BANK OF UGANDA
Working Paper Series

Working Paper No. 06/2026

Sentiment Analysis and Financial Stability in Uganda

Phillipa Mukasa and Joseph Ssentamu Nyanzi

June 2026

Sentiment Analysis and Financial Stability in Uganda

Prepared by

Phillipa MUKASA[1] Joseph Ssentamu NYANZI[2]

ABSTRACT

This study examines whether sentiment extracted from economic and financial texts can help explain and anticipate changes in Uganda's macro-financial environment over the period 2019–2025. Using FinBERT, a transformer-based natural language processing model trained for financial language, the paper constructs two sentiment indices: a Public Sentiment Index (PSI) from local media coverage and a Policy Sentiment Index (PoSI) from Bank of Uganda and other financial regulators' communications. The indices are evaluated against key indicators of banking sector soundness (Financial Soundness Indicators—FSIs), selected monetary policy variables, and a composite measure of aggregate macro-financial vulnerabilities (Systemic Risk Index—SRI). Empirical analysis applies correlation diagnostics, predictive regressions, lead–lag (Granger-type) tests, and comparative forecast evaluation to assess whether sentiment provides incremental predictive information relative to standard macro-financial models. The results indicate that PSI co-moves more closely with banking sector conditions, particularly liquidity, asset quality, and systemic risk dynamics, while PoSI provides forward-looking signals that precede adjustments in the policy rate. Forecast comparison results suggest that sentiment indicators can improve predictive performance for selected macro-financial variables. These relationships are interpreted as predictive and informational rather than causal. Overall, the findings suggest that sentiment analytics can complement existing surveillance tools by providing a timelier, expectations-based signal of emerging vulnerabilities and policy direction. Operationally, PSI and PoSI could be integrated into routine financial stability monitoring dashboards and early warning frameworks to support risk identification, communication assessment, and policy calibration.

Keywords: Macro financial, Sentiment Analysis, FinBERT, Financial Stability, Public Sentiment, Policy Communication, Natural Language Processing, Systemic Risk, Financial Soundness Indicators, Macroprudential Policy, Monetary Policy, Correlation

JEL: G210, G280, E5

[1] Financial Stability Department, Bank of Uganda, Kampala, Uganda, pmukasa@bou.or.ug
[2] Financial Stability Department, Bank of Uganda, Kampala, Uganda, jssentamu@bou.or.ug

1. INTRODUCTION

The soundness of a financial system is shaped by the interaction between macroeconomic conditions, market behavior, and the resilience of financial institutions (Saal, Lindgren, & Garcia, 1996). In developing economies such as Uganda, this interaction has become increasingly complex due to financial innovation, growing digitization, and faster information transmission through digital and traditional media. While Uganda's financial system remains largely bank-dominated, with banks accounting for about 55 percent of the financial system, the rapid expansion of digital financial services has increased the speed at which narratives, confidence, and expectations can influence economic decisions (Bank of Uganda, 2025). Between September 2024 and September 2025, electronic money transaction value increased by 28.4 percent while transaction volumes rose by 19.6, alongside growth in electronic wallets and agent networks (Bank of Uganda, 2025). These developments suggest that sentiment and information flows can now affect economic activity and financial conditions more rapidly than in earlier periods.

Traditional macro financial indicators, such as Gross Domestic Product (GDP) growth, inflation, credit aggregates, and prudential ratios, remain essential for monitoring financial stability, but they may not fully capture rapid changes in confidence, risk perceptions, and market narratives that often emerge during periods of stress or optimism (Shiller, 2017; Haldane & May, 2018). Narrative-driven shifts can affect asset prices, funding conditions, and liquidity dynamics before they are reflected in balance-sheet-based indicators (Naidoo, Moores-Pitt, & Muzindutsi, 2025). Consequently, central banks and researchers increasingly use text-based sentiment measures to complement conventional surveillance frameworks and strengthen early warning capacity.

The growing relevance of sentiment is consistent with behavioral finance and narrative economics, which emphasize that macro financial outcomes depend not only on fundamentals but also on shared beliefs and stories that shape expectations and behavior (Shiller, 2019). Empirical evidence from advanced economies shows that sentiment extracted from news and policy communications contains useful information for credit cycles, asset volatility, and systemic risk dynamics (Kräussl & Mirgorodskaya, 2013; Audrino, Janning, & Sigrist, 2024). However, such sentiment metrics remain relatively underutilized in frontier and developing markets, where structural constraints, limited market depth, and data challenges weaken traditional early warning systems (IMF, 2018; Luong, Nguyen, & Pham, 2024). This gap is particularly relevant for Uganda and similar shallow markets, where expectations and policy communication may play an outsized role in influencing financial conditions.

This study is situated within the predictive and surveillance-oriented strand of literature rather than the structural macro-financial modeling literature. The objective is not to estimate causal transmission mechanisms between sentiment and macro-financial outcomes, but to assess whether sentiment contains incremental information that can support monitoring and early warning. In this context, sentiment indicators are evaluated based on their ability to co-move with and anticipate macro-financial developments, consistent with approaches used in applied macro-financial forecasting and policy surveillance

The study contributes to closing this gap by developing and evaluating macro financial sentiment indicators for Uganda using Financial Bidirectional Encoder Representations from Transformers (FINBERT), a transformer-based natural language processing model designed for financial text (Araci, 2019). The paper constructs two complementary indices: a Public Sentiment Index (PSI) derived from local media narratives and a Policy Sentiment Index (PoSI) derived from Bank of Uganda communications. The novelty of this approach lies in combining public and policy sentiment within a single empirical framework and assessing their informational content against banking sector soundness indicators, monetary policy variables, and a composite systemic risk measure.

The study addresses three research questions.

RQ1: Does public sentiment co-move with and/or lead changes in banking sector conditions and systemic risk?

RQ2: Does policy sentiment provide forward-looking signals that anticipate monetary policy actions?

RQ3: Do public and policy sentiment indices provide complementary information that can strengthen financial stability surveillance in Uganda?

Anchored in behavioral and narrative theories, the analysis treats sentiment as both a reflection of prevailing macro financial conditions and a potential transmission channel through which expectations influence financial outcomes (Shiller, 2017).

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature, Section 3 outlines the data and methodology, Section 4 presents the empirical results and discussion, and Section 5 concludes with policy implications.

2. LITERATURE REVIEW

Sentiment influences macro financial outcomes by shaping expectations, confidence, and perceived risk, which in turn affect consumption, investment, portfolio allocation, and financial intermediation decisions. In this context, **public sentiment** refers to the prevailing tone in media narratives that reflects how households, firms, and financial market participants interpret economic and financial developments. **Policy sentiment** refers to the tone and content of official communications by monetary and regulatory authorities that are intended to guide expectations and signal policy direction. Narrative economics posits that shared stories and collective moods can spread through populations and influence economic decisions in ways that are not fully captured by traditional indicators (Shiller, 2017; Shiller, 2019). Complementary behavioral finance research shows that sentiment-driven expectations can amplify financial cycles and contribute to deviations from rational benchmarks, particularly during stress episodes (Baker, Bloom, & Davis, 2016). However, sentiment indicators are inherently imperfect proxies for underlying expectations: narratives may reflect media incentives, subjective reporting choices, and measurement noise, especially during market upheavals. These limitations underline the importance of interpreting sentiment measures as informative signals rather than direct measures of fundamentals, and they motivate robust methodological choices that account for bias, contextual nuance, and salience effects.

The measurement of sentiment has evolved from early dictionary-based approaches to advanced machine-learning models that capture context and nuance more effectively. Traditional lexicon-based methods, including general-purpose dictionaries and finance-specific lexicons (e.g., Loughran and McDonald, 2011), improved the classification of financial text but remain constrained by their inability to capture complex narrative structure, negation, and contextual dependencies. Transformer-based language models address these challenges by generating contextual embeddings that recognize semantic relations across entire texts. Bidirectional Encoder Representations from Transformers (BERT) introduced attention mechanisms that improve representation learning for complex language tasks (Devlin et al., 2019), and Financial Bidirectional Encoder Representations from Transformers (FINBERT)[3] adapts this architecture specifically for financial text. FinBERT's contextual understanding of finance terminology makes it a useful tool for analyzing both formal policy

[3] A key methodological caveat is domain transfer: FinBERT is trained largely on advanced-economy financial text, and tone expressions in emerging-market reporting and policy communication may differ in phrasing, institutional context, and local idioms. As a result, FinBERT-based sentiment should be interpreted as an informative signal rather than a literal measure of "true" beliefs. We mitigate these risks by using multiple sources, aggregating sentiment to quarterly frequency for stability, and conducting robustness checks that distinguish tone from reporting intensity (salience/volume).

documents and media narratives. Nonetheless, transformer models entail trade-offs: they can suffer from domain-transfer limitations when applied outside their pre-training corpora, and their output may be influenced by selection bias in news coverage or by difficulty in distinguishing tone from reporting intensity. These methodological challenges are active areas of research, with recent work highlighting issues of bias, interpretability, and robustness in transformer-based sentiment analysis as well as the utility of hybrid or complementary methods such as topic models, supervised fine-tuning on local corpora, and lexicon–model ensembles (Fatouros et al., 2023; Roos, 2024). The choice of FinBERT in this paper reflects its adaptation to financial language and its ability to provide consistent scoring across heterogeneous text sources, while robustness checks and alternative specifications help ensure the reliability of the findings.

A substantial empirical literature documents the predictive content of sentiment extracted from text for financial conditions, but the evidence varies by analytical focus, horizon, and outcome of interest. In financial markets, negative news has been shown to forecast near-term asset price movements and shifts in risk appetite, consistent with sentiment-driven trading behavior (Tetlock, 2007). Research on macroeconomic uncertainty and news-based indices further shows that spikes in negative narrative indicators coincide with weaker investment and slower employment growth, revealing linkages between narrative sentiment and real economic outcomes (Baker, Bloom, & Davis, 2016; Ahir, Bloom, & Furceri, 2022). Other studies extend these insights to broader financial conditions, documenting associations between news sentiment and interest rate expectations, credit spreads, and volatility measures (Audrino, Janning, & Sigrist, 2024). Central bank communication has also been recognized as a key source of information for financial markets and the macroeconomy, with evidence that the tone of policy statements and minutes influences yield curves, risk premia, and expectations beyond the effects of announced policy rates (Blinder et al., 2008; Hansen & McMahon, 2016; Tadle, 2021). These findings collectively support the use of both public sentiment and policy sentiment measures, but they also point to heterogeneity in effects across short-term market dynamics versus slower-moving systemic outcomes.

Sentiment may affect financial stability through multiple transmission channels including liquidity conditions, credit supply, risk appetite, and exchange rate pressures. In advanced markets, elevated narrative uncertainty can influence capital flows and broad financial conditions, contributing to shifts in funding costs and asset prices (Bloom, 2014; Caldara et al., 2022). Within banking systems, negative sentiment, whether in media narratives or policy communication, can encourage institutions to adopt precautionary behavior such as liquidity hoarding, wider interbank spreads, and tighter credit supply, thereby amplifying stress in credit and funding markets. In emerging and frontier markets such as Uganda, structural features including market thinness, limited liquidity, and information asymmetries can heighten the impact of sentiment on financial conditions. In such environments, the credit and liquidity channels are expected to be particularly salient, while channels related to equity markets may be less pronounced relative to advanced economies. Moreover, official communication may play a stronger role in anchoring expectations where policy credibility and information dissemination mechanisms are evolving.

Despite the expanding global evidence, sentiment-based surveillance tools remain underutilized in frontier and developing markets, where early-warning systems are constrained by low-frequency data, thin markets, and structural limitations (IMF, 2018; Luong, Nguyen, & Pham, 2024). In Uganda, the rapid expansion of digital news platforms and electronic financial services has increased the volume and speed of information diffusion, enhancing the potential influence of narratives on expectations and financial conditions (Mugisha, 2025). However, existing studies typically focus on either public/news sentiment or central bank communication in isolation and are largely concentrated in advanced economies with deeper financial markets.

This paper contributes to the literature by bridging these strands through a unified empirical framework that jointly evaluates public sentiment and policy sentiment within a single macro-financial surveillance context. In doing so, it allows for a direct comparison of their informational roles across key macro financial transmission channels, including banking sector soundness, liquidity conditions, and policy expectations. In addition, the study extends the application of transformer-based sentiment analysis to a frontier market setting, where structural characteristics, such as bank dominance and limited market depth, may amplify the role of narratives. The analysis further emphasizes the practical relevance of sentiment indicators by evaluating their informational and predictive content for variables directly used in central bank financial stability monitoring, including Financial Soundness Indicators and the Systemic Risk Index.

3. METHODOLOGY

3.1 Research Design and Analytical Framework

This study applies a dual-stream text analytics design that quantifies sentiment from (i) public economic and financial news and (ii) official policy communication to assess their informational content for Uganda's macro financial conditions. Sentiment is extracted using FinBERT, a transformer-based model fine-tuned for financial text (Araci, 2019). The analysis focuses on timing and informational content, that is, whether sentiment co-moves with or systematically leads/lags macro financial indicators, rather than structural causality. Accordingly, correlation diagnostics, lead–lag analysis, and Granger-type predictive regressions are used to examine whether sentiment contains incremental predictive information beyond the history of macro financial variables (Granger, 1969; Hamilton, 1994; Stock & Watson, 2016).

Two indices are constructed. The Public Sentiment Index (PSI) captures the tone of market narratives in third-party media, while the Policy Sentiment Index (PoSI) captures the tone embedded in official communications from the Bank of Uganda (BoU) and the Ministry of Finance, Planning and Economic Development (MoFPED). These indices are then compared across macro financial transmission channels, including banking-sector soundness, liquidity conditions, interest rates, exchange rates, inflation, and real activity.

3.1.1 Public Sentiment Index

The PSI is derived from economic and financial news articles published by major Ugandan media outlets. It is intended to reflect public-facing narratives that may influence expectations and risk perceptions. News-based sentiment has been shown to contain information about financial market conditions and uncertainty (Ahir, Bloom, & Furceri, 2022; Baker, Bloom, & Davis, 2016; Tetlock, 2007).

3.1.2 Policy Sentiment Index

While the Bank of Uganda (BoU) is the primary authority responsible for monetary and macroprudential policy in Uganda, the Ministry of Finance, Planning and Economic Development (MoFPED) shapes fiscal stance and broader macroeconomic policy signals that also influence expectations. Official fiscal statements, budget frameworks, and macroeconomic updates issued by MoFPED are closely monitored by markets and the public and often interact with monetary policy narratives. We therefore include key MoFPED publications in the Policy Sentiment Corpus to capture the broader spectrum of official policy communication that may affect market perceptions and macro financial dynamics Prior work shows that the tone of official communication can influence expectations and financial conditions beyond policy rate announcements (Blinder et al., 2008; Hansen & McMahon, 2016).

3.1.3 Overview of the Empirical Workflow

The analysis proceeds in four steps. First, two text corpora are assembled and cleaned. Second, sentiment scores are computed using FinBERT and aggregated to comparable time frequencies. Third, sentiment indices are aligned with macro financial indicators. Fourth, empirical evaluation is conducted through correlation/lead–lag diagnostics, robustness checks, and predictive regressions.

3.2 Data Sources and Processing

Two textual datasets are constructed: the Public Sentiment Corpus (PSC) and the Policy Sentiment Corpus (PoSC). The PSC captures media narratives, while the PoSC captures official communication. Together, they provide complementary measures of discourse relevant to macro financial developments.

3.2.1 Public Sentiment Corpus

The PSC consists of digital economic and financial news published between 2019 and 2025 from independent third-party media sources, including Daily Monitor, New Vision, Nile Post, and PML Daily. Articles are collected using web scraping tools (e.g., BeautifulSoup and newspaper3k) and filtered using macro financial keywords (e.g., inflation, exchange rate, credit, monetary policy, liquidity, bank performance). Each article is time-stamped and stored as plain text with metadata (headline, source, publication date).

A key challenge in news-based sentiment is the potential conflation of **tone** with **salience**: periods of stress may generate more negative coverage, which may influence sentiment even if tone merely reflects increased attention rather than a change in underlying expectations (Loughran & McDonald, 2011). To address this concern, the study constructs a news-volume (salience) index and evaluates whether sentiment contains information beyond reporting intensity (Ahir et al., 2022; Nyman et al., 2021).

As shown in Table 1, the public sentiment corpus comprises 4,286 articles from major Ugandan media outlets over the period 2019–2025, providing continuous temporal coverage and a stable monthly flow of text. The median article length of approximately 350–500 words and the total volume of roughly 2.1 million processed tokens are sufficient for FinBERT to generate reliable context-sensitive sentiment estimates. Using multiple independent outlets also reduces source-specific framing bias and improves the representativeness of public-facing macro financial narratives.

3.2.2 Policy Sentiment Corpus

The PoSC comprises official publications issued between 2019 and 2025 by BoU and MoFPED. BoU documents include Monetary Policy Statements and financial stability-related publications. MoFPED documents include macroeconomic and fiscal policy reports and statements that communicate policy positions to the public and markets. These sources jointly represent the official policy narrative shaping expectations in Uganda.

Reports are converted to plain text and cleaned to remove non-text elements (tables, charts, repeated headers, and boilerplate). Sentiment is generated at the document level and timestamped by release date. Given that official publications occur at discrete intervals, sentimental values are mapped to release dates and interpolated to a monthly series using a stepwise carry-forward approach. Table 2 summarizes PoSC coverage and text volume.

Table 2 shows that the policy sentiment corpus consists of 140 major publications issued by the Bank of Uganda and the Ministry of Finance, Planning and Economic Development between 2019 and 2025, yielding approximately 980,000 processed tokens. The length and structured nature of these documents are well suited for FinBERT-based sentiment extraction. Because policy communication occurs at discrete intervals, sentiment scores are mapped to release dates and carried forward until the next publication, reflecting how official guidance remains the prevailing narrative until updated.

Table 1: Public Sentiment Corpus (PSC) Summary, 2019 – 2025

Attribute	**Description**
Coverage period	2019–2025
Total documents	4,286 news articles
Sources	Daily Monitor, New Vision, Next Media (Nile Post), PML Daily and NTV

Average articles per month	50 – 70
Median article length	350 – 500 words
Total tokens processed	Approx. 2.1 million
Filtering criteria	Articles with keywords such as inflation, exchange rate, credit, interest rates, financial stability, liquidity, bank performance
Exclusions	Policy statements, speeches, BOU publications (kept strictly for PoSC)
Output frequency	Daily, Monthly, Quarterly sentiment index

Source: Authors' compilation

Table 2:Policy Sentiment Corpus (PoSC) Summary, 2019–2025

Attribute	**Description**
Coverage period	2019 – 2025
Total BOU and MOFPED publications	140 major reports (MPS, QFSR, Monthly Reports, Annual Reports)
Supplementary regulators	CMA, IRA, FIA (limited frequency)
Document structure	8 – 20 pages each (tables removed)
Total tokens processed	Approx. 980,000
Output frequency	Quarterly (stepwise interpolation between release dates)
Rationale	Captures official tone and forward guidance from BOU

Source: Authors' compilation

3.2.3 Integration of Public and Policy Corpora

The PSC reflects higher-frequency market narratives, while the PoSC reflects deliberate policy communication that is updated at discrete publication dates. Both series are harmonized into comparable time series and aligned with macro financial indicators to evaluate co-movement and lead–lag relationships.

3.2.4 Macro financial Indicators

Sentiment indices are evaluated against macro financial indicators capturing banking-sector soundness, liquidity, monetary policy transmission, price stability, external conditions, and real activity. Indicators are sourced primarily from BoU and UBOS and include Financial Soundness Indicators (FSIs), the 91-day Treasury bill yield, the 7-day interbank rate, the Central Bank Rate

(CBR), the USD/UGX mid-rate, core inflation, and GDP at market prices. The indices are also compared with BoU's Systemic Risk Index (SRI) as an additional validation benchmark. Table 3 lists the indicators, sources, frequency, and transformations.

To ensure coherent inference, variables are aligned to a common frequency, with monthly specifications used where data permit and quarterly aggregation applied for balance-sheet-based indicators such as FSIs. Where needed, higher-frequency series are aggregated (e.g., daily to quarterly averages) and lower-frequency series are carried forward or matched to reporting quarters. All variables are standardized using z-scores to improve comparability across units and scales.

Table 3:Summary of Macroprudential Indicators

Indicator	Description	Source	Frequency	Transformation
NPL ratio	Non-performing loans to gross loans	BOU FSIs Data	Quarterly	z-score
Liquid assets ratio	Liquid assets to deposits/short-term liabilities	BOU FSIs	Quarterly	z-score
CAR	Capital adequacy ratio	BOU FSIs	Quarterly	z-score
ROA/ROE	Profitability indicators	BOU FSIs	Quarterly	z-score
Insider loans ratio	Related party exposure	BOU FSIs	Quarterly	z-score
Interbank rate	7-day money market rate	BOU	Daily to Quarterly	Quarterly average
91-day T-bill	Short-term yield	BOU	Monthly to Quarterly	Quarterly average
CBR	Policy interest rate	BOU	Bi-monthly to Quarterly	Stepwise carry-forward
Exchange rate	USD/UGX mid-rate	BOU	Daily to Quarterly	End-of-quarter
Core inflation	CPI excluding food & energy	UBOS	Monthly to Quarterly	Quarterly average
GDP (market prices)	Real activity	UBOS	Quarterly	y/y and z-score

Source: Authors' compilation

3.3 Sentiment Measurement and Aggregation Procedure

3.3.1 Sentiment Measurement

The Sentiment is extracted using FinBERT (Araci, 2019), a financial-domain adaptation of BERT (Bidirectional Encoder Representations from Transformers; Devlin et al., 2019). Transformer models can better capture context and negation than lexicon methods, which is important for financial language where polarity depends on syntax and semantics (Malo et al., 2014). Text preprocessing follows standard NLP procedures (Manning & Schütze, 1999; Jurafsky & Martin, 2021).

For each paragraph P_i, FinBERT produces probabilities of positive, neutral, and negative tone:

$$(P_i^+, P_i^0, P_i^-)$$

The paragraph level sentiment score *(S)* is calculated as:

$$S_i = P_i^+ - P_i^- \qquad (1)$$

Document-level sentiment (S_d) is obtained by averaging across Nparagraphs:

$$S_d = \frac{1}{N}\sum_{i=1}^{N} s_i \qquad (2)$$

This yields a continuous score in $[-1, +1]$, where higher values indicate more optimistic tone and lower values indicate more pessimistic tone (Malo et al., 2014; Tetlock, 2007). Neutral probabilities $P_i^0$are retained to reduce distortions when polarity content is sparse. To ensure robustness, sentiment scores were cross-checked on a small validation sample and consistency across sources was assessed.

3.3.2 Aggregation of Public Sentiment

Each article $d$published on date $t$receives a sentiment score $S_{d,t}$. Daily PSI is computed as:

$$PSI_t = \frac{1}{D_t}\sum_{d=1}^{D_t} S_{d,t} \qquad (3)$$

where $D_t$is the number of articles on day t. Although PSI is constructed daily, it is aggregated to quarterly frequency for comparability with macrofinancial indicators:

$$PSI_q = \frac{1}{T_q} \sum_{t \in q} PSI_t \qquad (4)$$

where T_q is the number of days in quarter q..

3.3.3 Aggregation of Policy Sentiment

Policy sentiment is computed at the document level using equation (2) for each BoU and MoFPED publication. Because publications occur at discrete intervals, sentiment is mapped to release dates and interpolated to monthly frequency using a stepwise carry-forward approach:

$$PoSI_m = S_d \text{ for all months until the next release} \qquad (5)$$

This approach treats each official publication's tone as the prevailing policy narrative until updated by the next release, consistent with how guidance is typically absorbed between announcements (Blinder et al., 2008; Hansen & McMahon, 2016; Tadle, 2021)

3.3.4 Normalization and Scaling

To ensure comparability across variables, PSI and PoSI are standardized using z-scores. For visualization, standardized values are rescaled to a 0–100 index:

$$Index_t = 50 + 10 \cdot Z_t \qquad (6)$$

where 50 denotes a neutral tone, values above 50 indicate optimism, and values below 50 indicate pessimism.

3.4 Empirical Modeling and Evaluation

Empirical evaluation examines whether PSI and PoSI contain **informational value** for macro financial conditions. The analysis is implemented in three steps: correlation/lead–lag diagnostics, salience robustness checks, and predictive regressions. Importantly, these models evaluate predictive content and timing, not structural causality.

3.4.1 Correlation and Lead-Lag Structure

Contemporaneous and lead-lag Pearson correlations were computed between sentiment indices and macrofinancial indicators on a quarterly basis. This step identified the direction and timing of relationships, that is, whether sentiment led or followed economic dynamics. For each sentiment index S_t(either PSI_tor $PoSI_t$) and each macrofinancial variable X_t, the contemporaneous Pearson correlation is defined as:

$$\rho_0(S,X) = \frac{\sum_{t=1}^{T}(S_t - \bar{S})\,(X_t - \bar{X})}{\sqrt{\sum_{t=1}^{T}(S_t - \bar{S})^2}\,\sqrt{\sum_{t=1}^{T}(X_t - \bar{X})^2}} \qquad (7)$$

where S_t is the sentiment value in period t, X_t is the corresponding macrofinancial indicator, $\bar{S}$ and $\bar{X}$ are their sample means, and $T$is the number of time periods.

Lead–lag correlations are computed in the same way but shifting one of the series. When sentiment is allowed to lead the macro variable by k periods ($k > 0$):

$$\rho_k^{\text{lead}}(S,X) = \text{corr}(S_t, X_{t+k}) \qquad (8)$$

and when sentiment is allowed to lag the macrofinancial variable by k periods:

$$\rho_k^{\text{lag}}(S,X) = \text{corr}(S_{t+k}, X_t) \qquad (9)$$

Equations (1) – (3) are the standard Pearson correlation and lead-lag correlations (Hamilton, 1994; Stock & Watson, 2016).

To ensure comparability, all variables were standardized using z-scores and aligned by reporting date. Standardization is given by:

$$Z_t^X = \frac{X_t - \mu_X}{\sigma_X},\ Z_t^S = \frac{S_t - \mu_S}{\sigma_S} \qquad (10)$$

where μ_X & σ_X are the mean and standard deviation of a macrofinancial variable, and $\mu_S$and $\sigma_S$are the mean and standard deviation of the sentiment index. For indicators such as exchange rates and interbank rates, which vary daily, sentiment indices were aggregated to daily or monthly averages. For variables with less frequent updates, such as treasury yields or property prices, monthly or quarterly alignment was used. Sentiment series were aggregated to daily or monthly averages for faster moving indicators, and quarterly matching was used for slower moving indicators (e.g., property prices), consistent with standard frequency matching practices in macro finance (Hamilton, 1994). The sign and magnitude of correlations were interpreted contextually, that is, a positive correlation indicated procyclical sentiment (optimism with rising markets), whereas a negative one suggested countercyclical or crisis-linked sentiment.

3.4.2 Robustness Check Using Salience

To address the *salience bias* inherent in text-based approaches (Loughran & McDonald, 2011), a volume index, representing the number of documents per day mentioning financial keywords, was constructed and compared with the sentiment indices. This test distinguished whether sentiment changes merely reflected increased coverage (salience) or genuine changes in tone.

The salience or volume index V_t is defined as:

$$V_t = \sum_{d \in \mathcal{D}_t} 1\,\{\text{document } d \text{ contains financial keywords}\}, \qquad (11)$$

where $\mathcal{D}_t$ is the set of documents that are published at time t, and $\mathbf{1}\{\cdot\}$ is an indicator function that equals 1 if the condition is true and 0 if otherwise. In words, V_t counts how many documents at time t mention the chosen financial terms. This construction follows the treatment of news volume and coverage in Loughran and McDonald (2011) and salience-type measures used in Nyman et al. (2021) and Ahir (2022).

The first robustness check compares the correlation of the sentiment indices and the volume index with macro financial variables. Using the same Pearson correlation definition as in equation (1), two sets of correlations are computed:

$$\rho(S, X)\ \&\ \rho(V, X), \qquad (12)$$

for each macro financial variable X. If $|\ \rho(S, X)\ | > |\ \rho(V, X)\ |$ systematically across variables and horizons, this indicates that the sentiment indices capture more than just the intensity of coverage.

Specifically, if the sentiment index retained stronger correlations and predictive power than the volume index, it indicated that the model captured true sentiment, not just the frequency of reporting. Predictive power is evaluated through simple forecast regressions of the form:

$$X_{t+h} = \alpha + \beta S_t + \varepsilon_t, \qquad (13)$$

and

$$X_{t+h} = \alpha_V + \beta_V V_t + \varepsilon_t^V, \qquad (14)$$

where X_{t+h} is a macrofinancial variable in h periods ahead (e.g., credit growth, interbank spread, or an FSI), S_t is the sentiment index (either PSI_tor $PoSI_t$), V_t is the volume index, and ε_t, ε_t^V are error terms. If $\mid \beta \mid$ is statistically significant and economically larger than $\mid \beta_V \mid$ across horizons, it suggests that sentiment contains incremental predictive information beyond salience (Baker et al., 2016; Ahir et al.,2022; Nyman et al., 2021). In addition, joint specifications including both sentiment and volume are estimated to assess whether sentiment retains explanatory and predictive power conditional on reporting intensity.

3.4.3 Predictive Analysis

Predictive relationships were also tested using time series regression and Granger causality. The goal was to determine whether movements in sentiment help anticipate changes in macro financial indicators once the past behavior of those indicators is accounted for.

For each macro financial variable X_t, a single predictive model (Hamilton, 1994; Granger, 1969) of the following form was estimated:

$$X_t = \alpha + \sum_{i=1}^{p} \beta_i X_{t-i} + \sum_{j=1}^{q} \gamma_j S_{t-j} + \varepsilon_t \qquad (15)$$

Lag lengths $p$and $q$are selected using AIC and BIC. Statistical significance of $\gamma_j$indicates that sentiment adds predictive content beyond X's own history. To address concerns that model fit metrics can be misleading, model comparison is conducted using both in-sample and out-of-sample forecast evaluation. Benchmark models excluding sentiment are compared with augmented models including PSI or PoSI, and forecast performance is assessed using RMSE and adjusted R^2. (Diebold & Mariano, 1995).

3.4.4 Comparative Evaluation

The PSI and PoSI are compared across transmission channels (banking soundness, liquidity, interest rates, exchange rates, inflation, and output). Stronger PSI signals are interpreted as greater relevance of market narratives, while stronger PoSI signals are interpreted as greater relevance of official communication in shaping expectations. This comparison aligns with literature on communication as a policy tool and on narrative-driven macro financial dynamics (Blinder et al., 2008; Hansen & McMahon, 2016; Shiller, 2017).

4. PRESENTATION OF RESULTS AND DISCUSSION

4.1. Results

4.1.1 Public Sentiment and Financial Soundness Indica

Correlation analysis between the Public Sentiment Index (PSI) and core Financial Soundness Indicators (FSIs) reveals modest but systematic relationships. While correlation magnitudes are small, consistent with the comparison of high-frequency sentiment measures and low frequency balance sheet indicators, the direction of associations is stable across indicators and economically interpretable. Importantly, the estimated correlation coefficients are economically small in magnitude and should be interpreted as indicative of co-movement rather than quantitatively large effects on financial soundness indicators.

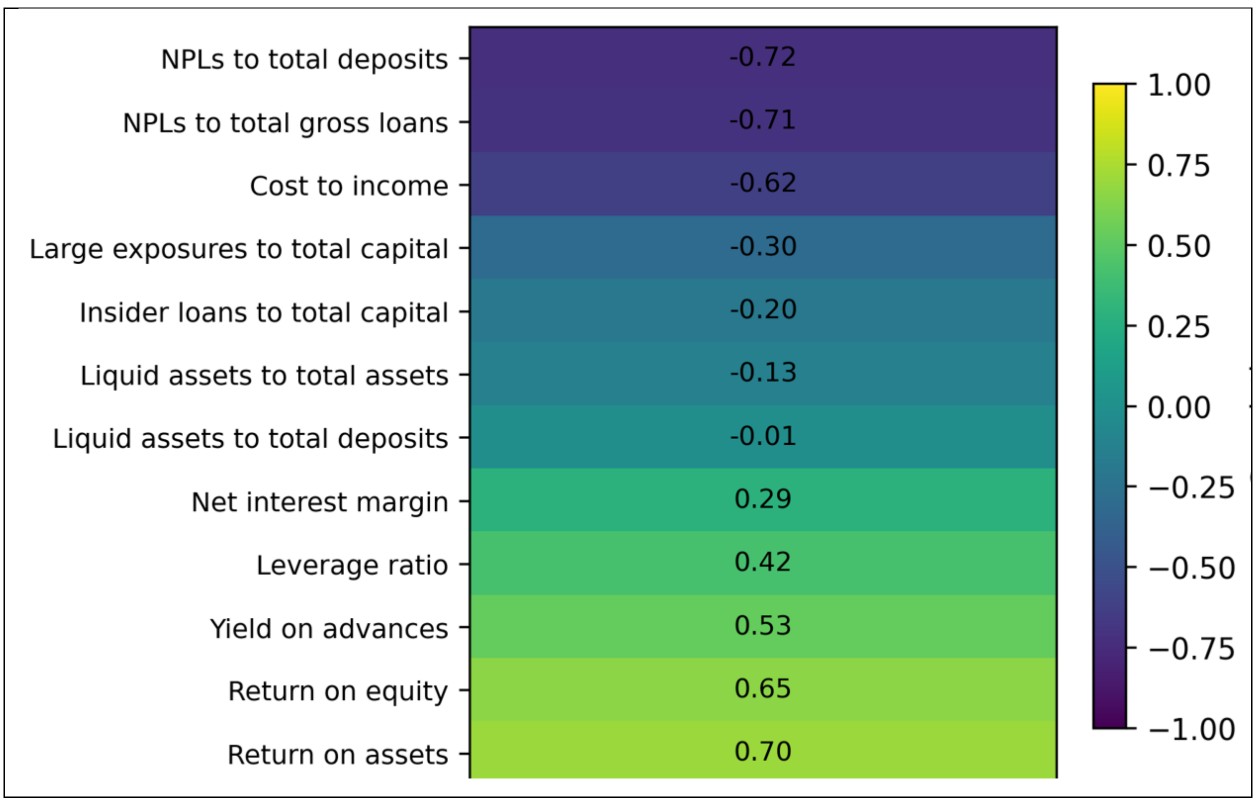

Figure 1: Correlation heatmap between Public Sentiment and FSIs

As shown in Figure 1 and summarized in Table 4, positive sentiment is associated with stronger profitability and capital positions, while negative associations are observed with credit risk and efficiency measures, including non-performing loans and cost-to-income ratios (see Appendix A2 for full correlations). These patterns suggest that optimistic public narratives tend to coincide with improved banking sector conditions, whereas deteriorating asset quality is reflected in more pessimistic sentiment.

Granger causality tests (Figure 2) indicate that public sentiment does not Granger-cause short-run changes in quarterly FSIs after correcting for non-stationarity. The quarterly frequency and limited time span also reduce test power, so non-rejection should be interpreted cautiously as "no robust short-run predictive content detected" rather than definitive absence of influence. Given the quarterly frequency of the data and the limited sample size, the power of Granger causality tests is inherently constrained, and alternative lag structures were considered but yielded qualitatively similar results. This outcome reflects the slow-moving, balance-sheet-based nature of FSIs, which adjust gradually to underlying economic conditions rather than responding immediately to shifts in narratives. Importantly, the absence of short-run causality does not imply informational irrelevance. Instead, the results support the interpretation of public sentiment as a high-frequency diagnostic indicator that co-moves with financial stability conditions over the financial cycle, rather than mechanically driving quarterly accounting outcomes.

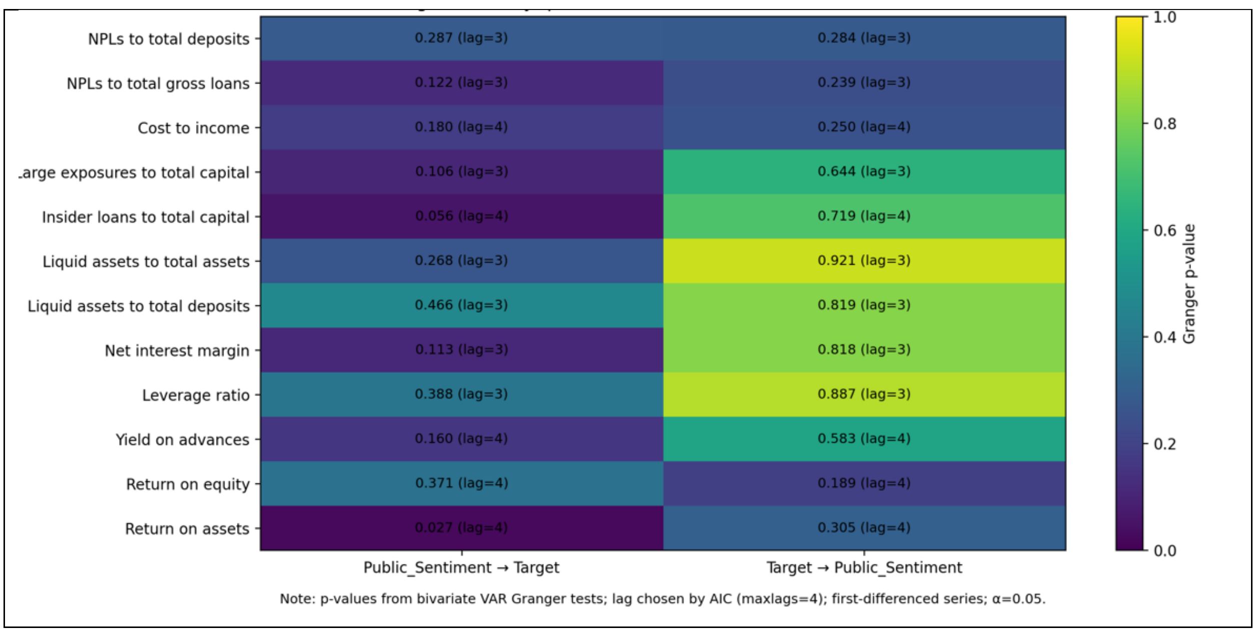

Figure 2: Granger causality results between Public Sentiment and FSIs

Table 4: Correlations between Public Sentiment and Selected Financial Soundness Indicators[4]

FSI category	Indicator	Direction	Economic interpretation
Profitability	Return on assets	+	Higher public optimism coincides with stronger bank profitability
Profitability	Return on equity	+	Positive narratives align with improved returns
Capital adequacy	Regulatory capital to RWA	+	Strong sentiment associated with better capital buffers
Credit risk	NPLs / gross loans	−	Deteriorating asset quality reflected in pessimistic sentiment
Credit risk	NPLs / deposits	−	Rising credit risk coincides with negative narratives
Efficiency	Cost to income	−	Operational inefficiency linked to adverse sentiment

4.1.2 Policy Sentiment and Macro Policy Indicators

Policy sentiment, extracted from Bank of Uganda Monetary Policy Statements and Financial Stability Reports, exhibits clearer and more directional relationships with macro-policy variables. As illustrated in Figure 3, positive policy sentiment is negatively correlated with short-term interest rates and core inflation, while more negative tones coincide with tighter financial conditions and heightened uncertainty. These correlations suggest that policy communication broadly tracks the stance of monetary conditions.

4 Correlations computed using quarterly data, 2019Q1–2025Q3. Full correlation matrices are reported in Appendix A4.

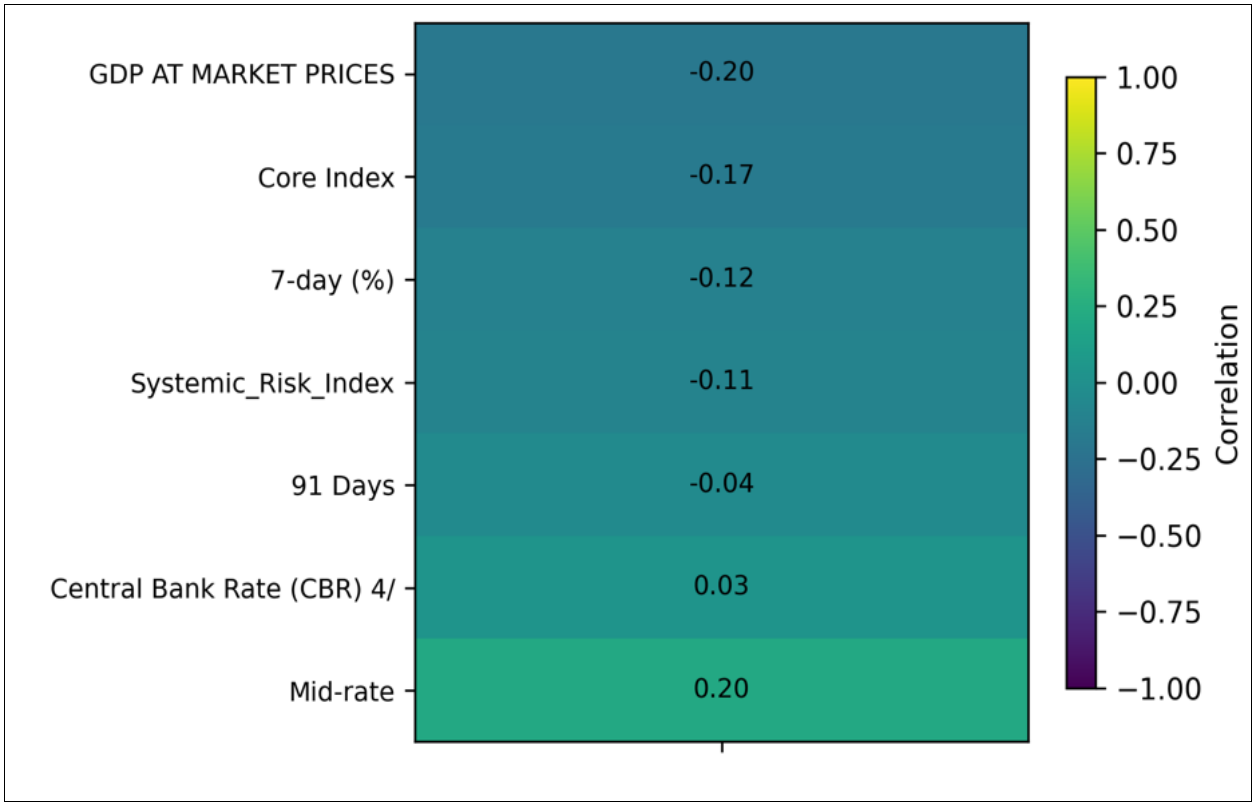

Figure 3: Correlation heatmap between Policy Sentiment and Macro-Policy Indicators

Granger causality results (Figure 4) provide stronger evidence of forward-looking behavior. Policy sentiment consistently provides forward-looking predictive signals for movements in the Central Bank Rate and short-term interest rates, while feedback from policy variables to sentiment is largely absent. These results should be interpreted considering the relatively short sample period (2019Q4–2025Q3) and the presence of major structural shocks, including the COVID-19 crisis and the subsequent global monetary tightening cycle. This asymmetry indicates that official communication adjusts in advance of formal policy actions, supporting the interpretation of central bank communication as an active expectations-management tool rather than a purely descriptive device.

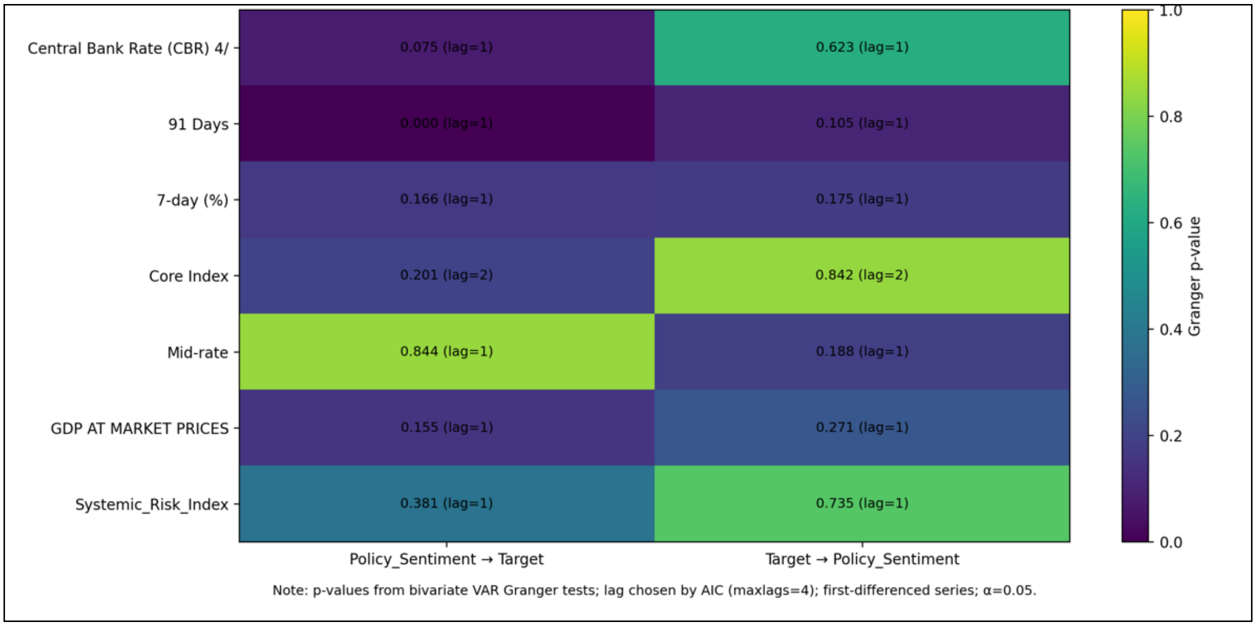

Figure 4: Granger causality between Policy Sentiment and Macro-Policy Indicators

4.1.3 Model Comparison and Predictive Performance

Predictive regressions and forecast evaluation results are summarized in Table 5. Public sentiment improves explanatory power for several financial soundness indicators, accounting for approximately 6.4 percentage points more variation in FSIs relative to comparable specifications using policy sentiment. This reflects the sensitivity of public narratives to evolving credit, liquidity, and asset quality conditions.

In contrast, policy sentiment exhibits stronger predictive performance for monetary policy variables, particularly the policy rate and short-term market rates. Diebold–Mariano tests confirm that policy sentiment delivers superior forecast accuracy for monetary policy indicators, while public sentiment performs better for banking sector FSIs. These results reinforce the complementary informational roles of the two sentiment measures.

4.1.4 Sentiment and Systemic Risk

Figure 5 and Figure 6 plot public and policy sentiment indices against the Systemic Risk Index (SRI). Public sentiment displays pronounced co-movement with systemic risk and exhibits anticipatory behavior around major turning points, particularly during the COVID-19 shock and subsequent normalization period. In contrast, policy sentiment moves more closely in tandem with the official risk cycle, reflecting its alignment with institutional risk assessments.

The timing differences underscore the complementary roles of the two indices: public sentiment acts as an early, reactive signal of emerging stress, while policy sentiment provides a confirmatory signal aligned with official macroprudential assessments.

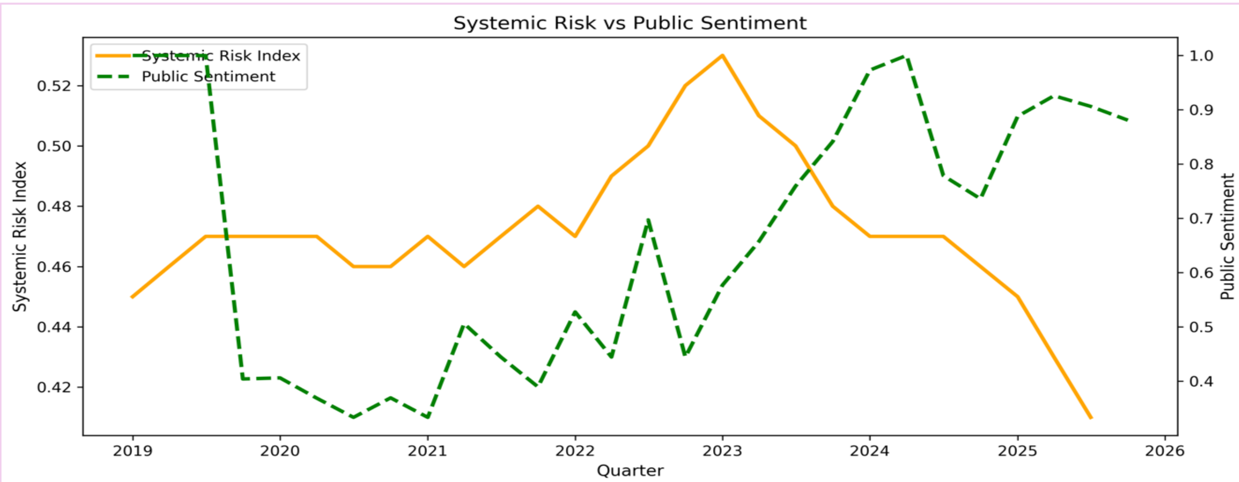

Figure 4: PSI and the SRI

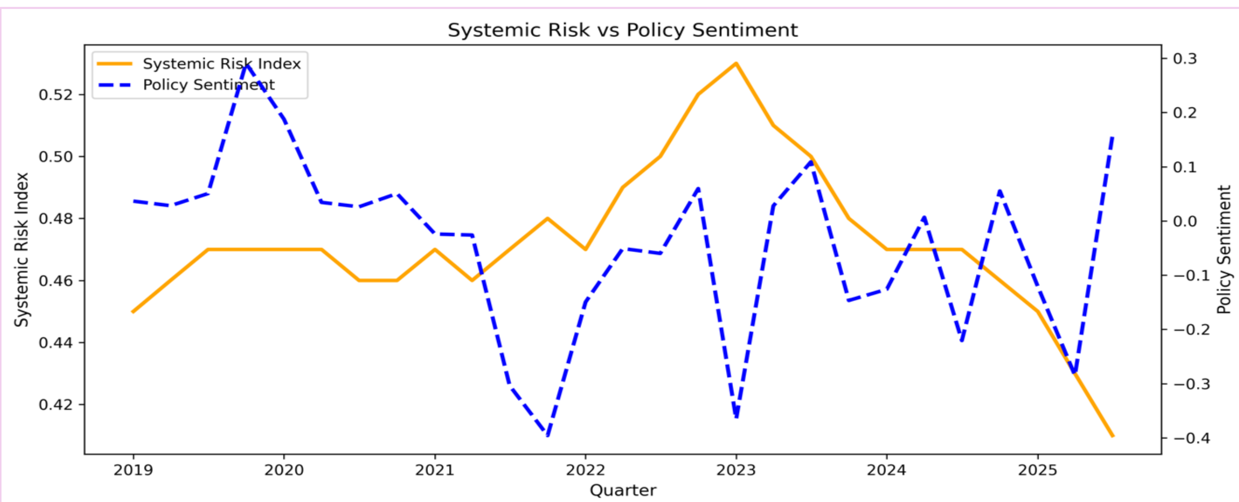

Figure 5: PoSI and SRI

4.2 Discussion of the Results

The results provide empirical support for distinct but complementary transmission channels. Policy sentiment operates primarily through a policy expectations channel, systematically preceding monetary policy actions and shaping expectations of future interest rate movements. Public sentiment, by contrast, captures fast-moving narratives that co-evolve with financial stability conditions through credit and liquidity channels, reflecting shifts in risk perceptions, asset quality dynamics, and funding conditions over the financial cycle.

Together, these findings suggest that integrating sentiment measures with traditional macroprudential indicators can enhance financial stability surveillance by improving early risk detection and interpretation of policy communication. There are also periods, particularly during crisis episodes, in which sentiment signals are noisier or provide weaker guidance for specific indicators, underscoring the importance of interpreting sentiment as a complementary, predictive signal rather than a causal driver, and always alongside traditional macro-financial metrics.

4.3 Limitations of the Study

Several limitations warrant consideration. First, sentiment indices depend on the availability and quality of textual data, which may be constrained in smaller media environments. Second, the quarterly frequency of FSIs limits alignment with higher-frequency sentiment variation. Third, FinBERT is trained primarily on text from advanced economies and may not fully capture local linguistic nuances. Finally, the analysis focuses on predictive relationships rather than structural causality; sentiment should therefore be viewed as a complementary analytical tool rather than a standalone measure.

We also acknowledge that domestic narratives may partly reflect global sentiment spillovers (e.g. global risk aversion, commodity price shocks, or major central bank tightening episodes). Isolating external versus domestic narrative components is beyond the scope of this paper, but it remains a plausible contributor to the co-movement observed in crisis periods.

5. POLICY IMPLICATIONS AND CONCLUSIONS

5.1 Key Findings and Conclusions

This study develops and applies a unified text-based analytical framework to assess the informational content of public and policy narratives in Uganda's macro financial environment. By constructing a Public Sentiment Index (PSI) from media narratives and a Policy Sentiment Index (PoSI) from official Bank of Uganda communications, the study provides empirical evidence on how narrative tone interacts with financial stability and monetary policy outcomes.

Three key conclusions emerge, with differing degrees of robustness across specification. First, public sentiment co-moves systematically with financial soundness indicators and aggregate systemic risk. Although short-run Granger causality between public sentiment and quarterly FSIs is limited, public sentiment responds rapidly to changes in liquidity conditions, credit risk, and systemic stress, and displays anticipatory behavior around major turning points, particularly during the COVID-19 shock and the subsequent normalization phase.

Second, policy sentiment exhibits a clear forward-looking relationship with monetary policy actions. The tone of official communication consistently precedes adjustments in the Central Bank Rate and short-term interest rates, supporting the interpretation of central bank communication as an active expectations-management instrument rather than a purely descriptive tool.

Third, public and policy sentiment capture distinct but complementary dimensions of macro financial dynamics. Public sentiment is more informative about evolving financial stability conditions, while policy sentiment provides clearer signals about the future policy stance. Their differing relationships with the Systemic Risk Index reinforce this distinction, with public sentiment reacting earlier to emerging stress and policy sentiment moving more closely with the official risk assessment cycle.

While the relationships involving policy sentiment and higher-frequency variables are relatively robust, those linking sentiment to slower-moving balance-sheet indicators such as FSIs are more sensitive to data frequency, sample length, and model specification.

5.2 Policy Implications

1. Integrate PSI into routine surveillance as a high-frequency diagnostic. PSI should be monitored at monthly frequency for formal reporting, with weekly internal updates where automated scraping permits. Rather than relying on fixed universal thresholds, BoU can use signal rules such as: (i) sharp quarter-on-quarter declines, (ii) persistent negative deviations over two or more quarters, or (iii) divergence between PSI and core FSIs/SRI. These flags should trigger deeper review of the drivers (liquidity conditions, NPL trends, funding stress) and targeted supervisory follow-up where warranted.
2. Use PoSI to strengthen communication consistency and forward guidance. PoSI can be monitored around policy communication cycles to assess whether tone shifts are aligned

with intended policy stance. Large changes in PoSI without corresponding policy actions should prompt internal review to reduce unintended signaling and to improve clarity and consistency of messaging.

3. Embed sentiment indicators alongside FSIs and the SRI in dashboards—not as standalone triggers. PSI and PoSI should be presented as complementary “context layers” that help interpret movements in balance-sheet indicators and systemic risk measures, improving timeliness and narrative-based interpretation during stress and turning points.
4. Operational development (next steps). Future work could refine thresholds using historical back-testing, and separate domestic from global narrative components using topic filters or inclusion of global risk proxies.

References

Ahir, H., Bloom, N., & Furceri, D. (2022). *The World Uncertainty Index* (NBER Working Paper No. 29763). National Bureau of Economic Research. https://www.nber.org/papers/w29763

Araci, D. (2019). FinBERT: Financial sentiment analysis with pre-trained language models. *arXiv preprint*. https://arxiv.org/abs/1908.10063

Audrino, F., Janning, A., & Sigrist, F. (2024). The impact of macroeconomic news sentiment on interest rates. *Journal of Financial Analytics, 94*, 105752.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics, 131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Bird, S., Klein, E., & Loper, E. (2009). *Natural language processing with Python*. O'Reilly Media.

Blinder, A. S., Ehrmann, M., Fratzscher, M., De Haan, J., & Jansen, D. J. (2008). Central bank communication and monetary policy: A survey of theory and evidence. *Journal of Economic Literature, 46*(4), 910–945.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives, 28*(2), 153–176. https://doi.org/10.1257/jep.28.2.153

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science, 2*(1), 1–8. https://doi.org/10.1016/j.jocs.2010.12.007

Bank of Uganda (BOU). (2025). *Quarterly Financial Stability Review – June 2025*. https://bou.or.ug/bouwebsite/bouwebsitecontent/FinancialStability/Quarterly-Financial-Stability-Review-June-2025.pdf

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A., & Raffo, A. (2022). The effect of global uncertainty on the global economy. *Journal of International Economics, 137*, 103629. https://doi.org/10.1016/j.jinteco.2022.103629

Chernykh, L., Davydov, D., & Sihvonen, J. (2023). Financial stability and public confidence in banks. *Journal of Financial Stability, 69*, 101187. https://doi.org/10.1016/j.jfs.2023.101187

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of NAACL-HLT*.

Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics, 13*(3), 253–263. https://doi.org/10.1080/07350015.1995.10524599

Fatouros, A., Siakoulis, V., Petropoulos, A., Stavroulakis, E., & Vlachogiannakis, N. (2023). Transformers in financial sentiment analysis: A survey. *ACM Computing Surveys, 55*(9), Article 186. https://doi.org/10.1145/3571150

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*.

Gürkaynak, R. S., Sack, B., & Swanson, E. (2005). Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *International Journal of Central Banking, 1*(1), 55–93.

Haldane, A. G., & May, R. M. (2018). Systemic risk in banking ecosystems. *Nature, 469*(7330), 351–355. https://doi.org/10.1038/nature09659

Hamilton, J. D. (1994). *Time series analysis*. Princeton University Press.

Hansen, S., & McMahon, M. (2016). Shocking language: Understanding the macroeconomic effects of central bank communication. *Journal of International Economics, 99*, 114–133. https://doi.org/10.1016/j.jinteco.2015.12.008

Hayo, B., & Neuenkirch, M. (2010). Do Federal Reserve communications help predict Federal Funds target rate decisions? *Journal of Macroeconomics, 32*(4), 1014–1024. https://doi.org/10.1016/j.jmacro.2010.07.002

Holbrook, M. (2019). *newspaper3k: Article scraping & curation*. GitHub repository. https://github.com/codelucas/newspaper

International Monetary Fund (IMF). (2018). *Macro-financial linkages in shallow markets: Experience from the African Department's pilot countries* (African Department Paper No. 2018/012). https://doi.org/10.5089/9781484361498.087

International Organization of Securities Commissions (IOSCO). (2007). *Factors influencing liquidity in emerging markets*. IOSCO Emerging Markets Committee.

Kahunde, R., Namulime, H., & Mudola, E. (2024). *The Uganda Business Climate Index* (Issue No. 49, October–December 2024). Economic Policy Research Centre.

Kräussl, R., & Mirgorodskaya, E. (2013). News media sentiment and investor behavior (Working Paper). Queen Mary University of London.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance, 66*(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Luong, M. T., Nguyen, T. M., & Pham, N. D. (2024). The development of research on investor sentiment in emerging and frontier markets: A bibliometric review. *Journal of Scientific Research, 13*(2), 58–74.

Malo, P., Sinha, A., Takala, P., Korhonen, P., & Wallenius, J. (2014). Good debt or bad debt: Detecting semantic orientations in economic texts. *Journal of the Association for Information Science and Technology, 65*(4), 782–796. https://doi.org/10.1002/asi.23062

Manning, C. D., & Schütze, H. (1999). *Foundations of statistical natural language processing*. MIT Press.

Mugisha, S. T. (2025). *Analysing government communication strategies in combating information disorder on social media: A study of Uganda's tax monitoring system* (Master's thesis). Aga Khan University.

Naidoo, T., Moores-Pitt, P., & Muzindutsi, P. F. (2025). The effect of investor sentiment on stock market liquidity under changing market conditions: Evidence from South Africa. *Cogent Economics & Finance, 13*(1). https://doi.org/10.1080/23322039.2024.2444395

Nyman, R., Kapadia, S., Tuckett, D., Gregory, D., Ormerod, P., & Smith, R. (2021). News and narratives in financial systems: Exploiting big data for systemic risk assessment. *Journal of Economic Dynamics and Control, 129*, 104191. https://doi.org/10.1016/j.jedc.2021.104191

Roos, M. W. M. (2024). What makes a narrative economically relevant? *Journal of Economic Methodology, 31*(1), 1–21. https://doi.org/10.1080/1350178X.2024.2305012

Saal, M. I., Lindgren, C.-J., & Garcia, G. G. (1996). *Bank soundness and macroeconomic policy*. International Monetary Fund. https://doi.org/10.5089/9781557755995.071

Shiller, R. J. (2017). Narrative economics. *American Economic Review, 107*(4), 967–1004. https://doi.org/10.1257/aer.107.4.967

Shiller, R. J. (2019). *Narrative economics: How stories go viral and drive major economic events*. Princeton University Press.

Silva, T. C., Moriya, K., & Veyrune, R. M. (2025). From text to quantified insights: A large-scale LLM analysis of central bank communication. *Working Paper*.

Tadle, A. (2021). Textual analysis of the FOMC minutes: Understanding shifts in forward guidance. *Journal of Macroeconomics, 68*, 103256. https://doi.org/10.1016/j.jmacro.2020.103256

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance, 62*(3), 1139–1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x