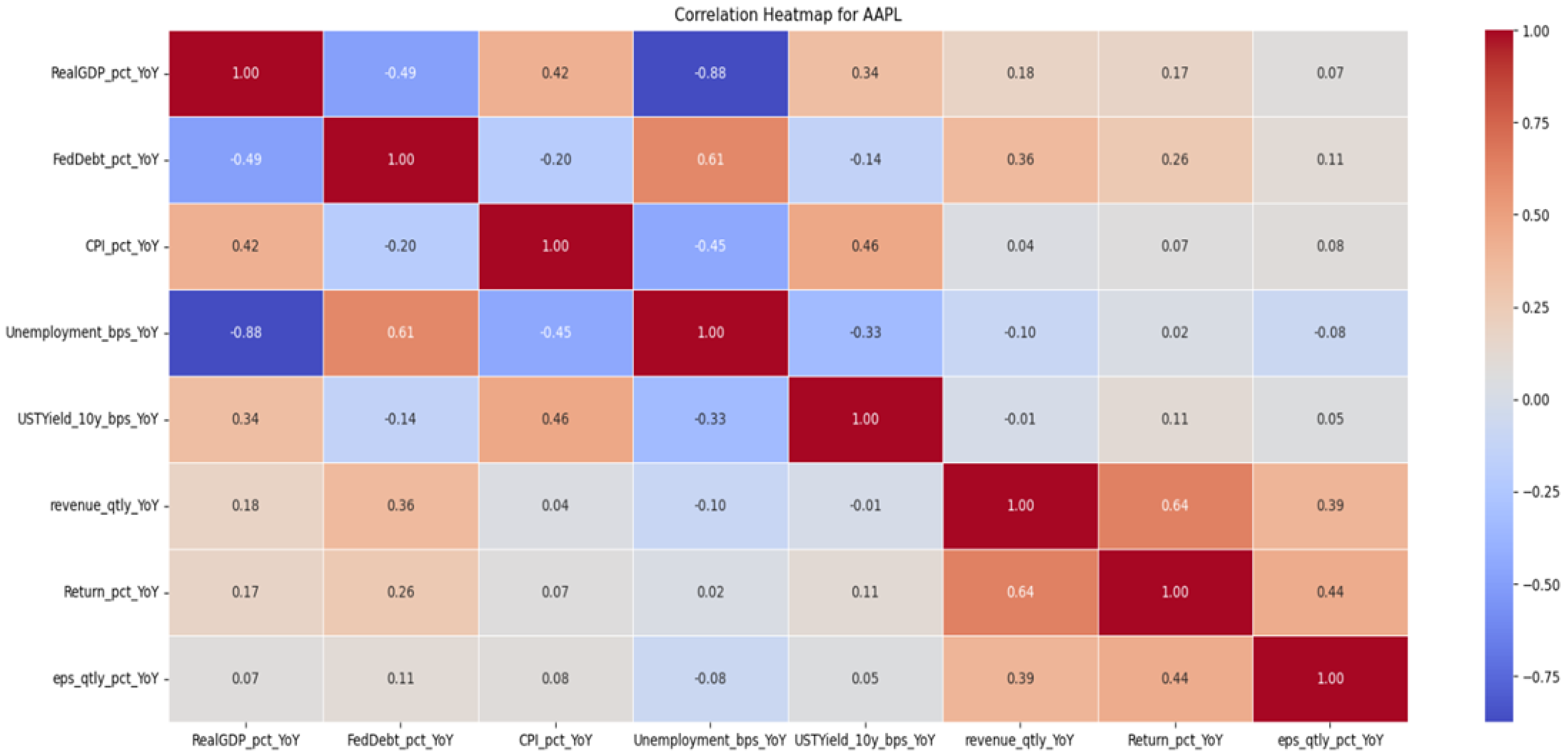
Key Insight #3:

News Sentiment has a negative drift on 5 days return post announcement.

Negative news sentiment leads to a drop on 2-3 days return post news publishing, however it neutralises thereafter

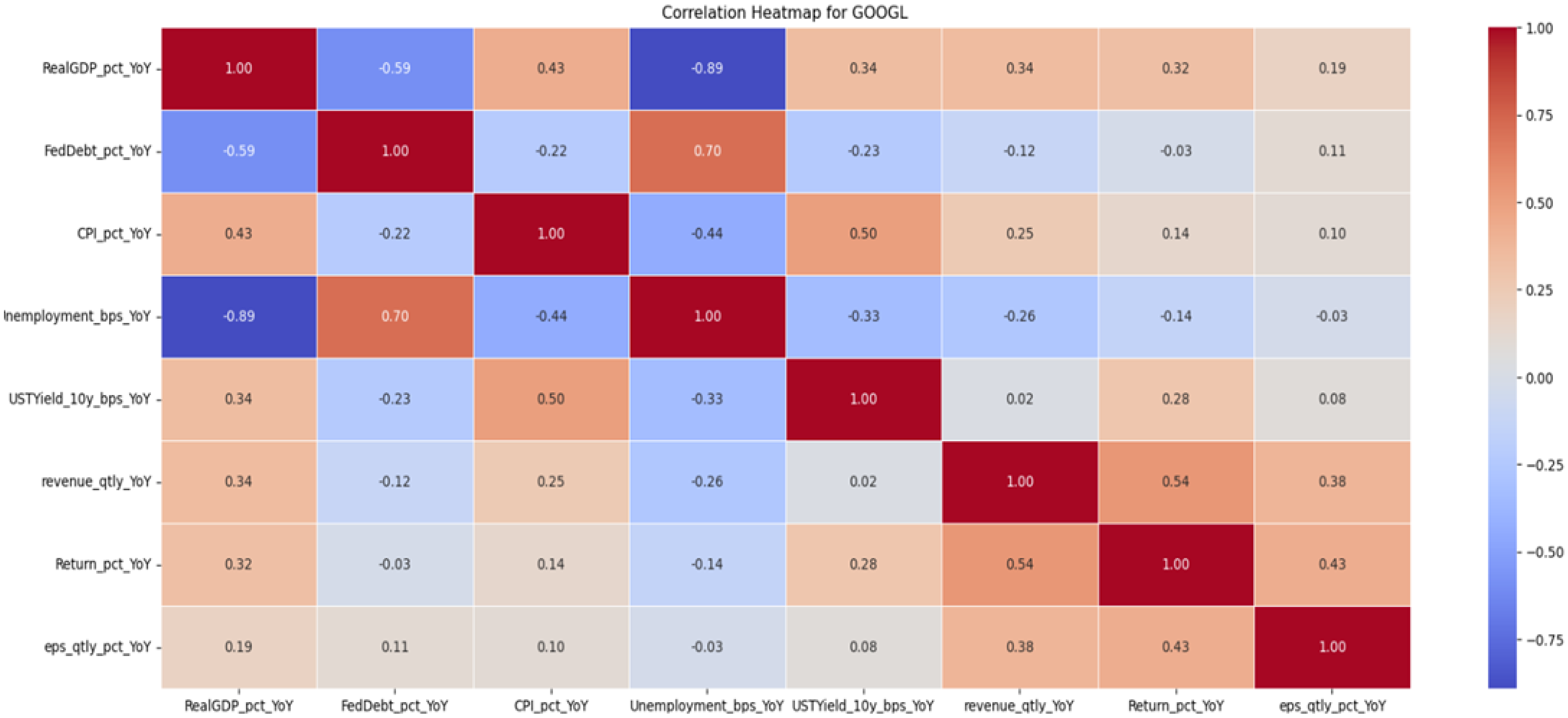
Macro Economic Indicators – Appendix 1 [Apple]

AAPL



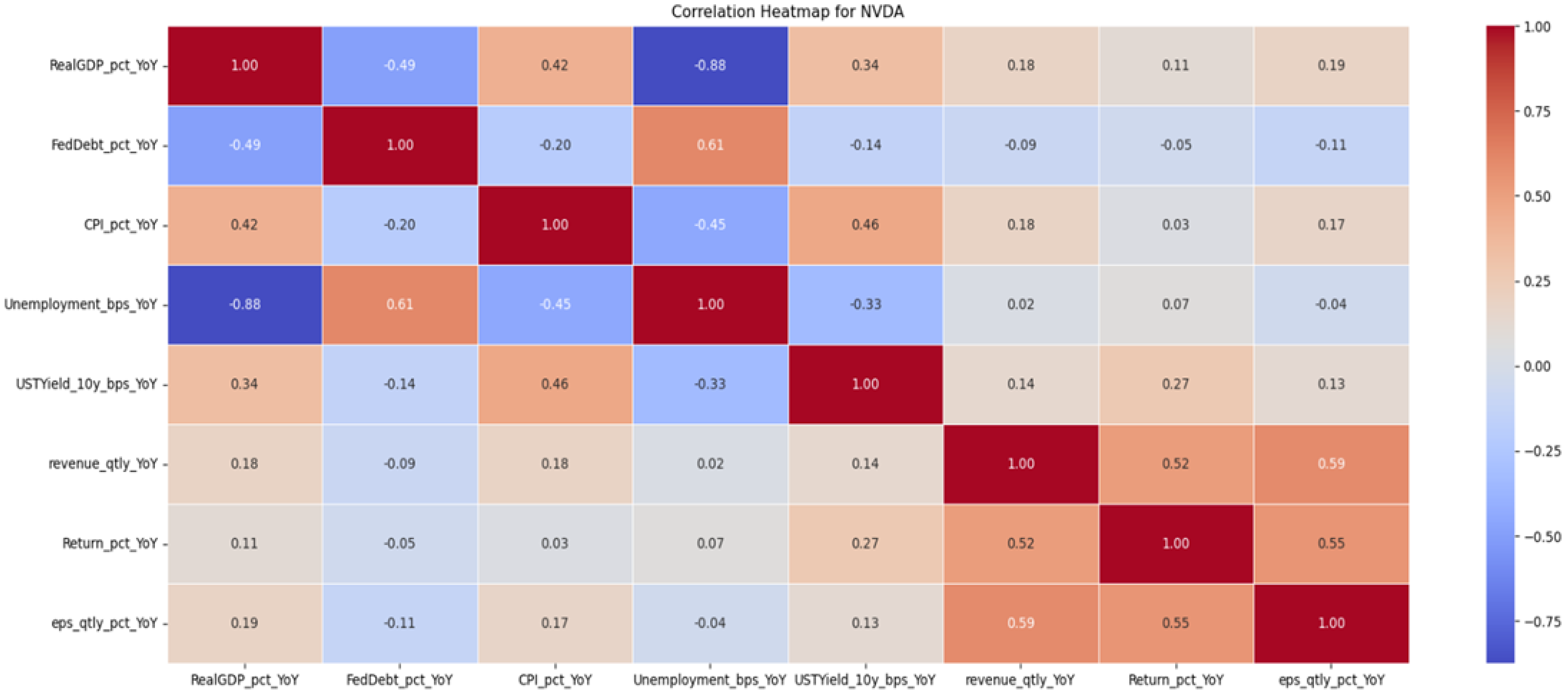
Macro Economic Indicators – Appendix 2 [Google]

GOOGL



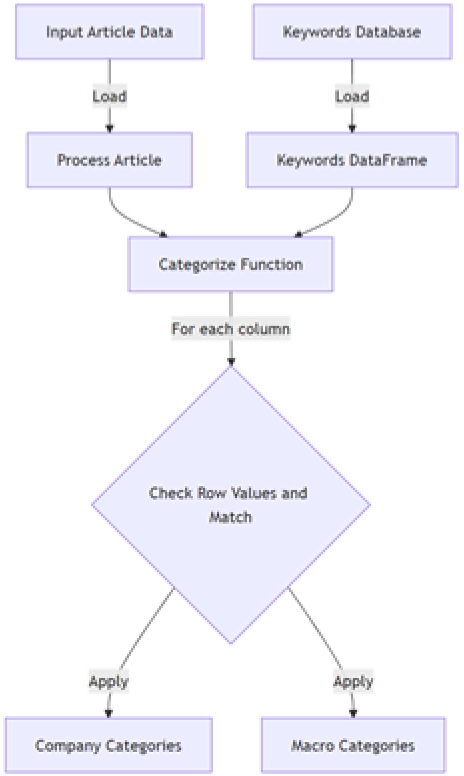
Macro Economic Indicators – Appendix 3 [NVIDIA]

NVDA



Sentiment – Rule based Classification Flow – Appendix 4

Pipeline flow:




```python
keywords_df = pd.read_csv('sentiment_keywords.csv')
keywords_df = keywords_df.fillna('').astype(str)

# Categorize function to get Company and Macro values
def categorize(row, keywords_df, columns, value_column):
    categories = set()

    for col in columns:
        # Convert row value to string and handle NaN/None
        row_value = str(row[col]) if pd.notna(row[col]) else ''

        for keyword, value in zip(keywords_df['keyword'], keywords_df[value_column]):
            # Skip empty keywords or values
            if keyword and value and keyword in row_value:
                categories.add(value)

    return ' and '.join(sorted(categories)) if categories else 'Other'

# Apply the modified function
VP_SD['Company'] = VP_SD.apply(lambda row: categorize(row, keywords_df, ['org_1', 'org_2', 'org_3'], 'Company_value'), axis=1)
VP_SD['Market'] = VP_SD.apply(lambda row: categorize(row, keywords_df, ['subject_1', 'subject_2', 'subject_3', 'org_1', 'org_2', 'org_3'], 'Macro_value'), axis=1)
```

Pipeline Evaluation:

1. The current logic is rule-based and will classify any new article, if the keywords are present (data schema remains the same).
2. The keywords have been custom-picked based on a manual review for each classification section. For a pipeline to be able to classify articles for any organisation, the keywords section would have to be expanded into a separate database that can be referred against
    - This would require more articles to get a more exhaustive set of keywords or the source's data dictionary could have an exhaustive set available already.
3. This approach gives us the customisability that would not be available if we go by ML / AI based classifications