Time Series Clustering for Macroeconomic Events

CFEM Greenmantle Project

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Outline

1. **Introduction**
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    b. Concept explanation
2. **Data Review**
    a. US Macroeconomic Data: interest rates, inflation, labour market, etc
    b. Market Future Prices: S&P 500, 10Y UST, Gold, Oil, etc
3. **Methodology Overview**:
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    b. Clustering
    c. Clustering Explanation
4. **Results**:
    a. Clusters Scatter Plot
    b. Clusters over Time

Introduction

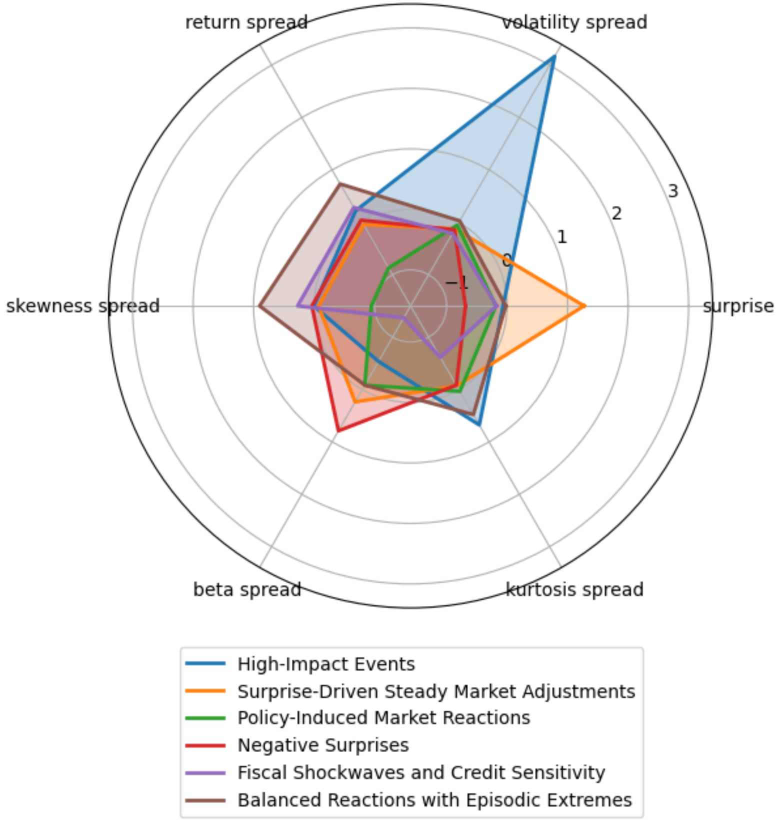
Project Scope

- **Importance**: Macroeconomic events heavily influence market pricing. Understanding these effects is key to informed investment decisions and risk management.
- **Gap:** Current analyses often focus on single assets. This misses a cross-asset view that captures a holistic macro narrative.
- **Challenge**: Key challenges are:
  - Building a dataset of relevant macro events and key cross-asset securities;
  - Selecting clustering methods to assign similarities;
  - Building models that capture cross-asset relationships.
- **Our Project**: Our project leveraged advanced machine learning methodologies to uncover and model the intricate relationships between market events and their corresponding impacts on financial markets.

Concept Explanation

1. **Data Cleaning**:
   a. There exists error data, inconsistent data, missing values in raw data
   b. The abnormal data are removed or fixed in data cleaning for further analysis
2. **Feature Engineering**:
   a. Feature: engineering term for data characteristics
   b. Feature engineering explores key patterns in raw data, and creates more informative and representative series from raw data
3. **Clustering**:
   a. An engineering method to group similar data points together based on their characteristics
4. **Cluster Interpretation**:
   a. Clusters generated by clustering models could be interpreted by some methods.

Overview of what the clusters look like



Clustering Results Overview :

- Clustering results highlight the distinct characteristics of market behavior by comparing key financial features across different groups, showcasing the diversity and patterns within the data.

Importance of this project:

- The clustering results provide valuable insights into market reactions during major macroeconomic events, offering guidance for more informed investment decisions.

Stage 0. Data Review

Stage 0. Data Review

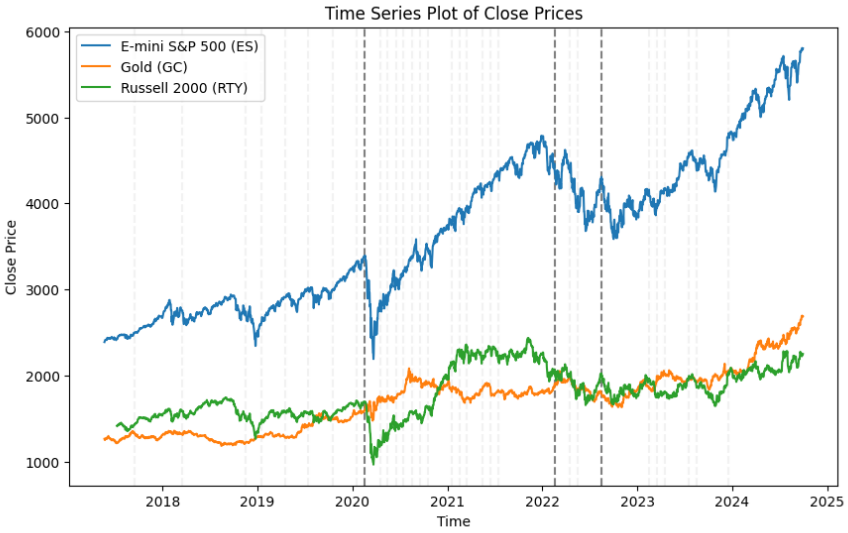
1. Data
    a. US macro event data
    b. Price series of market future contracts
2. We use price series around (before and after) events, to analyze the market influence of different events
    a. We standardize the data in these intervals around the events for the analysis.

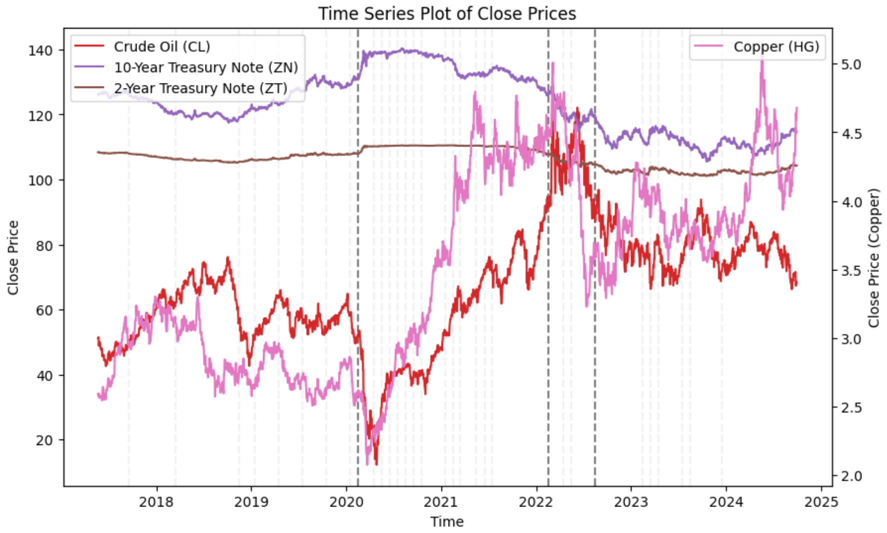
Stage 0. Data Review - Time Series Data

- **Time Series Data**:
  - **Horizon**: 2017-05-22 to 2024-09-29
  - **Frequency**: minute

Explanation	Symbol	Start	End
E-mini S&P 500 Futures	**ES**	2017-05-22	2024-09-29
Copper Futures	**HG**		
Crude Oil Futures	**CL**		
10-Year U.S. Treasury Note Futures	**ZN**		
Gold Futures	**GC**		
2-Year U.S. Treasury Note Futures	**ZT**		
Russell 2000 Futures	**RTY**	2017-07-09	

Stage 0. Data Review - Time Series Data





These graphs show the closing price trends for seven contracts :

- **Grid lines**: ±2.5 **σ** selected events
    - Dark grid lines: example events happenings

Significant to analyze event!

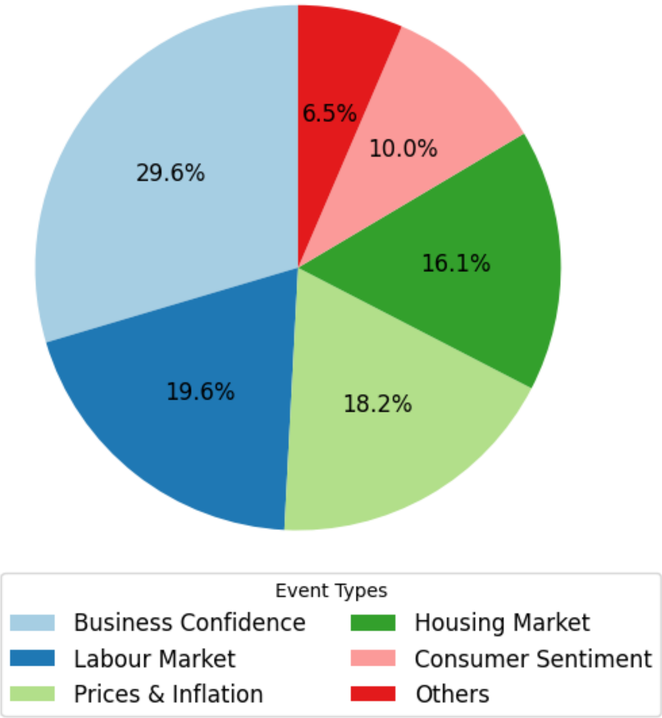
Stage 0. Data Review - Event Data

(Screenshot from trading economics)

Wednesday November 20 2024			Actual	Previous	Consensus	Forecast
08:00 AM	US	MBA 30-Year Mortgage Rate NOV/15	6.9%	6.86%		
08:00 AM	US	MBA Mortgage Applications NOV/15	1.7%	0.5%		
08:00 AM	US	MBA Mortgage Market Index NOV/15	195.6	192.4		
08:00 AM	US	MBA Mortgage Refinance Index NOV/15	514.9	506.0		
08:00 AM	US	MBA Purchase Index NOV/15	136.0	133.3		
11:30 AM	US	EIA Crude Oil Stocks Change NOV/15	0.545M	2.089M	0.4M	
11:30 AM	US	EIA Gasoline Stocks Change NOV/15	2.054M	-4.407M	1.62M	
11:30 AM	US	EIA Crude Oil Imports Change NOV/15	0.237M	-0.321M		
11:30 AM	US	EIA Cushing Crude Oil Stocks Change NOV/15	-0.14M	-0.688M		
11:30 AM	US	EIA Distillate Fuel Production Change NOV/15	-0.132M	-0.127M		
11:30 AM	US	EIA Distillate Stocks Change NOV/15	-0.114M	-1.394M	-0.2M	
11:30 AM	US	EIA Gasoline Production Change NOV/15	-0.98M	0.559M		
11:30 AM	US	EIA Heating Oil Stocks Change NOV/15	0.342M	-1.06M		
11:30 AM	US	EIA Refinery Crude Runs Change NOV/15	-0.281M	0.175M		
12:30 PM	US	17-Week Bill Auction	4.380%	4.370%		
02:00 PM	US	20-Year Bond Auction	4.680%	4.590%		

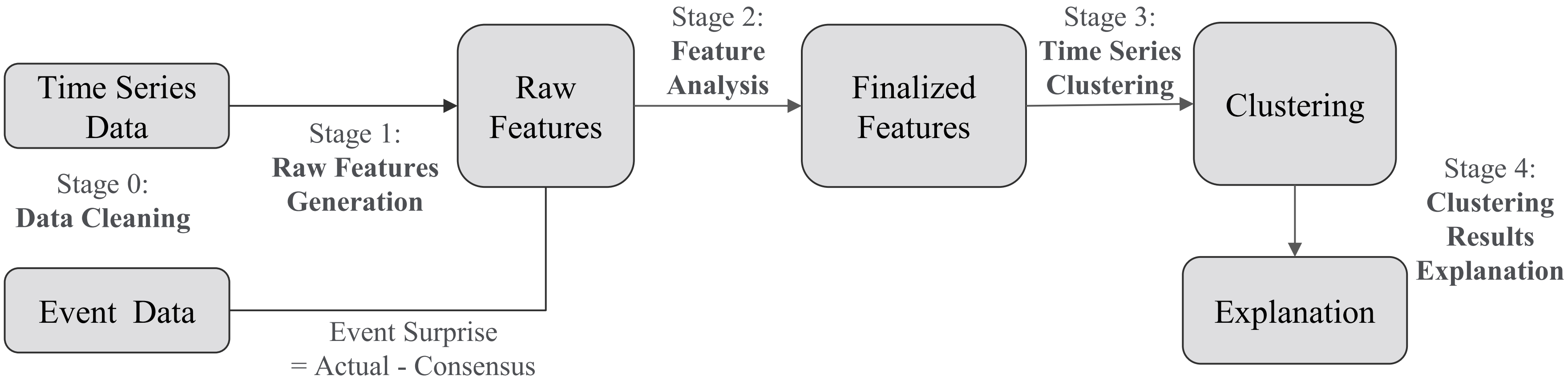
Stage 0. Data Review - Event Data

Event Categories	Examples
Interest Rate*	Fed Interest Rate Decision
Labour Market*	Job market Unemployment Wages and Compensation Labor Productivity and Costs Market Health
Prices & Inflation*	CPI and PPI Core Inflation Metrics Personal Consumption Expenditures (PCE) Inflation Expectation
Bond Auctions	Bill, Note, Bond Auction
Business Confidence	Business Output and Production Economic Sentiment and Business Conditions Corporate Performance Inventories and Supply Chain Transportation and Sales
Consumer Sentiment	Consumer Confidence and Sentiment Consumer Spending, Income, and Credit Retail and Sales Activity
Foreign Trade	Imports, Exports, Balance
GDP Growth	GDP Growth, Sales, and Real Consumer Spending
Government	Budget Statement
Housing Market	Housing Market Sales and Sentiment Home Prices and Indices Housing Construction and Permits Mortgage and Financing



Methodology

Four stage methodology



1. **Data Cleaning** (Stage 0) removes or fixes abnormal data such as missing values.
2. **Feature Engineering** (Stage 1 and Stage 2) creates more informative characteristic series from raw data, by exploring key patterns in original data.
3. **Clustering** (Stage 3) assigns similarity among events, in terms of event surprise and market movements.
4. **Clusters Explanation** (Stage 4) seeks to find which features are the most explanatory of why events in a group are similar to each other, and what characteristics these clusters have.

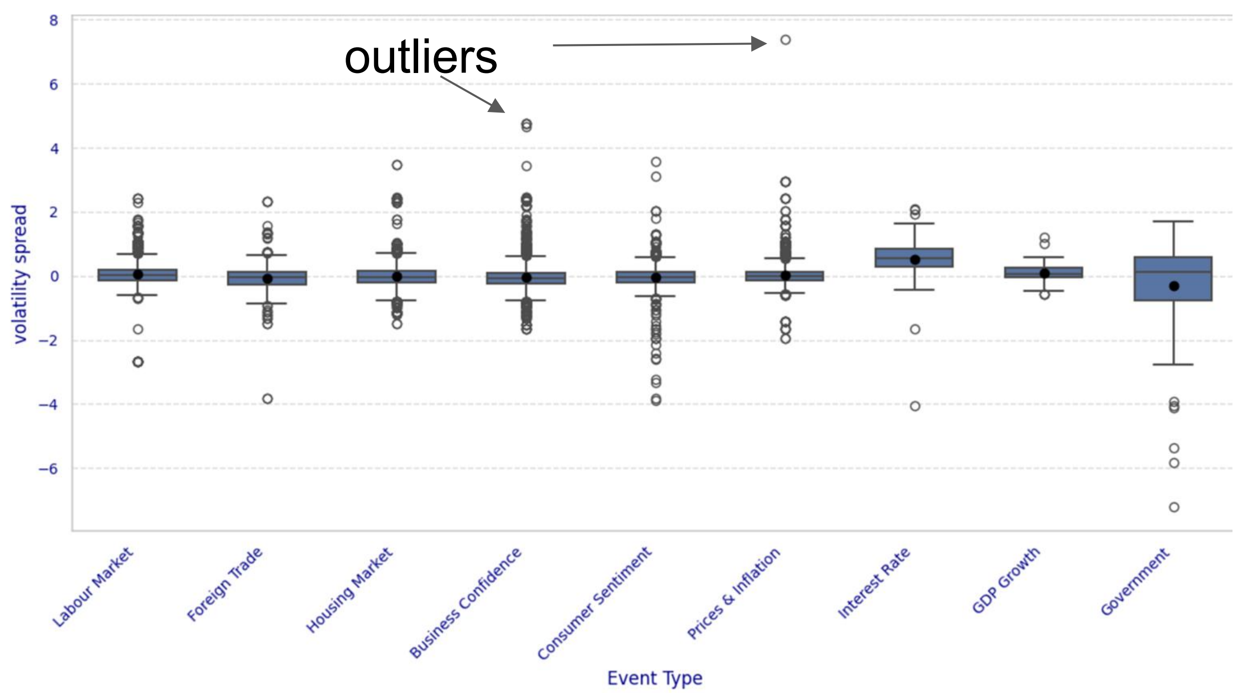
Stage 1 & 2. Feature Engineering

Stage 1 & 2. Finalized Features[1]

- Surprise
    - Surprise = Event surprise score (actual - consensus), standardized within each event type
- Spread Feature: Before event average minus after event average
    - Return Spread
    - Volatility Spread
    - Beta Spread (market sensitivity)
        - Beta measures the market sensitivity for different asset classes. The higher the beta, the higher the sensitivity. We use SPY returns as the proxies of the market return.
    - Skewness Spread (return distribution)
        - Skewness measures the asymmetric nature of asset return,
    - Kurtosis Spread (tail risk)
        - A higher kurtosis implies heavier tail.

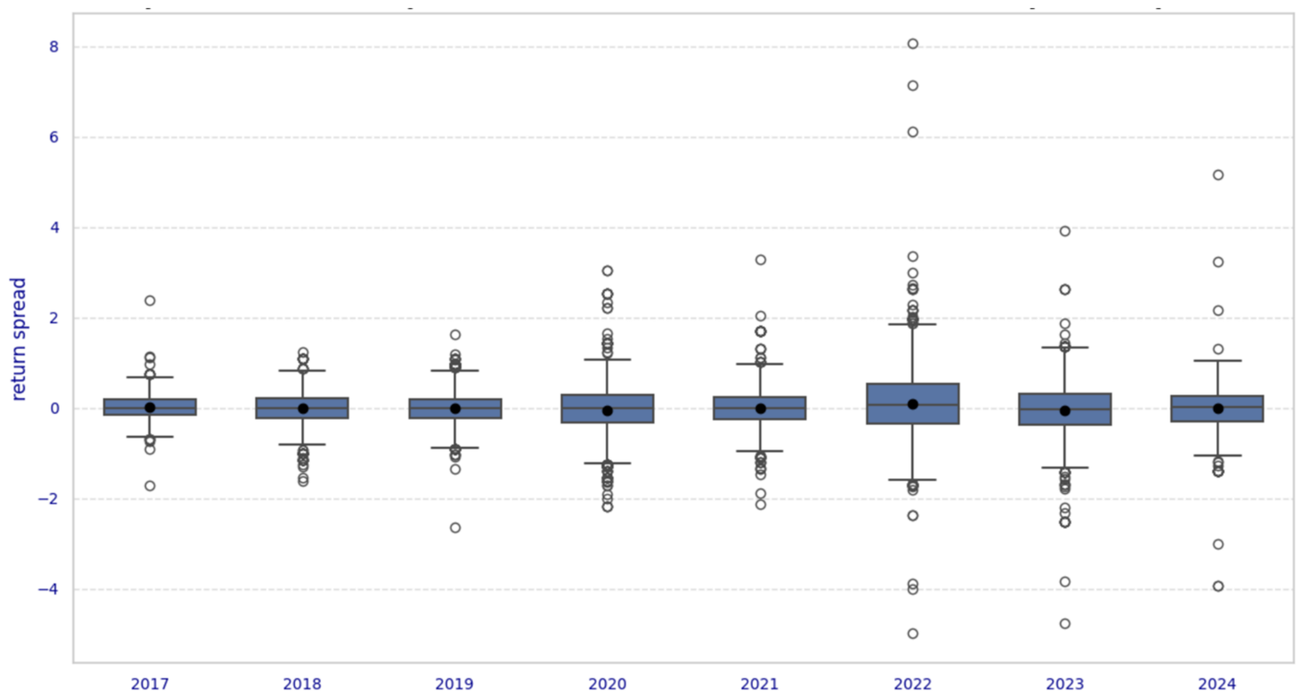
1. The raw data are transformed into a few representative characteristic series, and then used to construct our finalized features.

Stage 2. Volatility Spread Distribution by Event Type



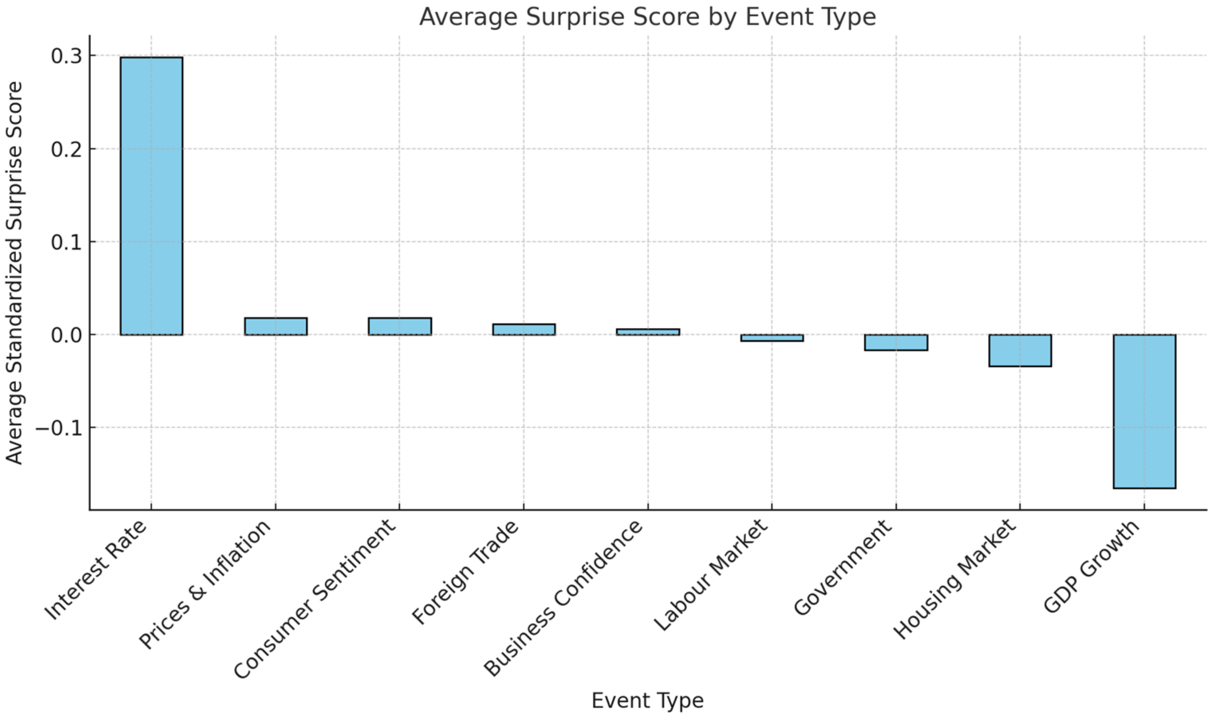
- Volatility spread in GDP growth has much less outlier compared to other event type
- Government related event is negatively skewed, while other event type is more symmetrical

Stage 2. Return Spread Distribution by Year



- After Covid, assets on average have more volatile returns around macroeconomic events.

Stage 2. Average Surprise Across Different Event Types



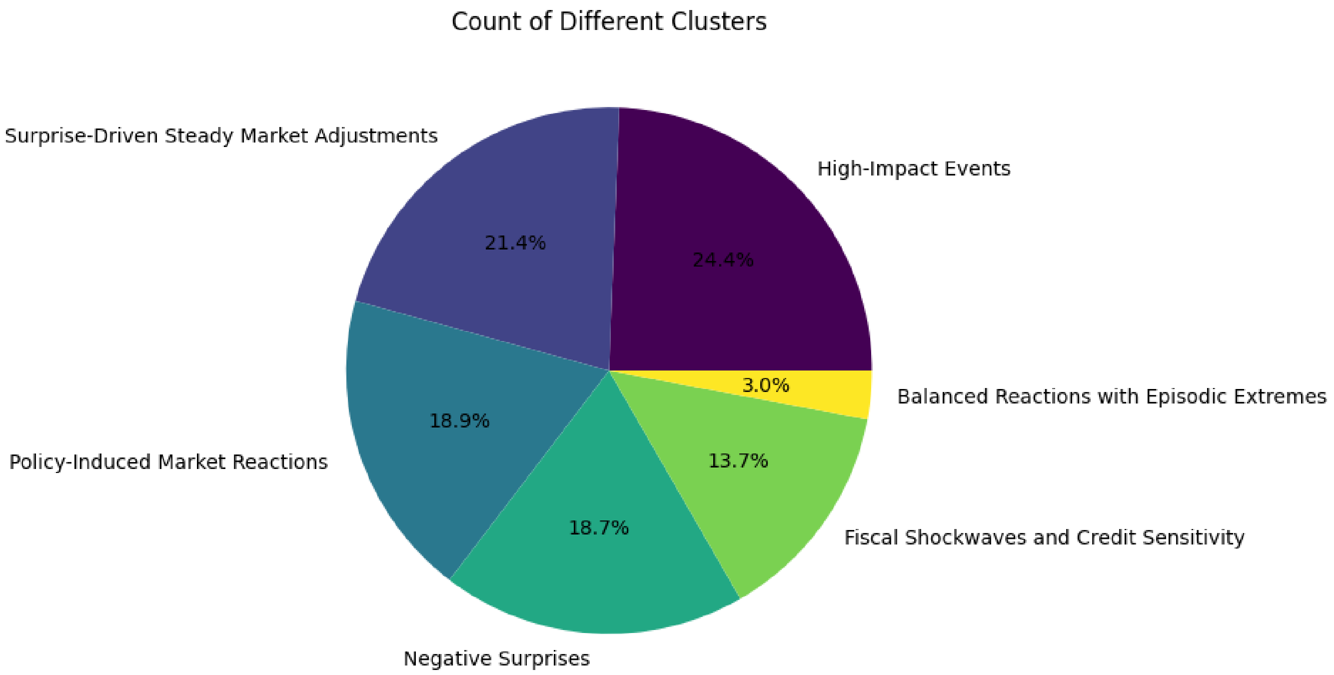
Surprise = Actual - Consensus

Stage 3. Clustering

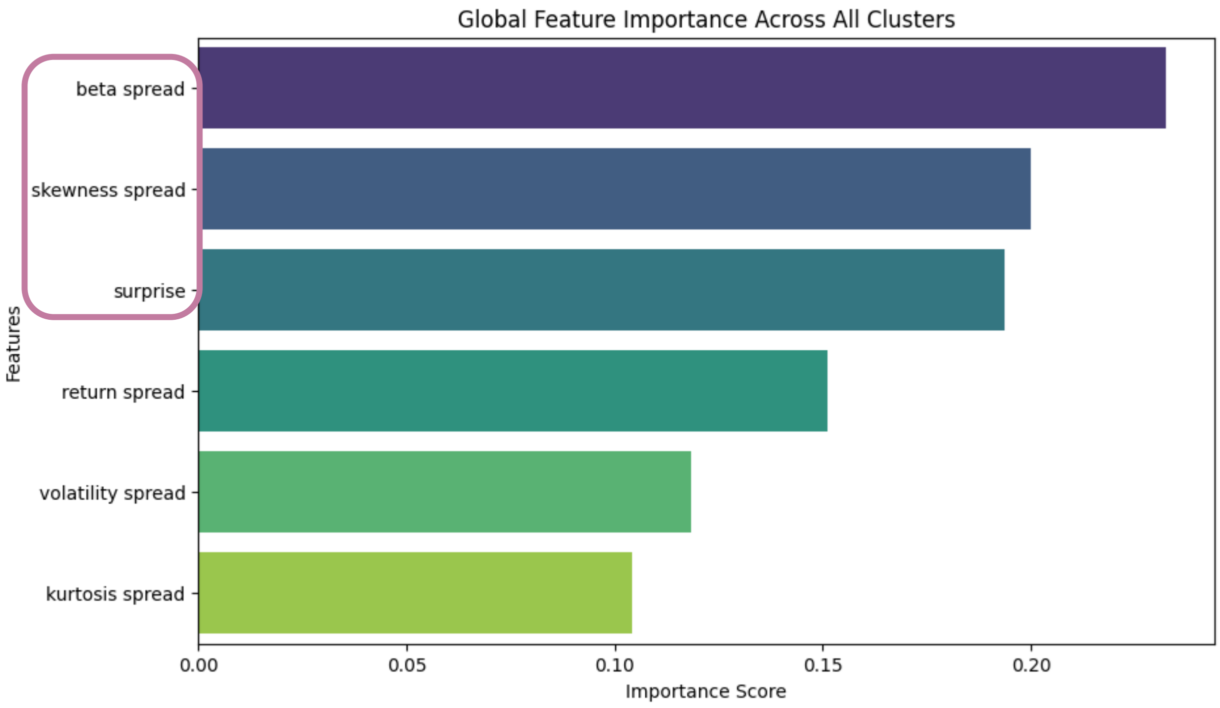
Stage 3. Clustering Methods using ML

1. **Machine Learning (ML):**
    a. ML refers to algorithms that enable systems to learn patterns from data and make predictions or decisions without explicit programming
2. **Clustering:**
    a. Recall that clustering groups similar data points together based on their characteristics
3. **K-Means Clustering:**
    a. K-Means clustering assigns events into k groups (in our case k = 6).
    b. Groups data by finding the centers of the groups and placing similar data points together based on their closeness to those centers (spherical clustering).
    c. Why K-Means
        i. Simplicity and effectiveness for grouping similar patterns in time series data.
        ii. Helps identify consistent reactions to macroeconomic events across clusters.
        iii. Offers clear and interpretable clustering results as baseline for actionable insights.
4. **Clustering Results:**
    a. Analyzing feature importance in cluster assignment
    b. Analyzing event type importance in cluster assignment

Stage 3. Cluster distribution

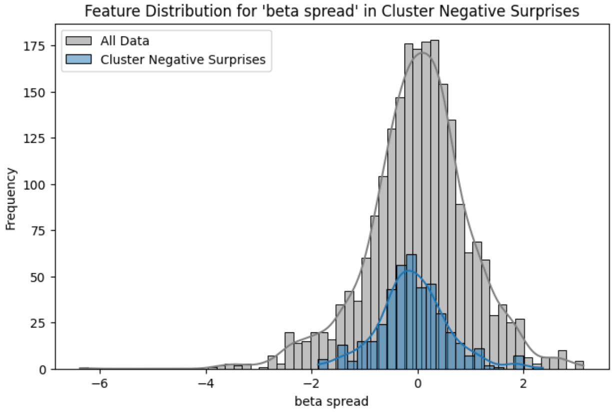


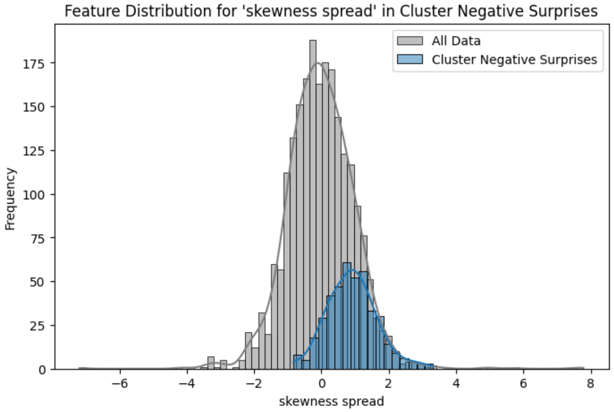
Stage 3. Feature Importance

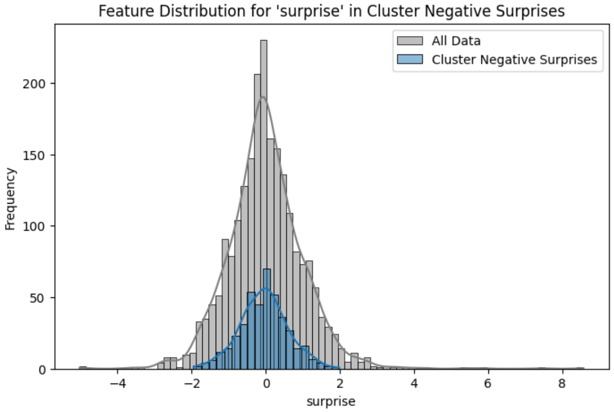


Importance Score measures how much a feature contributes to improving the clustering

Stage 3. Most important features in *Negative Surprises*

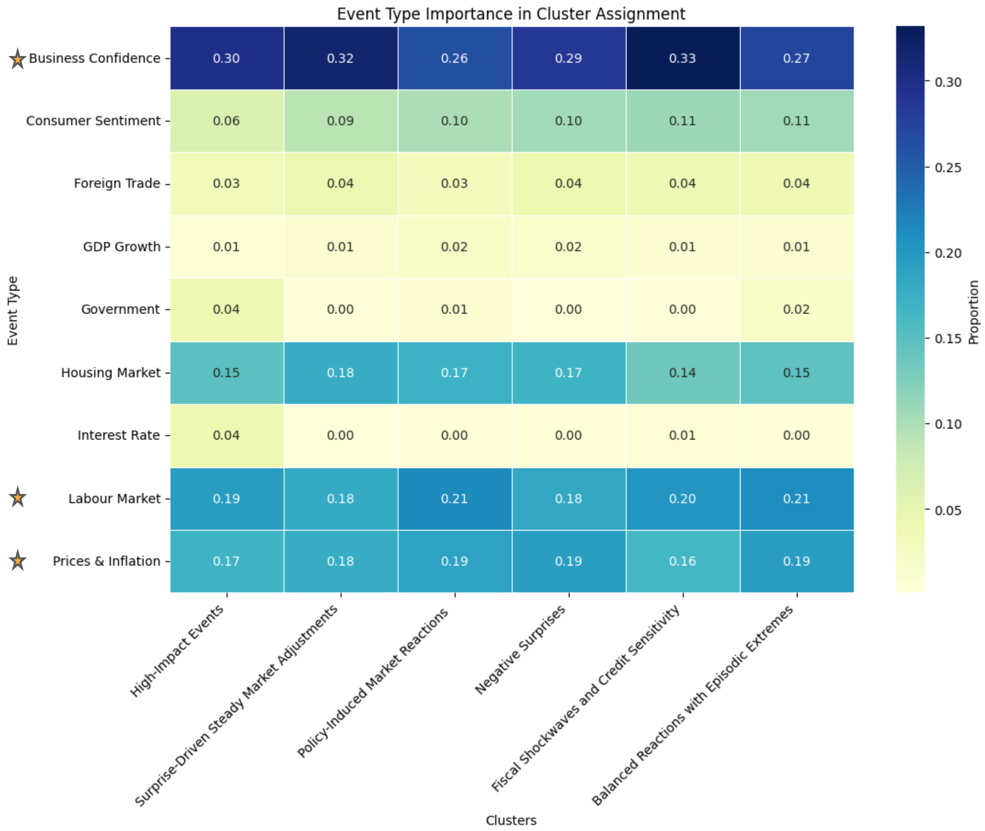






Exhibits concentrated distributions for **beta spread**, **surprise**, and **skewness spread**, differentiating it from the broader dataset with notable feature-specific patterns

Stage 3. Event type importance



In the heatmap, **lighter shades** indicate **higher proportions** of the corresponding event type within a cluster, while **darker shades** indicate **lower proportions**.

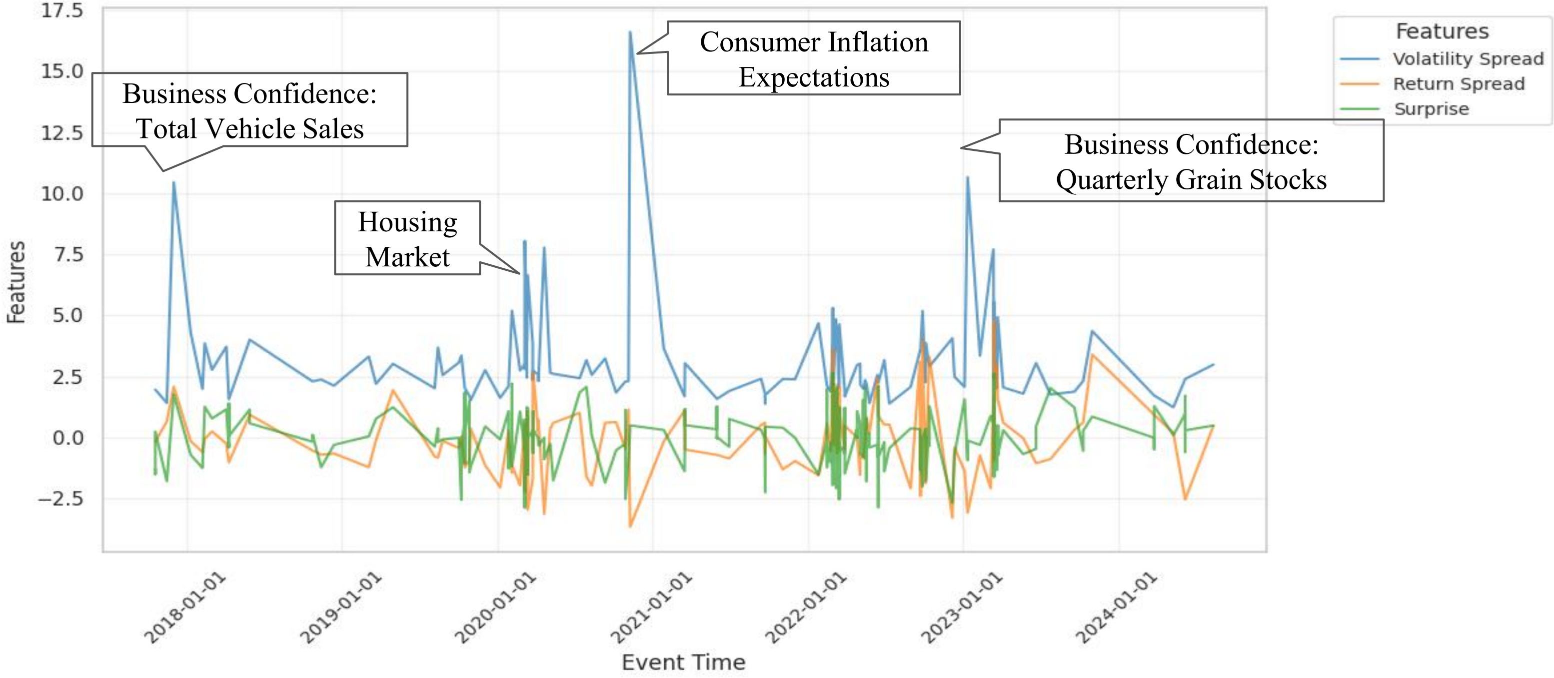
Top 3 Event Types with Maximum Importance Across All Clusters:

1. Business Confidence
2. Labour Market
3. Prices & Inflation

Stage 4. Building up Narratives

Cluster Narratives Based on Time Series Analysis

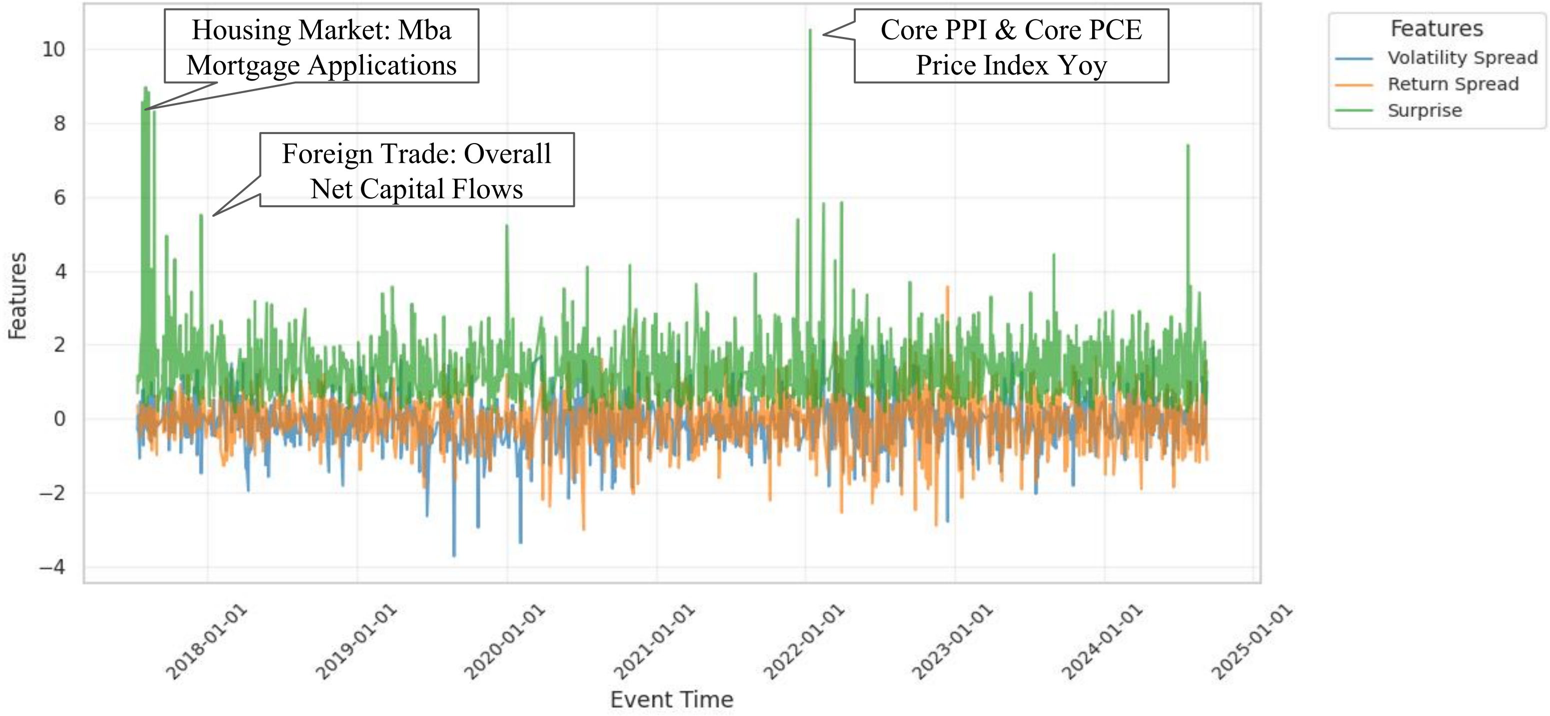
Stage 4. **Cluster Narratives** Based on Time Series Analysis



Cluster 1: High-Impact Market Events with Elevated Volatility

- Cluster 1 corresponds to **significant market events** characterized by **sharp spikes in volatility spread**.
- These events are typically linked to **critical macroeconomic releases, significant market-moving news**, or **periods of heightened market uncertainty**.

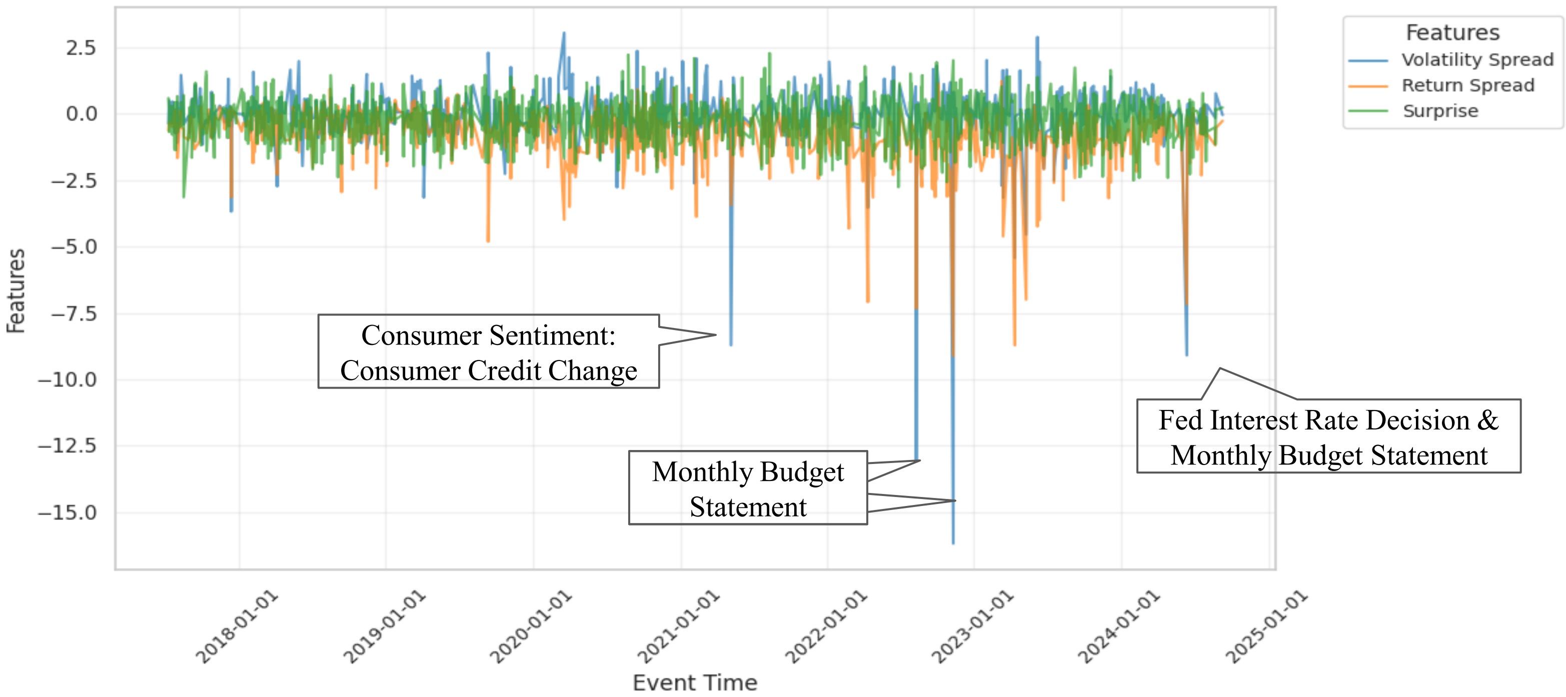
Stage 4. **Cluster Narratives** Based on Time Series Analysis



Cluster 2: Steady Market Adjustments with Surprise-Driven Trends

- Cluster 2 captures events with **consistently elevated surprise values**.
- Despite these high surprises, **volatility spread remains relatively stable.**

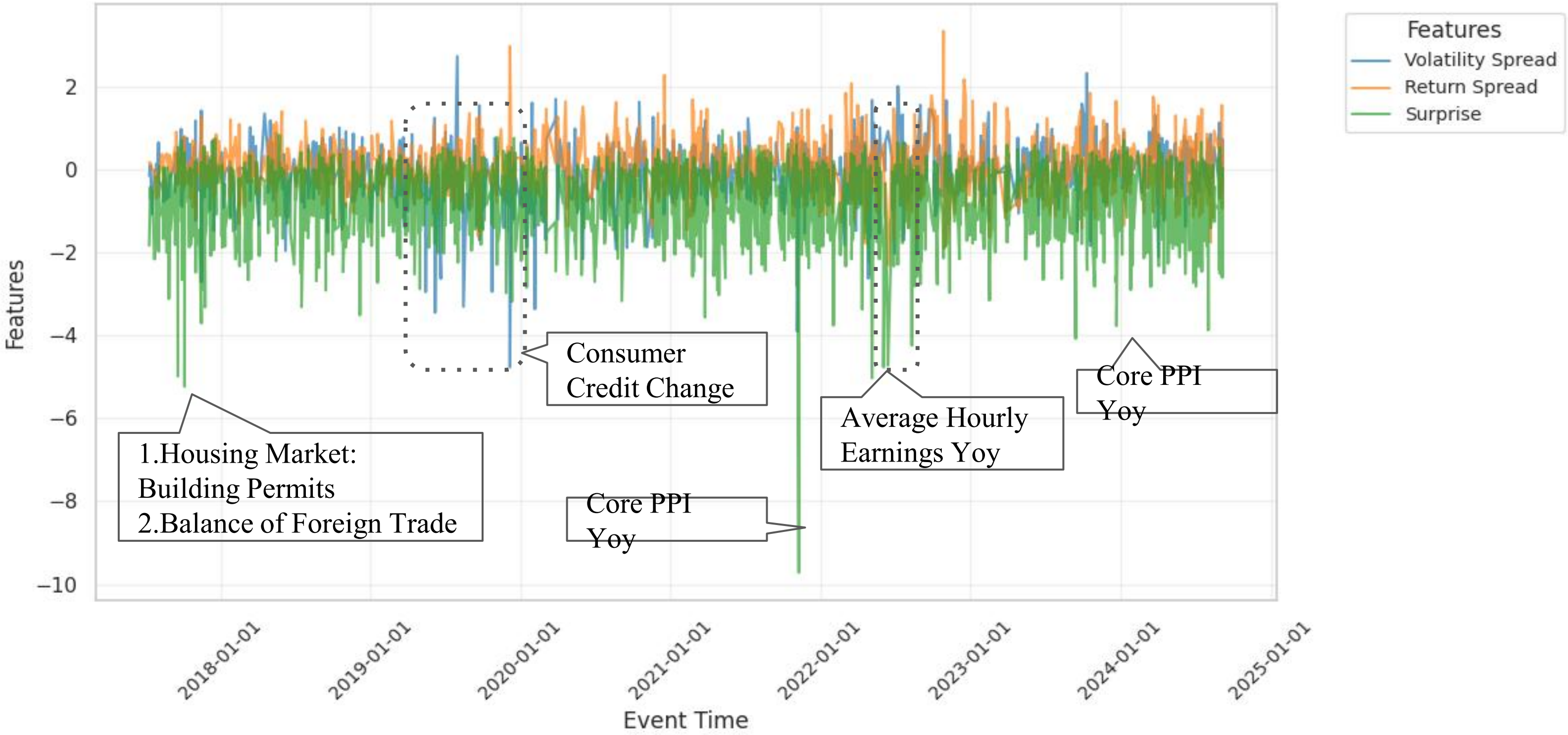
Stage 4. **Cluster Narratives** Based on Time Series Analysis



Cluster 3: Policy-Induced Market Reactions Reflecting Negative Sentiment

- Cluster 3 is marked by **significant negative volatility spreads and return spreads**.
- The features indicate **systemic market stress** and **declining confidence** in response to critical **fiscal and monetary policy-related events**.

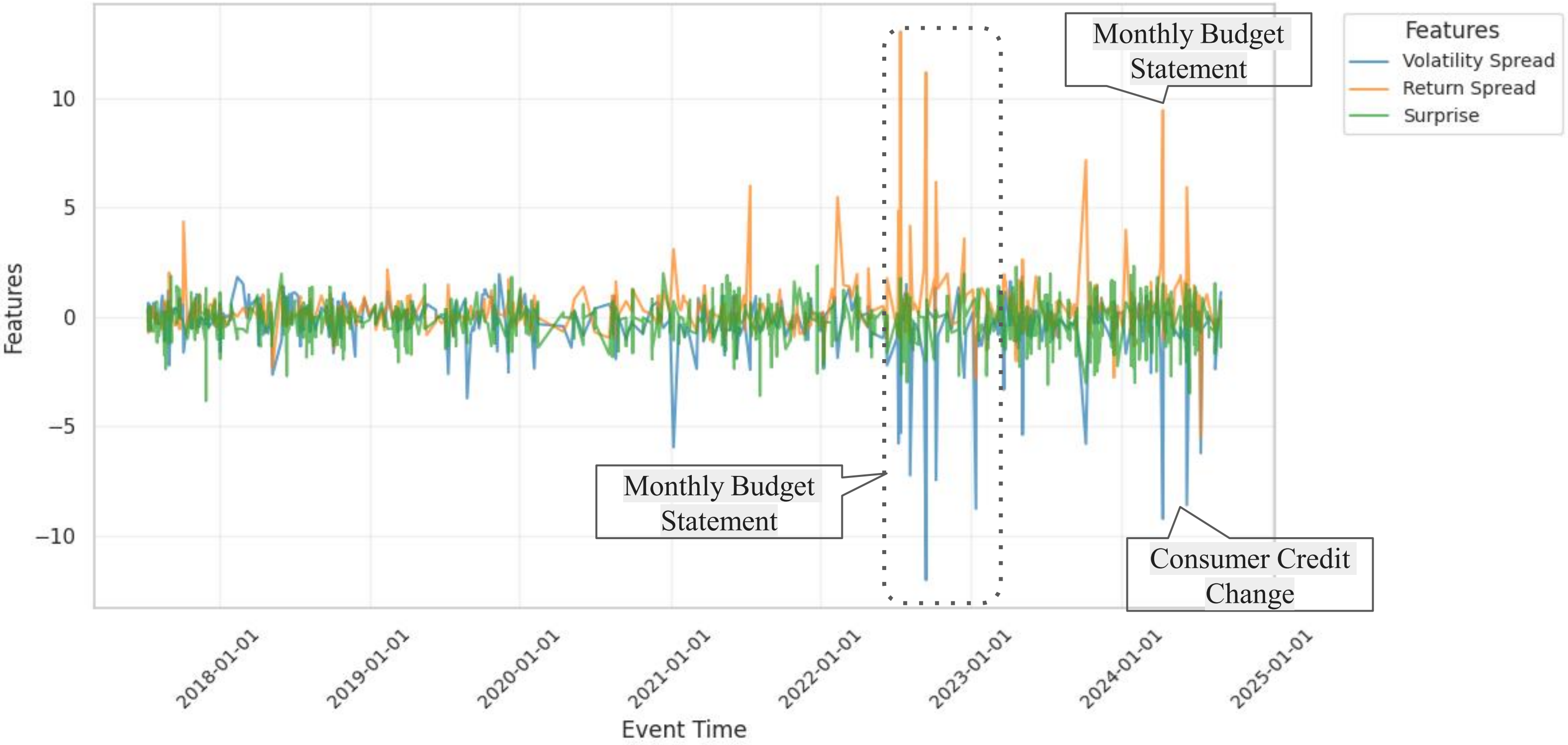
Stage 4. **Cluster Narratives** Based on Time Series Analysis



Cluster 4: Negative Surprises in Macroeconomic Indicators and Moderate Market Adjustments

- Cluster 4 is defined by **consistent negative surprises** in **macroeconomic** indicators, coupled with **moderate volatility and return spreads**.
- This cluster reflects the market's **measured reaction** to **worse-than-expected** economic data.

Stage 4. **Cluster Narratives** Based on Time Series Analysis



Cluster 5: Fiscal Shockwaves and Credit Sensitivity

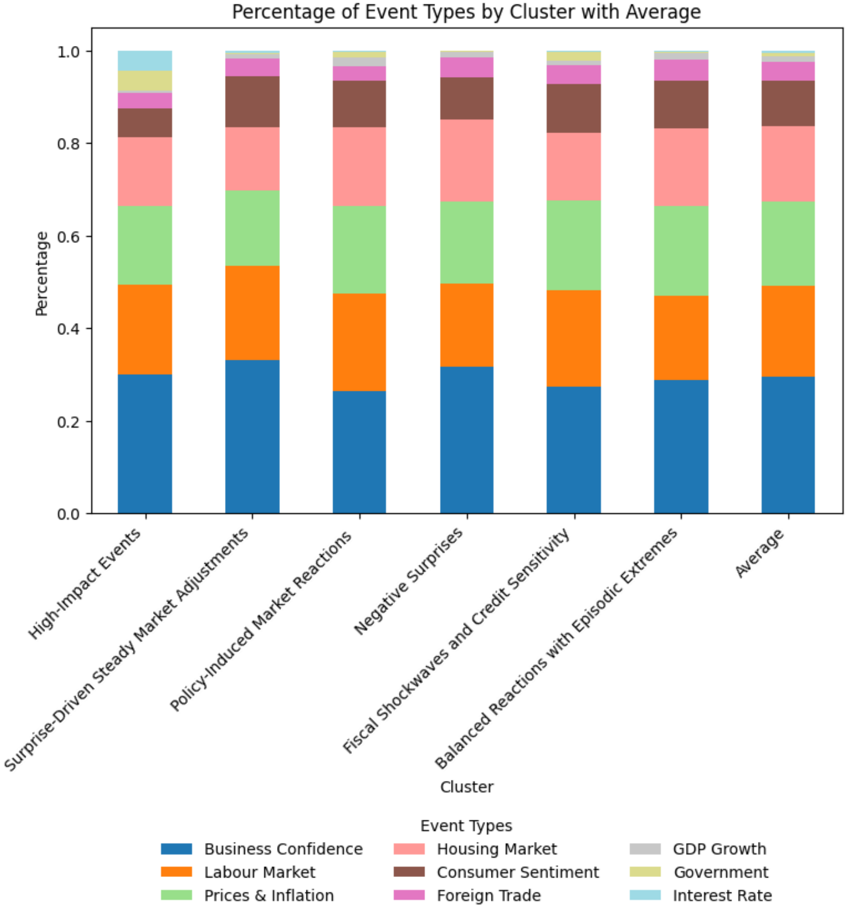
- Cluster 5 demonstrates **extreme reactions** in **volatility and returns**, driven by surprise announcements in fiscal and consumer credit events.

Stage 4. **Cluster Narratives** Based on Time Series Analysis

Cluster 6: Balanced Reactions with Episodic Extremes

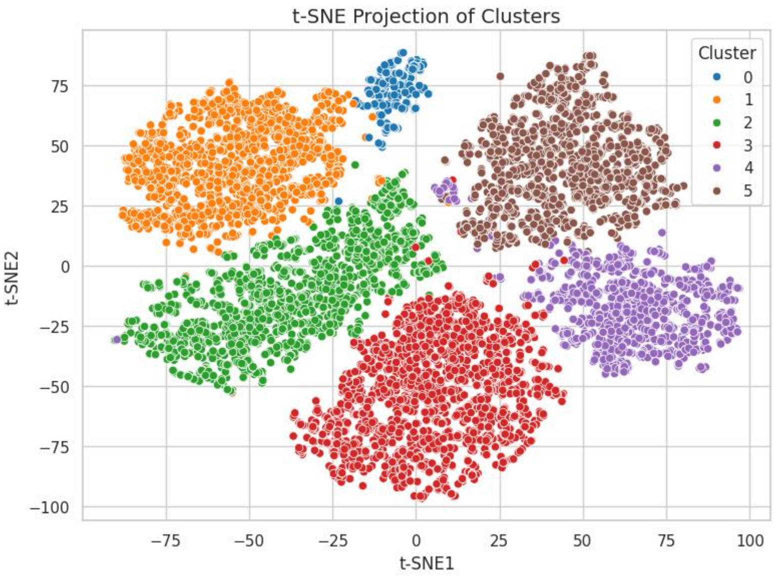
- Cluster 6 represents events characterized by overall market stability with occasional sharp reactions to

Stage 4. The Distributions of Different Event Types between Clusters



- Cluster 1 (High-Impact Market Events) has a higher proportion of Interest Rate events and Government events.
- The other clusters don’t differ from each other significantly.
- Suggests that our clustering is meaningful: The differences between clusters are not merely driven by dominant event types but **reflect deeper, more intrinsic distinctions in the data**.

Stage 4. How Well does Clustering Perform?



What is a t-SNE projection plot?

- A method used to **visually group similar items together** based on their patterns or features. **Each dot represents one item**, and the **colors show which group** (or "cluster") the item belongs to.

Key takeaways:

- **Distinct Groups:** There’s **little overlap between clusters**, which indicates that the clustering method **worked really well at separating different kinds of events**.
- **Tight Clusters:** Each cluster is tightly packed, showing that similar items are grouped closely.

Future Improvements

- Leverage other data sources like economic indices and analyst reviews.
- Develop and evaluate alternative feature engineering techniques, such as factor-based methodologies.
- Experiment with advanced clustering methods, including deep learning approaches.
- Integrate real-time event classification for predictive modeling and scenario analysis.
- Design and implement automated trading strategies informed by event-driven patterns.
- Strengthen risk management with a cluster-based early warning system to identify potential disruptions.

Conclusions

- Market events can be grouped based on their underlying narratives.
- Event surprises serve as a strong signal for identifying event groups.
- The market regime underwent a significant shift after COVID-19.
- Classification models[1] can leverage these existing event clusters to provide narratives for newly occurring events.

1. Classification models predict categories with given features of data. In our project, XGBoost is used for classification.

Thank you!

Appendix

Stage 1. Raw features

We generate raw features around events.

- Event Surprise
  - Surprise = Actual - Consensus
- Transformed Return Series in Time intervals around Events
  - Original Series: 3 return series (SP500, Gold, Treasury 10Y)
  - Time Intervals: [-90 Min, -60 Min, -30 Min, 0, 30 Min, 60 Min, 90 Min] around the event
  - Transformed Series: a few representative series for the return series (mean, volatility, etc)
- The raw features are then analyzed, and finalized features are constructed.

Clustering Method: DBSCAN

1. DBSCAN: DBSCAN is a clustering method that groups data points based on density, identifying clusters and isolating outliers in noisy datasets.
2. Feature Selection
    a. Selected relevant features(total_vol; bond_vol_spread; gold_vol_spread; surprise; before_m_after)
3. DBSCAN Parameter Optimization
    a. the parameters (optimal eps and min_samples) are chosen by testing all combinations and picking the best performing combination.
4. Cluster Analysis
    a. Results:

0	4122
-1	141

DBSCAN does not provide a good results.

Stage 3. Clustering Steps:

1. Perform K Means or GMM clustering
2. Train an XGBoost model to predict cluster labels
3. Use SHAP to explain the model's predictions
4. Summary plot to show feature importance across all clusters
5. SHAP Dependence Plot for a specific feature
6. Use decision tree to analyze clusters using feature importance

Stage 3. Clustering

Features including:

- surprise
- volatility spread
- return spread
- skewness spread
- beta spread
- kurtosis spread

Number of clusters: 6

Prediction for K-Means:

XGBoost with multiclass log loss

Accuracy: 95.39 %

Log loss: 1.5929

Prediction for GMM:

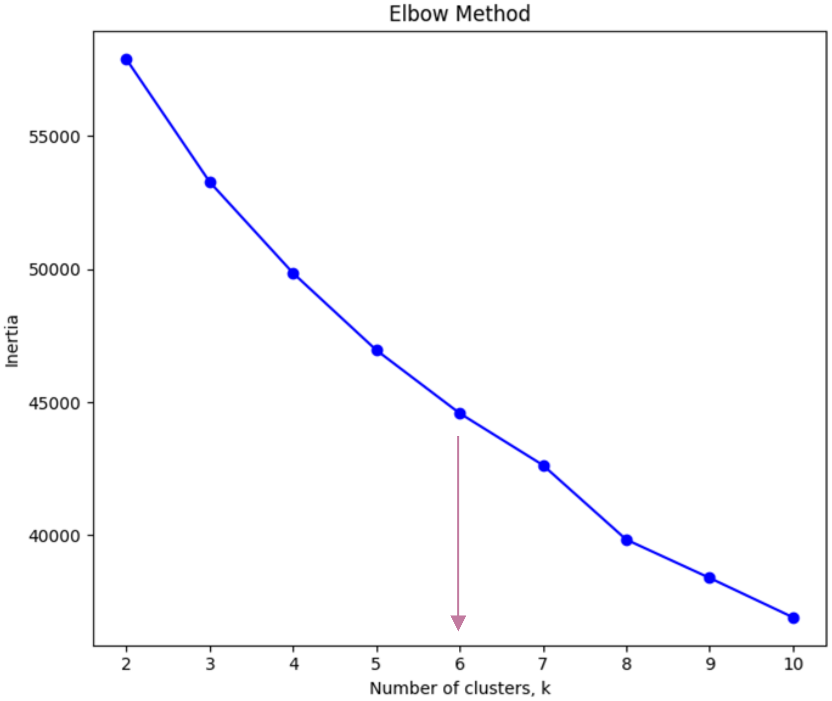
XGBoost with multiclass log loss

Accuracy: 95.39 %

Log loss: 1.5929

Since we see no significant difference between K-Means and GMM, we proceed with K-Means

Stage 3. K-Means

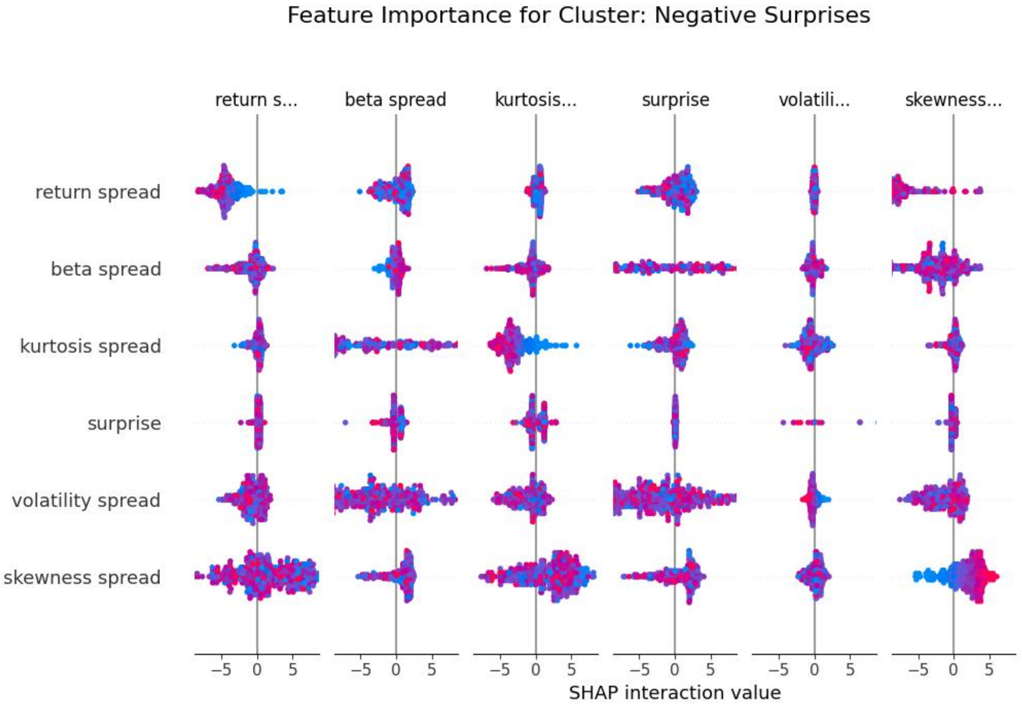


Optimal number of clusters: 6

Inertia: the sum of squared distances of points to their cluster centers (low inertia suggests compact and well defined clusters)

Elbow method: looking for the point where adding more clusters does not significantly reduce inertia

Stage 3. Summary Plot

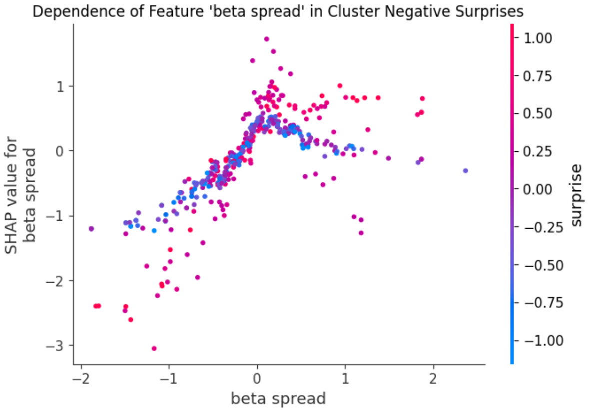


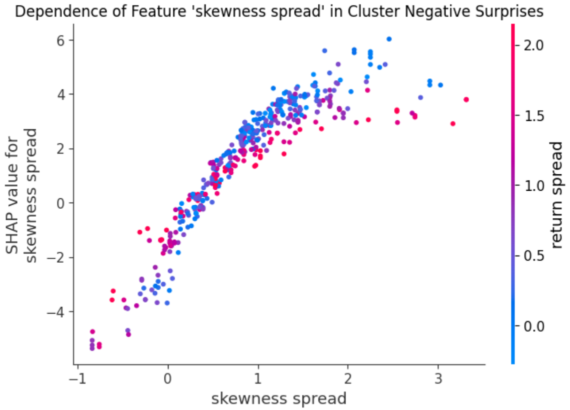
The summary plots the dependence of each pair of features on each other in a correlation matrix manner.

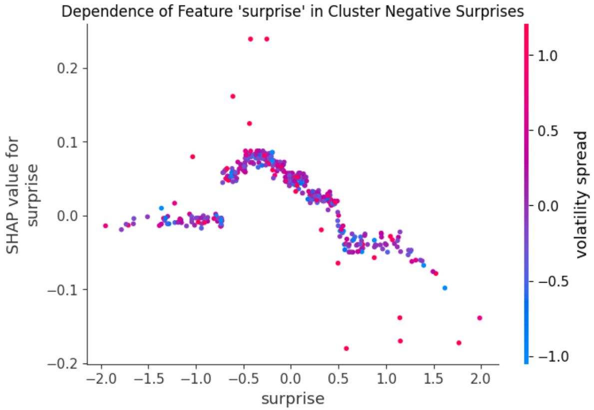
Red data points denote highly positive dependence and similarly blue data points denote highly negative dependence (inverse) based on SHAP interaction values.

The summary plot displays the interaction of features across cluster *Negative Surprises*.

Stage 3. Dependence of features on cluster assignment

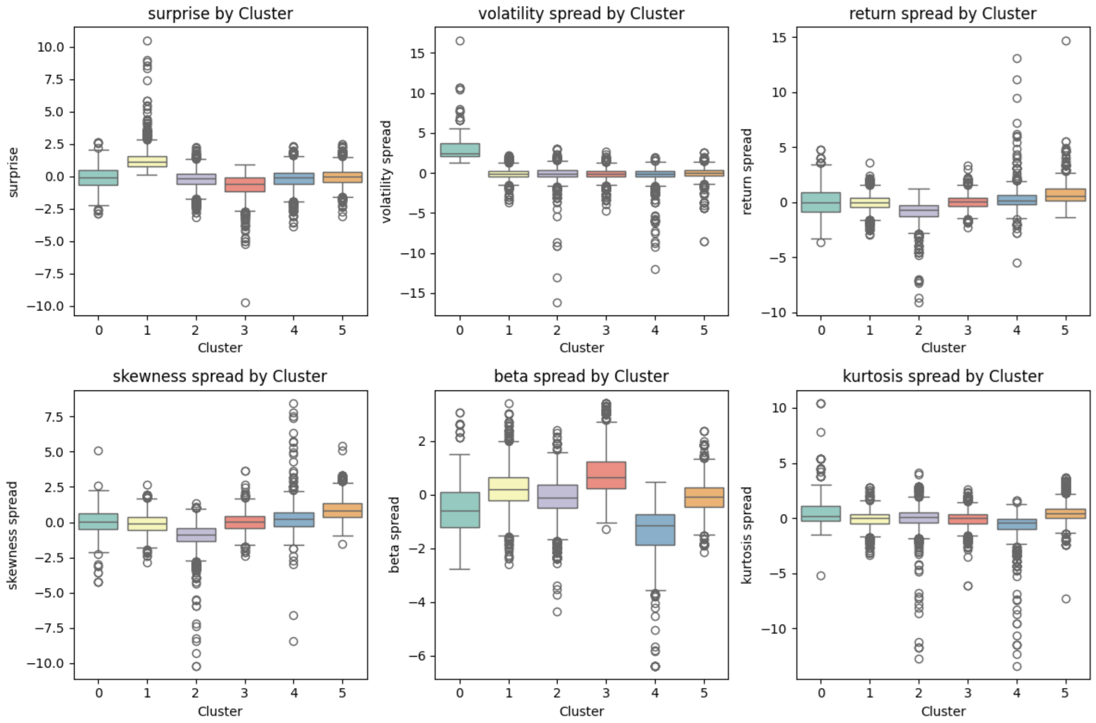




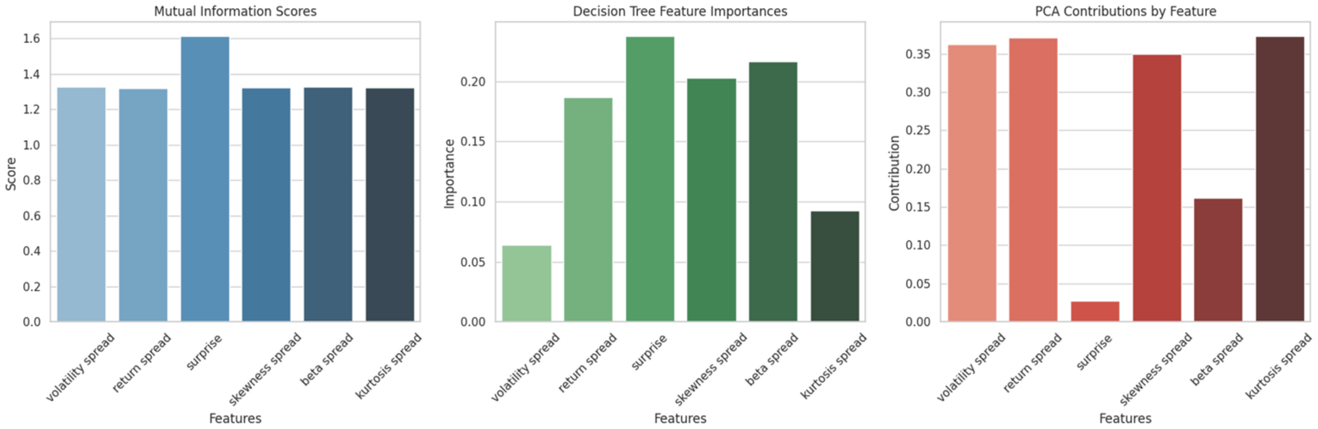


Other Results of Clustering

Overview of what the clusters look like



Feature Importance



1. Mutual Information Scores

- Introduction: Evaluates how much each feature contributes to distinguishing clusters.
- Conclusion: Surprise stands out as the most informative feature.

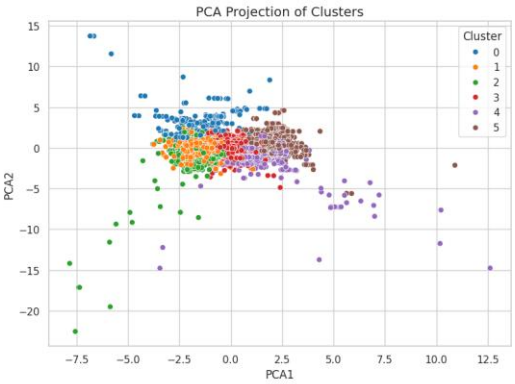
2. Decision Tree Feature Importances

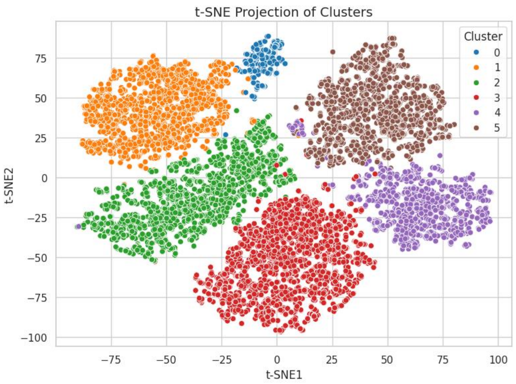
- Introduction: Assesses how effectively features split data in a decision tree.
- Conclusion: Surprise and skewness spread dominate, while volatility spread is less significant.

3. PCA Contributions by Feature

- Introduction: Measures how features contribute to overall data variance.
- Conclusion: Kurtosis spread and skewness spread are the key contributors.

PCA & t-SNE: linear & non-linear?





PCA Plot

- Key Insight
  - Clusters overlap significantly, particularly around the center, making boundaries less distinct.
  - Shows linear variance, highlighting how clusters differ along major components.
  - Best for understanding the overall variance and structure of the dataset.
- Limitation:
  - Less effective for distinguishing non-linear relationships between clusters.

t-SNE Plot

- Key Insights:
  - Clusters are well-separated, with distinct boundaries, showcasing clear grouping.
  - Captures non-linear relationships, revealing subtler separations in the data.
  - Useful for visualizing high-dimensional data in a more interpretable form.
- Limitation:
  - Does not retain global data structure; distances between clusters may not reflect true similarity.