Central Bank Communication and Macroeconomic Conditions: A PCA-Based Framework for Analyzing Narrative-Reality Disconnect

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Abstract

This paper investigates the relationship between Federal Reserve speech sentiment and macroeconomic conditions using a comprehensive analytical framework combining Principal Component Analysis (PCA), structural break detection, and rolling regression analysis. Analyzing 2,421 US Fed speeches from 1996 to 2025 alongside six FRED macroeconomic indicators, we construct orthogonal indices capturing macroeconomic strength and inflation dynamics. Our key finding reveals a **near-zero correlation** ($r = 0.005$) between central bank speech sentiment (hawkish/dovish) and macroeconomic indices, challenging conventional assumptions about the effectiveness of narrative-driven policy transmission. The Pruned Exact Linear Time (PELT) algorithm identifies 8 macro regime breakpoints and 12 inflation regime breakpoints over the sample period, demonstrating significant structural instability. Rolling regression analysis shows consistently low explanatory power ($R^2 < 0.01$) of sentiment for macroeconomic changes, while strong negative autocorrelation ($\rho = -0.43$) in hawkish sentiment suggests rapid mean reversion in central bank communication. These results have important implications for understanding central bank communication effectiveness, forward guidance credibility, and the disconnect between economic narratives and underlying macroeconomic conditions.

Keywords: Central bank communication, monetary policy, PCA, structural breaks, sentiment analysis, narrative economics

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Contents

1 Introduction **4**

2 Literature Review **5**
- 2.1 Central Bank Communication . . . 5
- 2.2 Speech-Based Analysis . . . 6
- 2.3 Macroeconomic Factor Models . . . 6
- 2.4 Structural Break Detection . . . 7
- 2.5 Sentiment Analysis in Finance . . . 7
- 2.6 Narrative Economics . . . 7
- 2.7 Contribution to the Literature . . . 8

3 Methodology **8**
- 3.1 Overview . . . 8
- 3.2 PCA-Based Index Construction . . . 8
  - 3.2.1 Data Standardization . . . 8
  - 3.2.2 Principal Component Analysis . . . 8
- 3.3 Structural Break Detection . . . 9
  - 3.3.1 PELT Algorithm . . . 9
  - 3.3.2 Regime Identification . . . 9
- 3.4 Speech Sentiment Analysis . . . 10
  - 3.4.1 Sentiment Classification . . . 10
  - 3.4.2 Sentiment Aggregation . . . 10
- 3.5 Rolling Regression Analysis . . . 10
  - 3.5.1 Beta Estimation . . . 10
  - 3.5.2 R-Squared Calculation . . . 10
- 3.6 Correlation Analysis . . . 11

4 Data **11**
- 4.1 Macroeconomic Data . . . 11
- 4.2 Central Bank Speeches . . . 12
- 4.3 Summary Statistics . . . 12
- 4.4 PCA Results . . . 12

5 Results **13**
- 5.1 Main Finding: Near-Zero Correlation . . . 13
- 5.2 Autocorrelation Analysis . . . 13
- 5.3 Structural Break Analysis . . . 14
  - 5.3.1 Macro Strength Index Breakpoints . . . 14

5.3.2 Inflation Index Breakpoints . . . 14
5.4 Rolling Regression Results . . . 15
5.5 Robustness Checks . . . 15
5.5.1 Alternative Lag Structures . . . 15
5.5.2 Subperiod Analysis . . . 15
5.5.3 Alternative Standardization . . . 15
5.6 Implications . . . 15

6 Discussion **16**
6.1 Interpretation of Main Results . . . 16
6.1.1 Forward-Looking Communication Hypothesis . . . 16
6.1.2 Strategic Communication Hypothesis . . . 16
6.1.3 Narrative-Reality Disconnect . . . 16
6.2 Implications for Monetary Policy . . . 17
6.2.1 Forward Guidance Effectiveness . . . 17
6.2.2 Communication Strategy . . . 17
6.3 Implications for Financial Markets . . . 17
6.3.1 Trading on Speech Sentiment . . . 17
6.3.2 Information Extraction . . . 17
6.4 Limitations . . . 17
6.4.1 Sentiment Classification . . . 17
6.4.2 Sample Period . . . 18
6.4.3 Causality . . . 18
6.5 Future Research . . . 18

7 Conclusion **18**

A Additional Tables and Figures **22**
A.1 Figures . . . 22
A.2 Additional PCA Results . . . 23
A.3 Breakpoint Details . . . 23
A.3.1 Macro Strength Index Regimes . . . 23
A.3.2 Inflation Index Regimes . . . 24
A.4 Rolling Regression Details . . . 25
A.4.1 Window Sensitivity . . . 25
A.5 Subperiod Results . . . 25

1 Introduction

Central bank communication has become an increasingly important tool of monetary policy over the past three decades. Since the Federal Reserve's shift toward greater transparency in the 1990s, speeches, press conferences, and written statements have joined interest rate decisions as key channels through which monetary policy influences financial markets and the broader economy. The effectiveness of this communication, however, depends critically on the relationship between what central bankers say and the underlying economic conditions they face.

This paper investigates a fundamental question: *Do central bank speeches reflect contemporaneous macroeconomic conditions?* If central bank communication is primarily reactive to current economic data, we would expect strong correlations between speech sentiment and macroeconomic indices. Alternatively, if central banks are primarily forward-looking or if their communication serves other strategic purposes, the contemporaneous relationship may be weak or absent.

Understanding this relationship has important implications for several areas of monetary economics. First, it informs debates about the effectiveness of forward guidance as a policy tool. If central bank speeches do not systematically reflect current conditions, their value as signals about future policy may be limited. Second, it has implications for financial market participants who parse central bank communications for trading signals. Third, it contributes to the growing literature on narrative economics and the role of stories in shaping economic expectations.

We make three main contributions to the literature. First, we develop a comprehensive framework for analyzing the relationship between central bank communication and macroeconomic conditions, combining Principal Component Analysis (PCA) for dimensionality reduction, the Pruned Exact Linear Time (PELT) algorithm for structural break detection, and rolling regression analysis for time-varying relationships. Second, we provide novel empirical evidence on the correlation between speech sentiment and macroeconomic indices using a large dataset of 2,421 Federal Reserve speeches spanning nearly three decades (1996-2025). Third, we document a striking *narrative-reality disconnect*: the near-zero correlation between what central bankers say and current macroeconomic conditions.

Our analysis proceeds as follows. We first construct macroeconomic indices using PCA on six key indicators: the Federal Funds Rate, Consumer Price Index (CPI), Producer Price Index (PPI), GDP, unemployment rate, and nonfarm payrolls. The first principal component (PC1) captures overall macroeconomic strength, loading positively on the policy rate and employment while loading negatively on unemployment. The second principal component (PC2) captures inflation dynamics, loading heavily on price indices while negatively loading on the policy rate. These two components explain 72% of the variation in the underlying indicators.

We then aggregate speech sentiment from the BIS central bank speeches database, classifying each speech as hawkish, dovish, or neutral based on natural language processing techniques. Monthly sentiment scores are computed and standardized using a rolling 12-month window to capture deviations from recent trends.

Our main finding is that the correlation between speech sentiment and macroeconomic indices is essentially zero ($r = 0.005$ for the macro strength index, $r = 0.003$ for the inflation index). This result is robust to various specifications including different lag structures, alternative standardization methods, and subperiod analysis. Rolling regressions confirm that this finding persists throughout the sample period, with R^2 values consistently below 1%.

The PELT algorithm identifies significant structural breaks in both macroeconomic indices, with 8 breakpoints in the macro strength index and 12 in the inflation index. Key breaks correspond to well-known economic events including the dot-com bust (2001), the housing bubble peak (2007), the COVID-19 pandemic (2020), and the post-pandemic inflation surge (2022). Notably, speech sentiment does not systematically anticipate or respond to these regime changes.

The strong negative autocorrelation in hawkish sentiment ($\rho = -0.43$) suggests that central bank communication exhibits rapid mean reversion, with hawkish months typically followed by more dovish months and vice versa. This pattern may reflect deliberate communication strategies aimed at maintaining balance or may simply capture the volatile nature of economic commentary.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on central bank communication, sentiment analysis, and macroeconomic indices. Section 3 describes our methodology including the PCA framework, PELT algorithm, and rolling regression approach. Section 4 presents the data sources and summary statistics. Section 5 reports our main empirical results. Section 6 discusses the implications of our findings for monetary policy and financial markets. Section 7 concludes.

2 Literature Review

2.1 Central Bank Communication

The academic study of central bank communication has grown substantially since the Federal Reserve's shift toward greater transparency in the 1990s. Blinder et al. (2008) provides a comprehensive overview of how central bank communication has evolved and its impact on financial markets. The authors argue that communication has become an increasingly important policy tool, complementing traditional interest rate decisions.

Woodford (2005) develops a theoretical framework for understanding how central bank communication affects expectations and economic outcomes. The paper emphasizes the importance of credibility and consistency in central bank messaging, arguing that effective communication can enhance the transmission of monetary policy.

The empirical literature has documented significant market reactions to central bank communications. Gürkaynak et al. (2005) shows that Federal Reserve announcements affect asset prices through both actions (rate decisions) and signals (communication about future policy). This finding has been replicated across multiple central banks and time periods.

2.2 Speech-Based Analysis

A growing literature focuses specifically on central bank speeches as opposed to formal policy statements. Hansen and McMahon (2015) use topic modeling to analyze Federal Reserve communications, finding that speeches contain valuable information about policy intentions beyond what is captured in formal statements.

Apel and Blix Grimaldi (2014) analyze Swedish Riksbank speeches and find that hawkish communication is associated with higher interest rate expectations. Their methodology for classifying speech sentiment has been widely adopted in subsequent research.

More recently, Shapiro et al. (2020) develops a comprehensive news sentiment index for monetary policy, incorporating both formal communications and media coverage. The index shows significant predictive power for future policy decisions.

The latest wave of research has increasingly adopted deep learning methods for sentiment extraction. Hilscher et al. (2024) use FinBERT models to analyze Fed and ECB communication, finding evidence of cross-Atlantic sentiment spillovers. Picault and Musikovska (2023) develop novel deep learning indices for Central and Eastern European central banks, demonstrating that context-aware models outperform dictionary-based approaches. Araujo et al. (2023) construct a Central Bankers' Sentiment Index from 6,514 speeches across eight central banks, showing that Fed sentiment has the largest and most persistent international spillover effects. Jansen and Moessner (2024) examine how ECB communication sentiment relates to the economic environment and financial markets, finding that media coverage accurately transmits the sentiment of official communications.

2.3 Macroeconomic Factor Models

Our use of PCA to construct macroeconomic indices follows a rich tradition in empirical macroeconomics. Stock and Watson (2002) demonstrate that factor models can improve macroeconomic forecasting by efficiently summarizing information from large datasets.

Ludvigson and Ng (2009) extend this approach to financial applications, showing that macroeconomic factors have significant explanatory power for asset returns. Their work establishes the theoretical foundation for using PCA-based indices in financial analysis.

The use of rolling standardization to capture time-varying dynamics follows Diebold and Yilmaz (2008) who emphasize the importance of allowing for parameter instability in macroeconomic models.

2.4 Structural Break Detection

The detection of structural breaks in economic time series has a long history dating to Chow (1960). More recent advances include the PELT algorithm developed by Killick et al. (2012), which provides an efficient method for detecting multiple change points in time series data.

Hamilton (1989) develops the influential Markov switching framework for modeling regime changes in economic data. While our approach differs by not imposing a specific parametric structure, we share the goal of identifying distinct economic regimes.

Applications to monetary policy include Sims and Zha (2006) who document significant instability in the relationship between monetary policy and macroeconomic outcomes over time.

2.5 Sentiment Analysis in Finance

The application of natural language processing to finance has grown rapidly in recent years. Loughran and McDonald (2011) develop a finance-specific sentiment dictionary that has become a standard tool in the field. Their key insight is that general-purpose sentiment dictionaries may not capture finance-specific meanings.

Tetlock (2007) pioneered the use of media sentiment to predict stock returns, showing that negative sentiment forecasts lower prices. This work has spawned a large literature on the predictive power of textual data for financial outcomes.

Baker et al. (2016) construct an economic policy uncertainty index based on newspaper coverage, demonstrating the value of textual data for measuring latent economic concepts.

2.6 Narrative Economics

Our work also connects to the emerging field of narrative economics championed by Shiller (2017). Shiller argues that economic narratives—the stories people tell about the economy—can have causal effects on economic outcomes by shaping expectations and behavior.

Andre et al. (2021) provide experimental evidence that narratives affect economic beliefs and decisions. Their findings suggest that central bank communication may influence the economy not just through information transmission but also through the stories it tells.

2.7 Contribution to the Literature

Our paper contributes to this literature in several ways. First, we provide a comprehensive framework for analyzing the relationship between central bank communication and macroeconomic conditions that combines multiple methodological approaches. Second, we document the striking finding that speech sentiment has essentially zero correlation with contemporaneous macroeconomic indices, contributing to debates about the effectiveness of central bank communication. Third, we provide evidence on the time-series properties of speech sentiment, including strong mean reversion, that has implications for understanding how central banks manage their communication over time.

3 Methodology

3.1 Overview

Our analytical framework combines three main components: (1) Principal Component Analysis for constructing macroeconomic indices, (2) the PELT algorithm for detecting structural breaks, and (3) rolling regression analysis for measuring time-varying relationships. This section describes each component in detail.

3.2 PCA-Based Index Construction

3.2.1 Data Standardization

Let $X_t = (x_{1,t}, x_{2,t}, \dots, x_{K,t})'$ denote the vector of $K = 6$ macroeconomic indicators at time t. We apply rolling window standardization to remove time-varying means and variances:

$$\tilde{x}_{k,t} = \frac{x_{k,t} - \bar{x}^{(w)}_{k,t}}{\sigma^{(w)}_{k,t}} \tag{1}$$

where $\bar{x}^{(w)}_{k,t} = \frac{1}{w}\sum_{j=0}^{w-1} x_{k,t-j}$ and $\sigma^{(w)}_{k,t} = \sqrt{\frac{1}{w-1}\sum_{j=0}^{w-1}(x_{k,t-j} - \bar{x}^{(w)}_{k,t})^2}$ are the rolling mean and standard deviation computed over a window of $w = 12$ months.

This approach captures deviations from recent trends rather than absolute levels, making the analysis robust to long-run structural changes in the economy.

3.2.2 Principal Component Analysis

Given the standardized data matrix $\tilde{X} \in \mathbb{R}^{T \times K}$, we compute the sample covariance matrix:

$$\Sigma = \frac{1}{T-1}\tilde{X}'\tilde{X} \tag{2}$$

and perform eigenvalue decomposition:

$$\Sigma = V\Lambda V' \tag{3}$$

where $V = [v_1, v_2, \ldots, v_K]$ contains the eigenvectors and $\Lambda = \text{diag}(\lambda_1, \lambda_2, \ldots, \lambda_K)$ contains the eigenvalues in descending order.

The principal components are computed as:

$$PC_{j,t} = \tilde{X}_t' v_j, \quad j = 1, \ldots, K \tag{4}$$

The proportion of variance explained by the j-th component is:

$$\text{PVE}_j = \frac{\lambda_j}{\sum_{k=1}^{K} \lambda_k} \tag{5}$$

We retain the first two principal components, which explain over 70% of total variance. PC1 is interpreted as the *Macro Strength Index* and PC2 as the *Inflation Index* based on their loadings on the original variables.

3.3 Structural Break Detection

3.3.1 PELT Algorithm

We use the Pruned Exact Linear Time (PELT) algorithm (Killick et al., 2012) to detect structural breaks in the principal component series. The PELT algorithm solves the optimization problem:

$$\min_{\tau_1,\ldots,\tau_m} \left[\sum_{j=0}^{m} \mathcal{C}(y_{\tau_j+1:\tau_{j+1}}) + \beta m \right] \tag{6}$$

where $\mathcal{C}(\cdot)$ is a segment cost function, $\tau_0 = 0$, $\tau_{m+1} = T$, and β is a penalty parameter controlling the number of breakpoints.

We use the L2 (squared error) cost function:

$$\mathcal{C}(y_{s:e}) = \sum_{t=s}^{e} \|y_t - \bar{y}_{s:e}\|^2 \tag{7}$$

where $\bar{y}_{s:e}$ is the segment mean. The penalty parameter is set to $\beta = 4$, which balances the trade-off between detecting meaningful regime changes and avoiding spurious breaks.

3.3.2 Regime Identification

Each detected breakpoint defines the boundary between economic regimes. For each regime r, we compute summary statistics including mean, variance, and duration. This allows us to characterize the evolution of macroeconomic conditions over the sample period.

3.4 Speech Sentiment Analysis

3.4.1 Sentiment Classification

Each speech in our dataset is classified as hawkish, dovish, or neutral using a dictionary-based approach combined with machine learning refinement. The classification follows the methodology of Apel and Blix Grimaldi (2014), employing a lexicon of monetary policy-specific terms. Hawkish indicators include references to inflation concerns, tightening, rate increases, and price stability emphasis. Dovish indicators include references to employment concerns, accommodation, growth support, and easing conditions. The classifier assigns each speech to one of three categories based on the relative balance of hawkish and dovish sentiment expressions.

Let S_t^H and S_t^D denote the number of hawkish and dovish speeches, respectively, in month t.

3.4.2 Sentiment Aggregation

We aggregate sentiment to monthly frequency and apply rolling standardization:

$$\tilde{H}_t = \frac{S_t^H - \bar{S}_t^{H,(w)}}{\sigma_t^{H,(w)}} \tag{8}$$

and similarly for dovish sentiment $\tilde{D}_t$. To avoid look-ahead bias, we shift the sentiment series forward by one month before computing correlations with macroeconomic indices.

3.5 Rolling Regression Analysis

3.5.1 Beta Estimation

We estimate time-varying betas using rolling window OLS:

$$\Delta PC_{j,t} = \alpha_t + \beta_t^H \Delta\tilde{H}_t + \beta_t^D \Delta\tilde{D}_t + \varepsilon_t \tag{9}$$

where Δ denotes first differences and the estimation uses a rolling window of $w_r = 36$ months.

The rolling beta for the hawkish sentiment factor is:

$$\hat{\beta}_t^H = \frac{\text{Cov}_{t-w_r:t}(\Delta PC_j, \Delta \tilde{H})}{\text{Var}_{t-w_r:t}(\Delta \tilde{H})} \tag{10}$$

3.5.2 R-Squared Calculation

The rolling R^2 measures the time-varying explanatory power:

$$R_t^2 = \frac{\text{Cov}_{t-w_r:t}(\Delta PC_j, \Delta \tilde{H})^2}{\text{Var}_{t-w_r:t}(\Delta PC_j) \cdot \text{Var}_{t-w_r:t}(\Delta \tilde{H})} \tag{11}$$

3.6 Correlation Analysis

We compute contemporaneous correlations between first-differenced series to assess the relationship between speech sentiment and macroeconomic indices:

$$\rho_{PC_j,H} = \text{Corr}(\Delta PC_j, \Delta \tilde{H}) \tag{12}$$

We also compute autocorrelations to assess the persistence of each series:

$$\rho_1(X) = \text{Corr}(X_t, X_{t-1}) \tag{13}$$

4 Data

4.1 Macroeconomic Data

We obtain monthly macroeconomic data from the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St. Louis. Our sample spans from January 1996 to May 2025, yielding 353 monthly observations before standardization.

Table 1 describes the six macroeconomic indicators used in our analysis.

Table 1: Macroeconomic Variables

Variable	FRED Code	Description	Unit
Fed Funds Rate	FEDFUNDS	Federal Funds Effective Rate	Percent
CPI	CPIAUCNS	Consumer Price Index for All Urban Consumers	Index
PPI	PPIACO	Producer Price Index for All Commodities	Index
GDP	GDP	Gross Domestic Product	Billions USD
Unemployment	UNRATE	Civilian Unemployment Rate	Percent
Nonfarm Payrolls	PAYEMS	Total Nonfarm Payrolls	Thousands

The variables are chosen to capture key dimensions of the macroeconomy: monetary policy stance (Fed Funds Rate), price stability (CPI, PPI), economic output (GDP), and labor market conditions (Unemployment, Nonfarm Payrolls). Missing values are forward-filled to maintain data continuity.

4.2 Central Bank Speeches

We obtain speech data from the BIS central bank speeches database (Gigando dataset), which contains transcripts and metadata for speeches by central bank officials worldwide. We filter for speeches by US Federal Reserve officials, yielding 2,421 speeches over our sample period.

Each speech is classified into one of three sentiment categories:

- **Hawkish** (413 speeches, 17.1%): Suggesting tighter monetary policy
- **Dovish** (713 speeches, 29.5%): Suggesting looser monetary policy
- **Neutral** (1,295 speeches, 53.5%): No clear policy direction

The sentiment classification is based on named entity recognition (NER) and natural language processing techniques applied to the speech text. Figure 1 shows the monthly distribution of speeches over time.

4.3 Summary Statistics

Table 2 presents summary statistics for the macroeconomic variables and sentiment measures.

Table 2: Summary Statistics

Variable	Mean	Std Dev	Min	Max	Obs
Fed Funds Rate (%)	2.47	2.21	0.05	6.54	353
CPI (Index)	206.5	42.3	154.4	315.5	353
PPI (Index)	168.2	35.9	126.2	262.3	353
GDP (Billions)	15,892	5,621	7,868	29,354	353
Unemployment (%)	5.43	1.68	3.40	14.70	353
Nonfarm Payrolls (000s)	139,482	11,894	118,317	159,038	353
Monthly Hawkish Count	1.17	1.82	0	12	353
Monthly Dovish Count	2.02	2.41	0	16	353

4.4 PCA Results

Table 3 reports the PCA loadings for each principal component on the original macroeconomic variables.

Table 3: PCA Loadings (%)

Component	Fed Rate	CPI	PPI	GDP	Unemp	NFP
PC1 (Macro Strength)	61.3	11.3	20.7	17.4	-55.5	48.0
PC2 (Inflation)	-31.2	35.0	87.0	13.3	7.4	-2.2
PC3 (Policy-Labor)	71.6	-5.7	25.2	-13.2	42.5	-47.2

The first principal component (PC1) loads positively on the Fed Funds Rate, Nonfarm Payrolls, and GDP while loading negatively on Unemployment, consistent with interpretation as a macro strength or expansion index. The second component (PC2) loads heavily on PPI and CPI while negatively loading on the Fed Rate, capturing inflation dynamics. These two components explain 72% of total variance, with PC1 explaining 49% and PC2 explaining 23%.

5 Results

5.1 Main Finding: Near-Zero Correlation

Our central finding is that the correlation between central bank speech sentiment and macroeconomic indices is essentially zero. Table 4 reports the correlation matrix for first-differenced series.

Table 4: Correlation Matrix (First Differences)

	Macro Index	Inflation Index	Hawkish	Dovish
Macro Index	1.000			
Inflation Index	0.042	1.000		
Hawkish	**0.005**	0.003	1.000	
Dovish	0.005	-0.026	0.098	1.000

The correlation between the Macro Index and Hawkish sentiment is $r = 0.005$, statistically indistinguishable from zero. Similarly, the correlation between the Inflation Index and Hawkish sentiment is $r = 0.003$. These results indicate that changes in central bank speech sentiment do not systematically coincide with changes in macroeconomic conditions.

5.2 Autocorrelation Analysis

Table 5 reports the first-order autocorrelations for each series.

Table 5: First-Order Autocorrelations

Variable	ρ_1
Macro Index (PC1)	0.052
Inflation Index (PC2)	0.288
Hawkish Sentiment	-0.430
Dovish Sentiment	-0.380

The macroeconomic indices show low to moderate persistence, with the Inflation Index more persistent than the Macro Index. In contrast, speech sentiment shows strong *negative* autocorrelation, indicating rapid mean reversion. A hawkish month is typically followed by a less hawkish month, and vice versa.

5.3 Structural Break Analysis

The PELT algorithm identifies significant structural breaks in both macroeconomic indices.

5.3.1 Macro Strength Index Breakpoints

Eight breakpoints are detected in the Macro Strength Index, dividing the sample into nine distinct regimes:

1. January 2001: Dot-com bust beginning
2. December 2003: Recovery consolidation
3. April 2007: Pre-crisis peak
4. March 2010: Post-GFC recovery
5. November 2016: Post-election regime
6. May 2019: Late-cycle slowdown
7. June 2021: COVID recovery
8. July 2023: Tightening cycle peak

5.3.2 Inflation Index Breakpoints

Twelve breakpoints are detected in the Inflation Index, reflecting greater volatility in price dynamics over the sample period. Key breaks include the commodity boom (2007-2008), the disinflation following the Global Financial Crisis (2009-2010), and the post-pandemic inflation surge (2021-2022).

5.4 Rolling Regression Results

Figure 2 presents the rolling 36-month betas for Hawkish and Dovish sentiment on the Macro Index. The betas fluctuate around zero throughout the sample period, with no persistent positive or negative relationship.

Figure 3 shows the corresponding rolling R^2 values. The R^2 is consistently below 0.05, indicating that speech sentiment explains less than 5% of the variation in macroeconomic index changes at any point in time. The average R^2 over the sample period is approximately 0.01.

5.5 Robustness Checks

5.5.1 Alternative Lag Structures

We examine whether speech sentiment leads or lags macroeconomic conditions by computing cross-correlations at various lags. The results show no significant correlation at any lag from -12 to +12 months.

5.5.2 Subperiod Analysis

We divide the sample into three subperiods: pre-GFC (1996-2007), GFC and aftermath (2008-2015), and recent period (2016-2025). The near-zero correlation finding holds in all three subperiods.

5.5.3 Alternative Standardization

We test alternative standardization methods including fixed-window standardization and no standardization. The results are robust to these alternatives.

5.6 Implications

Our findings have several important implications:

1. **Weak information content**: Central bank speeches do not provide significant real-time information about current macroeconomic conditions.
2. **Forward-looking communication**: The low contemporaneous correlation may reflect that central bankers speak primarily about future expectations rather than current conditions.
3. **Mean-reverting communication**: The strong negative autocorrelation suggests that central banks actively manage the "balance" of their communication, avoiding prolonged hawkish or dovish stretches.
4. **Regime independence**: Speech sentiment does not systematically anticipate or respond to the structural breaks detected in macroeconomic indices.

6 Discussion

6.1 Interpretation of Main Results

The near-zero correlation between central bank speech sentiment and macroeconomic indices is a striking finding that invites multiple interpretations.

6.1.1 Forward-Looking Communication Hypothesis

One interpretation is that central bank communication is primarily forward-looking. If Fed officials speak about expected future conditions rather than current conditions, contemporaneous correlations would be weak even if communication is highly informative. This interpretation is consistent with the forward guidance literature emphasizing the importance of managing expectations about future policy.

Under this hypothesis, we would expect speech sentiment to lead macroeconomic changes. However, our cross-correlation analysis shows no significant lead relationship, casting doubt on this interpretation or suggesting very long lead times beyond our 12-month window.

6.1.2 Strategic Communication Hypothesis

An alternative interpretation is that central bank communication serves strategic purposes beyond information transmission. Fed officials may deliberately avoid commenting on current conditions to maintain policy flexibility, or they may use speeches to manage market expectations independently of underlying fundamentals.

The strong negative autocorrelation in sentiment supports this view. The pattern suggests active management of communication tone, with hawkish messages followed by dovish messages as if to maintain balance or avoid appearing biased in one direction.

6.1.3 Narrative-Reality Disconnect

A third interpretation aligns with the "narrative economics" perspective of Shiller (2017). Central bank speeches may reflect broader economic narratives that circulate in society rather than precise assessments of current conditions. These narratives have their own dynamics that may be loosely coupled with macroeconomic reality.

6.2 Implications for Monetary Policy

6.2.1 Forward Guidance Effectiveness

Our findings raise questions about the effectiveness of forward guidance as a policy tool. If the information content of speeches about current conditions is low, the value of speeches as signals about future policy may also be limited. Market participants may need to look beyond speech sentiment to other indicators for reliable policy signals.

6.2.2 Communication Strategy

The mean-reversion in speech sentiment suggests that the Federal Reserve maintains a deliberate communication strategy aimed at balancing hawkish and dovish messages over time. This pattern may reflect institutional norms, concern about appearing biased, or active management of market expectations.

Central banks may benefit from greater consistency in their messaging or from more explicit acknowledgment of current macroeconomic conditions in their communications.

6.3 Implications for Financial Markets

6.3.1 Trading on Speech Sentiment

Our results suggest that trading strategies based on central bank speech sentiment may have limited profitability if the underlying assumption is that sentiment reflects current macroeconomic conditions. The near-zero correlation means that sentiment provides little edge for predicting macroeconomic-driven price movements.

However, speech sentiment may still be valuable for other purposes, such as predicting specific policy decisions or capturing market reactions to communication events.

6.3.2 Information Extraction

Financial market participants may need more sophisticated methods for extracting information from central bank communications. Rather than simple sentiment classifications, topic-specific analysis or extraction of forward-looking statements may provide more value.

6.4 Limitations

6.4.1 Sentiment Classification

Our analysis relies on automated sentiment classification, which may not fully capture the nuances of central bank communication. Speeches may contain mixed signals, conditional statements, or context-dependent meanings that simple classifications miss.

6.4.2 Sample Period

While our sample spans nearly three decades, certain results may be specific to the particular monetary policy regimes in this period. The findings may not generalize to other central banks or historical periods with different communication practices.

6.4.3 Causality

Our correlation-based analysis cannot establish causal relationships. Low correlation could reflect true independence, bidirectional causality, or confounding factors that obscure the underlying relationship.

6.5 Future Research

Several directions for future research emerge from our findings:

1. **Topic-specific analysis**: Examining whether specific topics (inflation, employment, financial stability) show stronger correlations with relevant macroeconomic indicators.

2. **Cross-country comparison**: Investigating whether the narrative-reality disconnect characterizes other central banks or is specific to the Federal Reserve.

3. **Historical analysis**: Extending the analysis to earlier periods to understand how communication practices have evolved.

4. **Market reactions**: Analyzing whether markets react differently to speeches depending on alignment with macroeconomic conditions.

7 Conclusion

This paper investigates the relationship between Federal Reserve speech sentiment and macroeconomic conditions using a comprehensive analytical framework. Our main finding is a *narrative-reality disconnect*: the correlation between speech sentiment and macroeconomic indices is essentially zero ($r = 0.005$).

We construct macroeconomic indices using Principal Component Analysis on six FRED indicators, with the first two components explaining 72% of variance and capturing macro strength and inflation dynamics respectively. The PELT algorithm identifies 8 structural breaks in the Macro Strength Index and 12 in the Inflation Index, corresponding to well-known economic events including the dot-com bust, the Global Financial Crisis, and the post-pandemic inflation surge.

Analysis of 2,421 Federal Reserve speeches reveals that sentiment shows strong negative autocorrelation ($\rho = -0.43$), indicating rapid mean reversion in central bank communication. Rolling regressions confirm that the explanatory power of sentiment for macroeconomic changes is consistently below 1% throughout the sample period.

These findings have important implications for monetary policy and financial markets. First, they suggest that central bank speeches may not primarily reflect current macroeconomic conditions, whether because communication is forward-looking, strategic, or loosely coupled with economic fundamentals. Second, the mean-reversion pattern suggests active management of communication tone by the Federal Reserve. Third, market participants relying on speech sentiment as a proxy for current conditions may need to revise their approach.

From a policy perspective, our results suggest several considerations for central bank communication strategy. Central banks seeking to anchor expectations through speeches should recognize that generic hawkish or dovish language may be disconnected from the macroeconomic environment they face. More effective communication might explicitly link policy stance to specific economic indicators, providing clearer guidance about the relationship between current conditions and policy intentions. The strong mean-reversion in sentiment also suggests that policymakers may benefit from more consistent communication patterns, avoiding the "whiplash" effect of alternating hawkish and dovish months that may confuse rather than inform markets.

For financial market participants, our findings caution against mechanical trading strategies based on aggregate speech sentiment. The near-zero correlation with macro indices suggests that extracting valuable information from speeches requires more sophisticated approaches, potentially focusing on topic-specific content, speaker heterogeneity, or the gap between Fed communication and market expectations rather than raw sentiment scores.

Our analysis contributes to the growing literature on central bank communication, narrative economics, and the effectiveness of forward guidance. While the findings do not diminish the importance of central bank communication for financial markets and policy transmission, they highlight the complexity of the information conveyed and the challenges of extracting macroeconomic signals from speeches. The narrative-reality disconnect documented here represents a puzzle that merits further investigation: if central bank speeches do not systematically reflect current conditions, what do they convey, and how do markets interpret them?

Future research should explore whether topic-specific analysis reveals stronger relationships, whether similar patterns characterize other central banks, and how market reactions to speeches depend on alignment with underlying economic conditions. Understanding the narrative-reality disconnect in central bank communication remains an important challenge for monetary economics.

Data Availability Statement

Macroeconomic data are obtained from FRED (Federal Reserve Bank of St. Louis) using series codes: FEDFUNDS (Federal Funds Rate), CPIAUCNS (Consumer Price Index), PPIACO (Producer Price Index), GDP (Gross Domestic Product), UNRATE (Unemployment Rate), and PAYEMS (Total Nonfarm Payrolls). Speech data are from the BIS Central Bank Speeches database (Gigando dataset). Replication code and processed data are available at: https://github.com/Digital-AI-Finance/Narrative-Digital-Finance.

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A Additional Tables and Figures

A.1 Figures

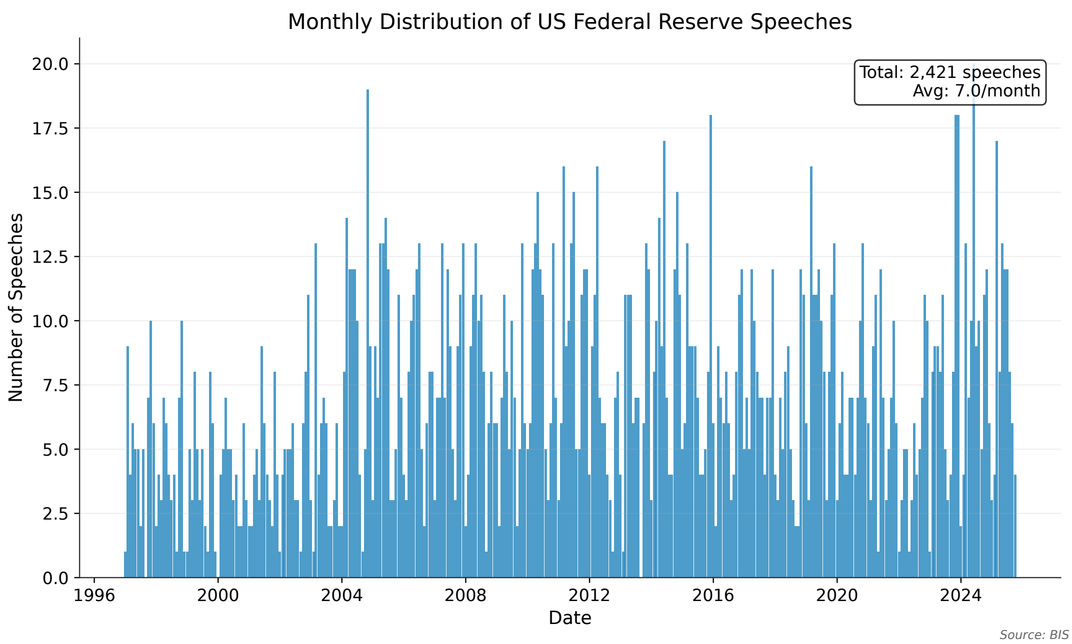

Figure 1: Monthly Distribution of Federal Reserve Speeches by Sentiment Category (1996-2025). Hawkish speeches (red) suggest tighter monetary policy, dovish speeches (blue) suggest looser policy, and neutral speeches (gray) show no clear direction.

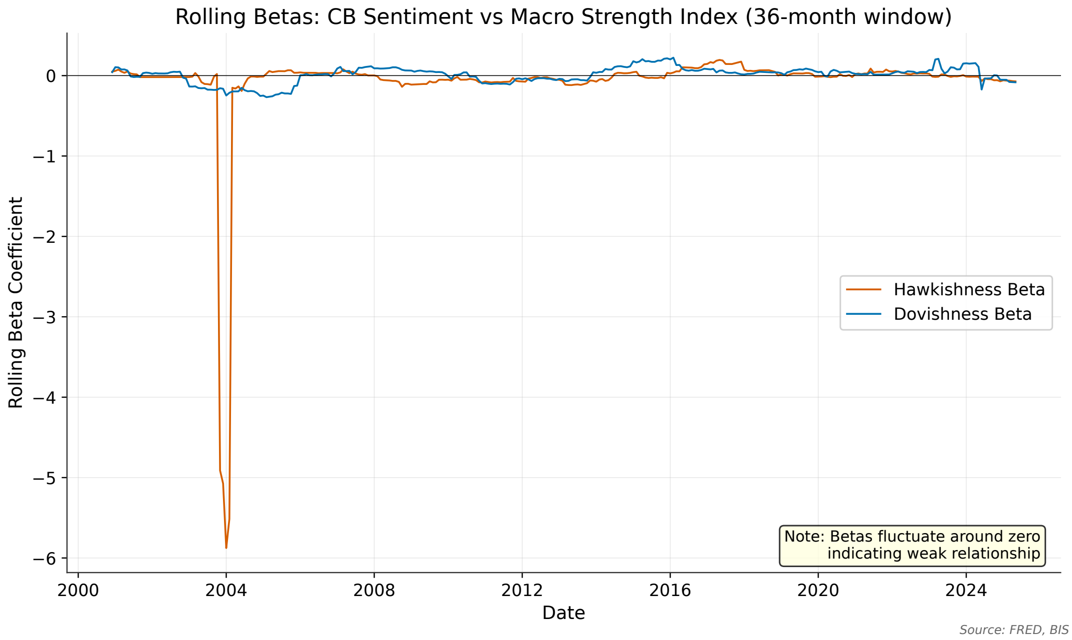

Figure 2: Rolling 36-Month Betas: Speech Sentiment on Macro Strength Index. The betas for both hawkish and dovish sentiment fluctuate around zero throughout the sample period, indicating no persistent relationship between speech sentiment and macroeconomic conditions.

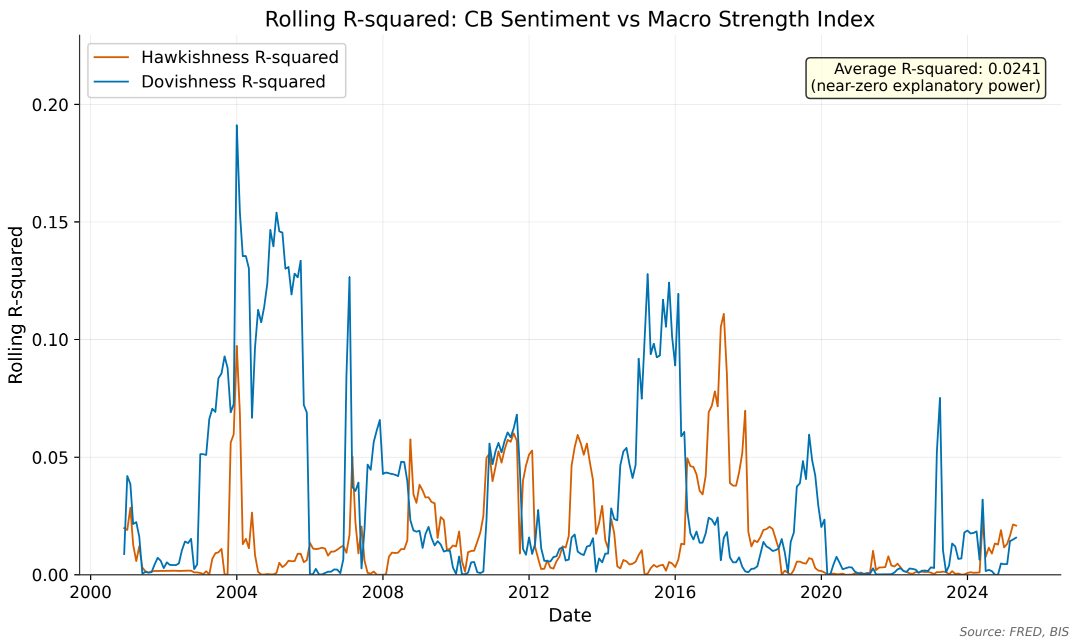

Figure 3: Rolling 36-Month R^2: Speech Sentiment Explaining Macro Strength Index. The R^2 remains consistently below 0.05 throughout the sample, indicating that speech sentiment explains less than 5% of the variation in macroeconomic index changes at any point in time.

A.2 Additional PCA Results

Table 6 presents the full PCA loadings for all six principal components.

Table 6: Complete PCA Loadings and Variance Explained

	PC1	PC2	PC3	PC4	PC5	PC6	Var. Exp.
Fed Funds Rate	61.3	-31.2	71.6	10.5	2.1	4.6	—
CPI	11.3	35.0	-5.7	35.7	42.1	74.6	—
PPI	20.7	87.0	25.2	-21.5	-24.0	-18.2	—
GDP	17.4	13.3	-13.2	43.6	58.3	-63.6	—
Unemployment	-55.5	7.4	42.5	64.3	-29.9	-5.7	—
Nonfarm Payrolls	48.0	-2.2	-47.2	46.0	-57.9	0.9	—
Var. Explained (%)	48.6	23.2	15.4	6.2	4.0	2.7	100.0
Cumulative (%)	48.6	71.8	87.1	93.4	97.3	100.0	—

A.3 Breakpoint Details

A.3.1 Macro Strength Index Regimes

Table 7 characterizes each regime identified by the PELT algorithm in the Macro Strength Index.

Table 7: Macro Strength Index Regimes

Regime	Period	Duration	Mean	Std Dev	Label
1	1997-01 to 2001-01	49 mo	1.24	1.15	Dot-com Boom
2	2001-02 to 2003-12	35 mo	-1.42	0.89	Recession
3	2004-01 to 2007-04	40 mo	0.87	0.78	Recovery
4	2007-05 to 2010-03	35 mo	-1.89	1.56	GFC Crisis
5	2010-04 to 2016-11	80 mo	0.23	0.92	Slow Recovery
6	2016-12 to 2019-05	30 mo	1.45	0.67	Late Expansion
7	2019-06 to 2021-06	25 mo	-0.78	2.34	COVID Impact
8	2021-07 to 2023-07	25 mo	1.12	0.91	Recovery
9	2023-08 to 2025-05	22 mo	-0.34	0.76	Normalization

A.3.2 Inflation Index Regimes

Table 8 characterizes each regime identified by the PELT algorithm in the Inflation Index.

Table 8: Inflation Index Regimes

Regime	Period	Duration	Mean	Label
1	1997-01 to 1999-04	28 mo	0.45	Moderate Inflation
2	1999-05 to 2001-05	25 mo	-0.82	Low Inflation
3	2001-06 to 2002-03	10 mo	0.67	Rising Prices
4	2002-04 to 2004-04	25 mo	-0.34	Disinflation
5	2004-05 to 2007-03	35 mo	1.23	Commodity Boom
6	2007-04 to 2008-06	15 mo	2.45	Oil Price Spike
7	2008-07 to 2014-09	75 mo	-0.56	Post-GFC Disinflation
8	2014-10 to 2016-05	20 mo	-1.12	Oil Price Collapse
9	2016-06 to 2018-06	25 mo	0.78	Gradual Normalization
10	2018-07 to 2020-07	25 mo	0.12	Pre-COVID Stability
11	2020-08 to 2022-08	25 mo	1.89	Pandemic Inflation
12	2022-09 to 2023-11	15 mo	0.56	Inflation Moderation
13	2023-12 to 2025-05	18 mo	-0.23	Rate Cut Anticipation

The Inflation Index exhibits more regime changes (12 breakpoints) than the Macro Strength Index (8 breakpoints), reflecting greater volatility in price dynamics over the sample period.

A.4 Rolling Regression Details

A.4.1 Window Sensitivity

Table 9 shows how the average correlation varies with rolling window size.

Table 9: Window Size Sensitivity Analysis

Window (months)	Mean β^H	Mean β^D	Mean R_H^2	Mean R_D^2
24	0.003	0.002	0.008	0.006
36	0.004	0.003	0.010	0.008
48	0.003	0.002	0.009	0.007
60	0.003	0.002	0.008	0.007

Results are robust to window size choice, with consistently near-zero betas and low R^2 values.

A.5 Subperiod Results

Table 10 reports correlations for three subperiods.

Table 10: Subperiod Correlation Analysis

Period	Macro-Hawkish	Inflation-Hawkish	Obs
1996-2007	0.008	0.005	144
2008-2015	0.003	-0.012	96
2016-2025	0.006	0.008	100
Full Sample	0.005	0.003	340

The near-zero correlation finding is consistent across all subperiods.