# Monetary Policy Communication in Times of War and Political Turmoil:

## *Evidence from Emerging and Developing Economies*

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# Financial Market Reactions to MPC Tone and Clarity

- Markets react to how decisions are communicated, not just to decisions (Blinder 2009; Chaboud et al. 2024).
- Transparency aims to reduce noise and surprises; clearer MPC linked to lower announcement-window volatility (Woodford 2005; Dincer et al. 2022; Vyshnevskyi et al. 2024).
- *EMDE evidence*: readability generally better than AEs in recent years, but information asymmetries and shallower markets keep reactions sizable (Nagy-Mohácsi et al. 2024; Ahokpossi et al. 2020).
- During political instability, effective MPC can mitigate uncertainty and panic (Szyszko et al. 2025).
- *Takeaway*: clarity is a policy instrument—especially when institutional credibility is strained.

# MPC during political turmoil events

- Turmoil brings inflation pressures, fiscal dominance, financial instability → communication must balance reassurance and realism (Rockoff 2015; Apel & Ohlsson 2022; Poast 2015).
- *No playbook*: policy responses vary; wars tend to raise inflation; communication must justify temporary deviations (Apel & Ohlsson 2022; Ozili et al. 2024).
- *Ukraine* (NBU): wartime measures + continuous, explicit messaging on temporariness and path back to IT/FX flexibility; multi-channel outreach to preserve trust (Burban et al. 2024; Szyszko et al. 2025).
- *Dilemma under pressure*: defend independence via transparency vs. accommodative messaging when independence is constrained (Ezzat & Fayed 2020); Turkey case shows credibility costs (Gürkaynak et al. 2023).
- *Overall*: crises raise complexity of MPC and the stakes of getting it right (BIS 2024; Tumala & Omotosho 2019).

# Theory behind

- *Public signals & volatility*: More precise public signals reduce belief dispersion and near-term price volatility (Morris & Shin 2002; Woodford 2005; Blinder et al. 2008).
- *Two effects of news*: New info raises informedness and consensus; each can push volatility differently (Holthausen & Verrecchia 1990).
- *Event-study fact*: Macro announcements spike high-freq volatility as information arrives quickly (Andersen, Bollerslev, Diebold & Vega 2003; Chaboud et al. 2004).
- *Communication clarity*: Readability/context lower uncertainty and anchor expectations (Bulíř et al. 2014; Jansen 2011; Vyshnevskyi et al. 2024; Fernandes 2025).
- *Political instability channel*: Heightened uncertainty magnifies communication effects (Born et al. 2014; Brogaard et al. 2020); conflict pressures induce strategic ambiguity (Alesina & Drazen 1989; Cerdeira & Rimkutė 2024).
- *Coordination role*: Structured details (policy contingencies, liquidity backstops, FX conduct) act as coordination devices, compressing short-window FX volatility (Fratzscher 2006; Cavusoglu 2010; Moschella & Pinto 2019; Beine et al. 2009).

# Textual Analysis of Central Bank MPC

- *Rapid shift* from niche to core tool in central-bank research (Bholat et al. 2015; Benchimol et al. 2022; Voicilă & Șerbu 2025).
- *Toolkit* spans dictionaries, topic models, ML/LLMs for stance, tone, audience (Leek & Bischl 2025; Masciandaro et al. 2023; Vyshnevskyi et al. 2024).
- *New datasets & models* enable scale and comparability (Araujo 2023; Baird et al. 2026; Gambacorta et al. 2024; Kim et al. 2024; Pfeifer & Marohl 2023; Silva et al. 2025).
- *Beyond sentiment*: readability/complexity and linguistic structure (e.g., dependency depth, parse trees) now measurable and comparable across banks and time.
- *EMDE evidence*: readability often improving, sometimes surpassing AEs, but stress degrades clarity (Evdokimova et al. 2023; Vyshnevskyi et al. 2024).

# Motivation

- *High-stakes context*: Many EMDE central banks face rising political instability, with growing pressures to communicate credibly in crisis while managing FX volatility and public expectations.
- *Why this matters now*: Clear communication under turmoil is not just about transparency—it can directly shape near-term financial stability and risk premia, with spillovers across borders and asset classes.
- *Gaps in the literature*:
  - Most evidence is single-country or conflict-specific, limiting generalizability.
  - Few studies systematically analyze EMDEs using modern text-based metrics of communication quality.
  - The link between turmoil-related content and short-term asset-price risk remains largely unexplored.
- Theoretical tension:
  - Classical theory: Clearer public signals reduce disagreement and dampen volatility (Morris & Shin 2002; Woodford 2005).
  - But under turmoil: Credibility strains, audiences shift, and the marginal value of structure/detail rises—or not—depending on context.

# Research questions

- Investigate whether and how the language used by central banks to describe political turmoil influences near-term FX volatility.
- Two hypotheses.
  1. Richer and more structured turmoil-related language should reduce announcement-window volatility by narrowing disagreement and clarifying the outlook.
     - Proxies: syntactic depth (parse-tree depth), dependency chaining (avg. dependency length), information content (contextual surprisal), lexical simplicity (word frequency), message length (token count).
  2. The effectiveness of that language may vary with conflict intensity (two competing mechanisms)
     - H2a – Salience overload: When conflict is intense, markets are already hyper-attentive; extra elaboration has less room to calm prices → the volatility-reducing effect weakens at high intensity.
     - H2b – Information demand: Intense conflict raises demand for precise guidance; structure/detail become more valuable → the volatility-reducing effect strengthens at high intensity.
     - Test strategy: Estimate interactions between turmoil language and conflict intensity.

# Contribution

- This paper contributes to the literature.
  - Build a new cross-country corpus of policy-rate statements, identify the sentences that discuss political turmoil, and pair each turmoil-related language measure with its non-turmoil analogue from the same document.
  - Apply a language-structure and information-density lens, capturing syntactic depth, dependency chaining, contextual surprisal, lexical frequency, and message length as well as sentiments, at the sentence level
  - Link these measures to forward-looking realized foreign exchange (FX) volatility alongside external conflict data, allowing to study the communication channel under political stress in EMDEs.
- Provide the first multi-country EMDE estimates showing how central banks talk about turmoil systematically relates to short-horizon FX risk.

# Data

- Conflict and violence data:
  - Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED) (Davies et al., 2025);
  - Peace Research Institute Oslo (PRIO) Conflict Trends Report : A Global Overview, 1946–2024
  - Armed Conflict Location & Event Data Project (ACLED, 2024a)
- Policy and macro data
  - Central-bank websites (policy-rate statements)
  - S&P Connect (FX, macro)
  - Political Risk Services (PRS) Group’s country risk indicators (ICRG).
- Sample selection
  - ACLED Conflict Index: EMDEs with high/very high turbulence => Afghanistan, Bangladesh, India, Iraq, Lebanon, Myanmar, Pakistan, Palestine, Philippines, russia, Syria, Ukraine, and Yemen.
  - PRIO/UCDP dataset: state-based conflict history => Indonesia, Thailand, Azerbaijan, Iran, and Turkey
  - Exclusions: Broad sanctions (e.g., Afghanistan, Iran, Myanmar, russia, Syria); no accessible statements (Yemen, Palestine, Iraq).
  - Final sample: 10 countries (AZ, BD, IN, ID, LB, PK, PH, TH, TR, UA), 1,257 policy statements, 72,747 sentences, 1998–2025.

# Policy Statement Corpus

- *Policy-rate statement*: any official document that communicates a rate decision with justification (or closest substitute where no standalone release exists).
- *Collection*: Country-specific Python scrapers; HTML/PDF ingestion; PDF-to-text conversion; date parsing from source.
- *Cleaning & segmentation*

  ⇒Syntactically/semantically well-formed sentences, aligned by country–date for downstream NLP.

- *MPSD: Monetary Policy Statement Database*
  - MPSD provides a standardized, machine-readable dataset of policy statements from major central banks worldwide - built for research on communication trends, inflation dynamics, and global monetary policy transmission.
  - https://centralbanktexts.github.io/

# Policy Statement Corpus

- The average number of sentences in each statement varies significantly, ranging from very detailed reports to short announcements.
- This shows fundamentally different approaches to interest rate statements, with some banks prioritizing extensive explanation while others favor brevity.
- Variance in textual complexity, as measured by sentence length.

**Table 1. Summary Statistics for Policy Rate Statements Used in the Analysis**

| Country name | Country code | Number of Statements | Number of Sentences | Average Number of Sentences per Statement | Period Covered | Mean Words | Median Words | Min Words | Max Words |
|---|---|---|---|---|---|---|---|---|---|
| **Azerbaijan** | AZ | 85 | 2914 | 34.28 | 2007–2025 | 20.77 | 19 | 3 | 77 |
| **Bangladesh** | BD | 36 | 7080 | 196.67 | 2006–2025 | 28.32 | 27 | 4 | 94 |
| **Indonesia** | ID | 186 | 9769 | 52.52 | 2005–2025 | 25.09 | 23 | 3 | 110 |
| **India** | IN | 116 | 28850 | 248.71 | 1998–2025 | 25.87 | 24 | 2 | 121 |
| **Lebanon** | LB | 23 | 675 | 29.35 | 2002–2024 | 26.11 | 25 | 4 | 62 |
| **Philippines** | PH | 220 | 2751 | 12.5 | 2001–2025 | 25.96 | 25 | 4 | 68 |
| **Pakistan** | PK | 84 | 9520 | 113.33 | 2005–2025 | 26.15 | 25 | 4 | 82 |
| **Thailand** | TH | 196 | 3768 | 19.22 | 2000–2025 | 22.24 | 21 | 3 | 68 |
| **Turkey** | TR | 223 | 3709 | 16.63 | 2006–2025 | 22.11 | 20 | 5 | 77 |
| **Ukraine** | UA | 88 | 3711 | 42.17 | 2014–2025 | 23.39 | 22 | 3 | 97 |
| | **Total** | **1257** | **72747** | **-** | **1998–2025** | **-** | **-** | **-** | **-** |

# Policy Statement Corpus

- The dataset's timeline begins with statements from India (IN) in 1998, with the data for most institutions until 2025.
- The volume of communication fluctuates considerably.

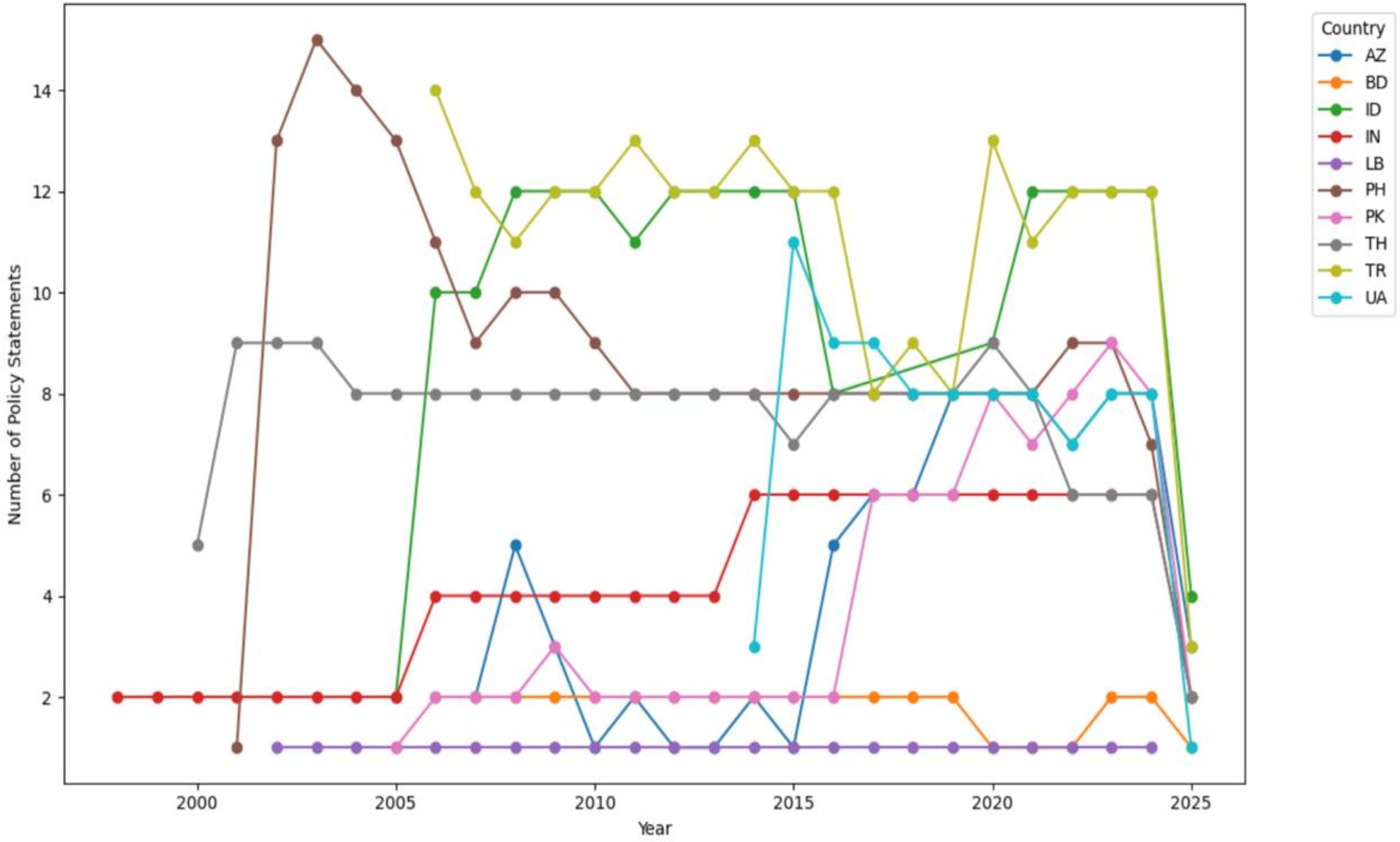



**Figure 2. Number of Statements by Country per Year**

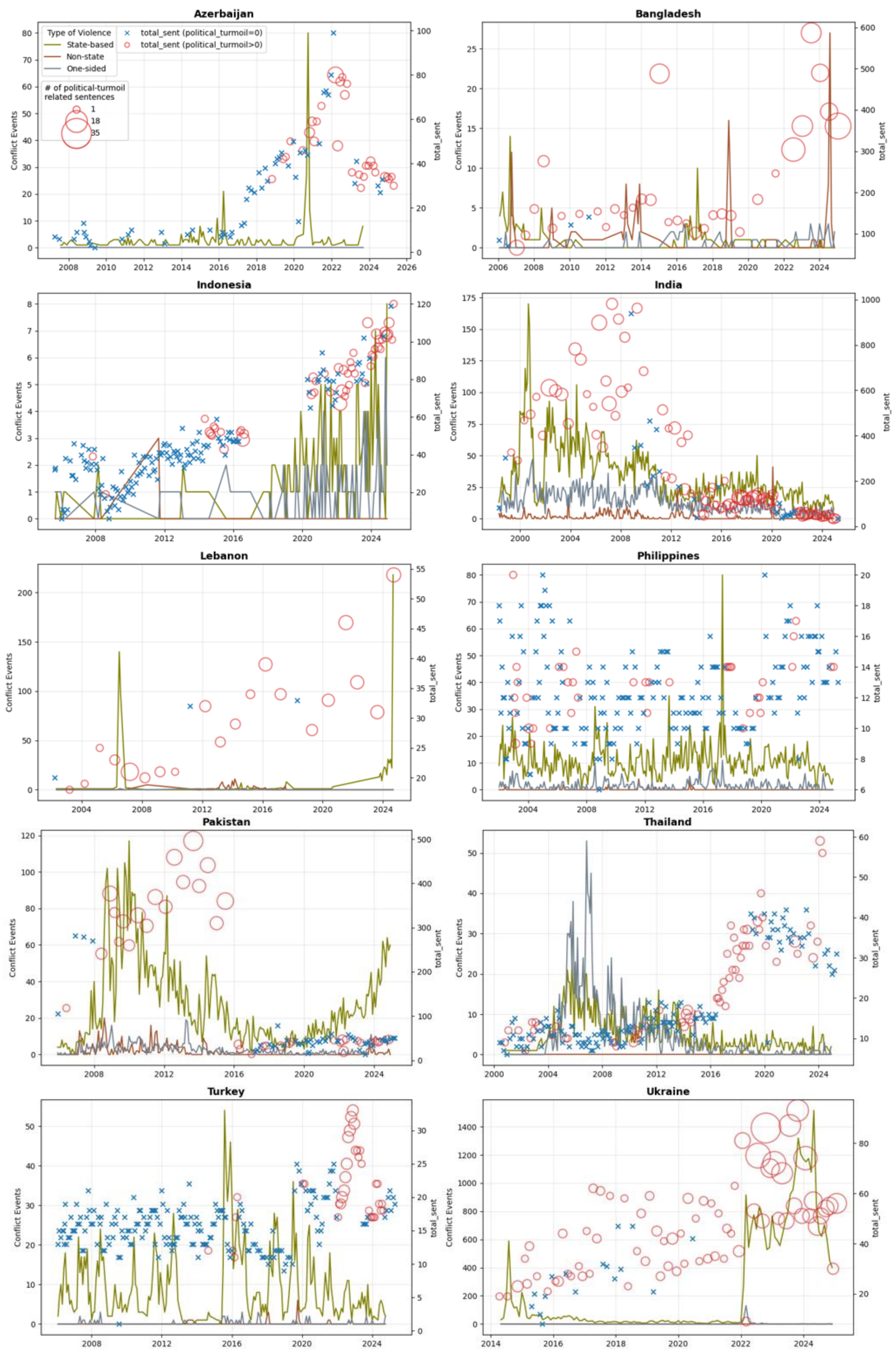
# Text Feature Construction

- *Political-Turmoil Sentences Annotation*
  - *Training set construction using LLM-assisted protocol*:
    1. 9,255 sentences (using stratified random sampling and removing duplicates)
    2. Google Gemini 2.5 Flash to label turmoil-related sentences
    3. Expert validation

    295 out of 9,255 labeled as political turmoil sentences in training set
  - *Classifier*: Fine-tuned a FinBERT model (Araci, 2019).
    - Oversampling + class-weighted loss to address imbalance (Johnson & Khoshgoftaar, 2019).
    - Validation: Macro-F1 = 0.95, minority-class F1 = 0.90, overall accuracy = 0.99.
  - *Prevalence*: Only 1.9% of sentences (1,372 of 72,747) reference political turmoil—underscoring how rarely central banks comment directly on such events.

# Text Measures

- *Sentence-level measures* (then averaged to statement level within turmoil / non-turmoil subsets):
  - Language structure: average dependency length (syntactic chaining), parse-tree depth (syntactic depth).
  - Information density: contextual PLL surprisal (FinBERT, whole-document context; sliding window >512 tokens; mean per token).
  - Message scale: tokens per sentence (detail/elaboration).
  - Lexical simplicity: average word frequency.
  - Sentiment: FinBERT labels + excess-over-chance polarity in $[-1,1]$, token-weighted aggregation.
- *Key descriptive facts*: Turmoil sentences are longer, deeper, denser, and more negative; they remain a small share of total statement text.



# Text Feature Construction 1: Conflicts vs Sentence Count

- Turmoil language is sparse even in severe episodes.
- References are often to external events.
- Mapping from events to communication is non-linear.
- Turmoil sentences are generally more complex.
- Tone diverges systematically.
- Volume is limited.

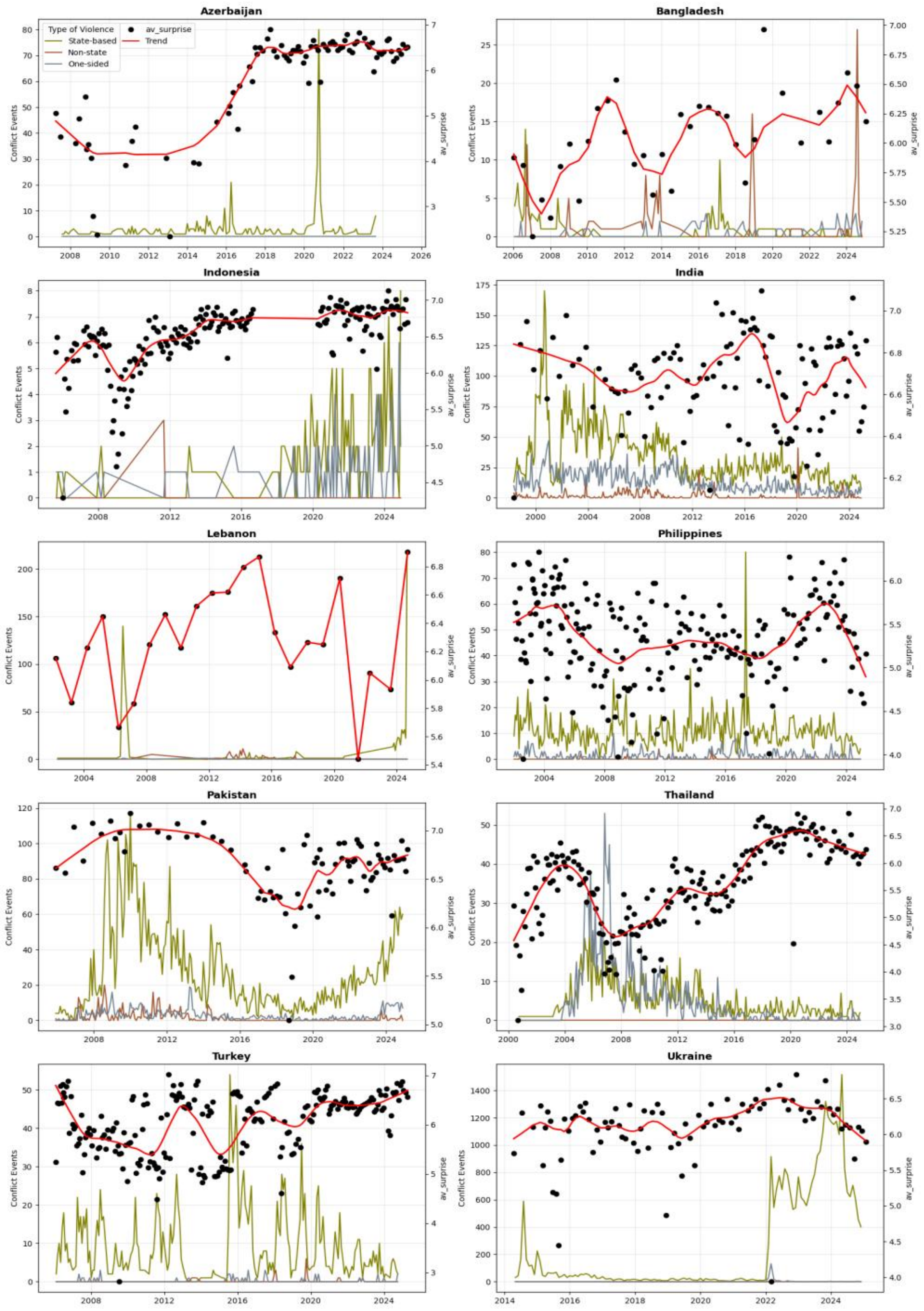
**Figure 3. Monthly Conflict Events and Per-Statement Sentence Counts by Country (Total and Turmoil-Related)**

# Text Feature Construction 1: Conflicts vs Sentence Count

**Table 2. compares lexical properties of turmoil-related sentences ("turmoil") with other sentences ("non-turmoil") across countries**.

| Country | Political turmoil-related sentences | AZ | BD | ID | IN | LB | PH | PK | TH | TR | UA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| token_count_mean | Yes | 26.70 | 31.09 | 28.58 | 28.60 | 33.26 | 34.34 | 32.12 | 29.37 | 27.10 | 30.95 |
| avg_dependency_length_mean | Yes | 2.61 | 2.57 | 2.42 | 2.65 | 2.79 | 2.73 | 2.83 | 2.67 | 2.77 | 2.69 |
| parse_tree_depth_mean | Yes | 6.92 | 6.70 | 8.62 | 7.35 | 7.11 | 8.01 | 7.42 | 7.74 | 7.28 | 7.44 |
| pll_surprisal_contextual_mean | Yes | 7.54 | 7.06 | 7.19 | 7.15 | 5.59 | 7.04 | 6.96 | 6.37 | 6.11 | 6.06 |
| avg_wordfreq_mean | Yes | 0.0081 | 0.0080 | 0.0072 | 0.0076 | 0.0090 | 0.0087 | 0.0079 | 0.0085 | 0.0081 | 0.0094 |
| sentiment_polarity_score_mean | Yes | -0.33 | -0.17 | -0.29 | -0.30 | 0.12 | -0.43 | -0.36 | -0.07 | 0.11 | -0.31 |
| sentences_mean | Yes | 1.6 | 5.3 | 1.7 | 3.0 | 4.1 | 1.1 | 3.7 | 1.3 | 1.9 | 5.3 |
| sentences_sum | Yes | 48 | 171 | 85 | 276 | 81 | 40 | 142 | 80 | 65 | 384 |
| token_count_mean | No | 23.92 | 30.13 | 25.85 | 25.49 | 26.68 | 26.79 | 26.07 | 23.26 | 23.89 | 24.09 |
| avg_dependency_length_mean | No | 2.44 | 2.59 | 2.44 | 2.51 | 2.43 | 2.57 | 2.59 | 2.41 | 2.57 | 2.42 |
| parse_tree_depth_mean | No | 6.01 | 6.81 | 6.81 | 6.47 | 6.85 | 6.90 | 6.41 | 6.04 | 6.03 | 6.28 |
| pll_surprisal_contextual_mean | No | 5.87 | 6.03 | 6.50 | 6.67 | 6.39 | 5.33 | 6.64 | 5.63 | 6.04 | 6.10 |
| avg_wordfreq_mean | No | 0.0092 | 0.0074 | 0.0078 | 0.0079 | 0.0084 | 0.0088 | 0.0080 | 0.0084 | 0.0088 | 0.0092 |
| sentiment_polarity_score_mean | No | 0.13 | 0.17 | 0.35 | 0.11 | 0.35 | 0.18 | 0.15 | 0.20 | 0.10 | 0.16 |
| sentences_mean | No | 34 | 192 | 52 | 246 | 26 | 12 | 112 | 19 | 16 | 38 |
| sentences_sum | No | 2,866 | 6,909 | 9,684 | 28,574 | 594 | 2,711 | 9,378 | 3,688 | 3,644 | 3,327 |

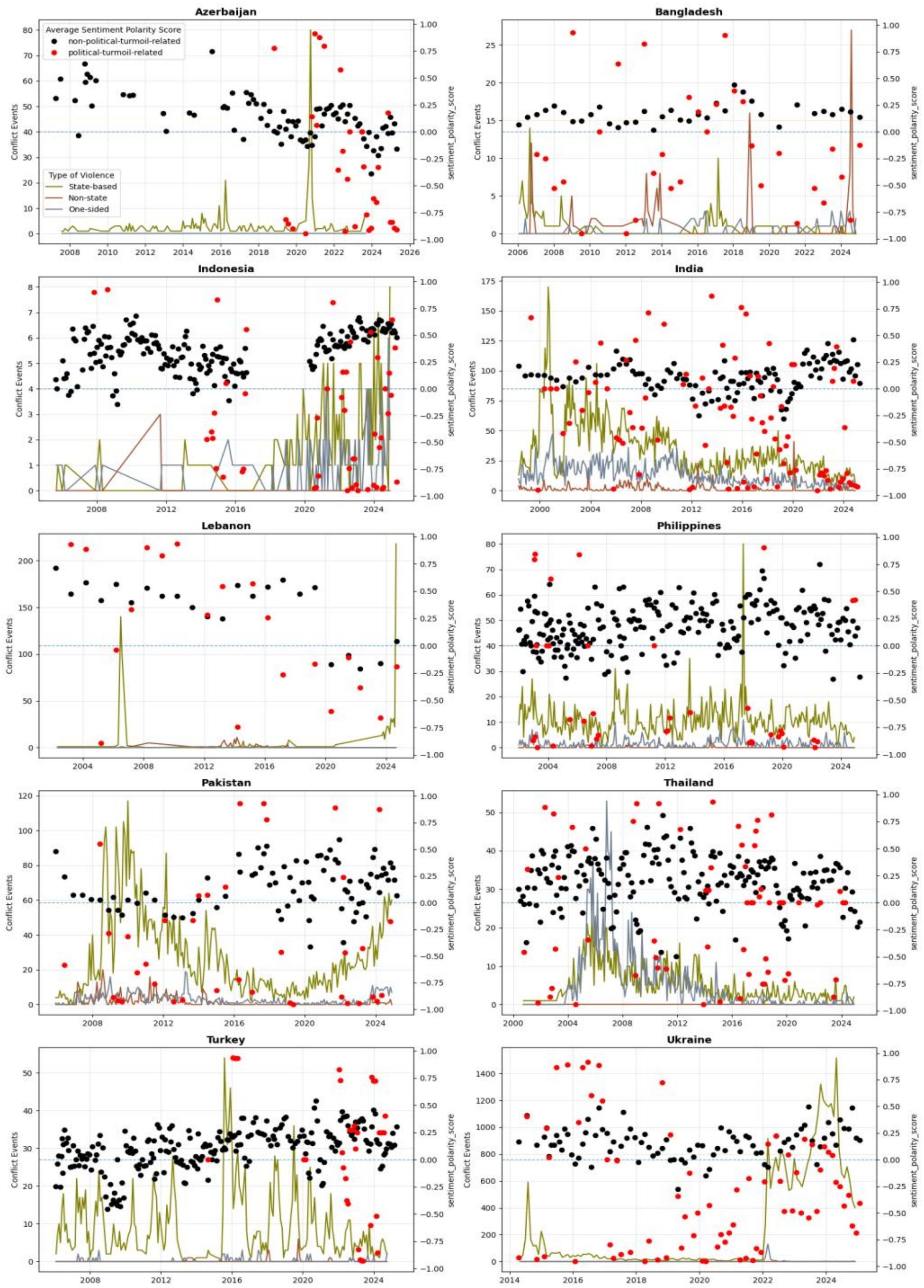
# Text Feature Construction 2: PLL surprisal




- Per-statement surprisal exhibits no common cross-country pattern.

**Figure 4. Monthly Conflict Events and Average PLL Surprisal per Statement by Country**

# Text Feature Construction 3: Sentiments




- Across countries the turmoil-related text is systematically more negative than the non-turmoil-related text.
- The gap widens around conflict outbursts.
- The non-turmoil tone remains relatively stable and mildly positive, with limited sensitivity to event spikes

**Figure 5. Monthly Conflict Events and Sentiment polarity score per Statement by Country**

# Descriptive Insight: Topic Modeling of Policy Narratives

- *Method*: Structural Topic Modeling (STM) applied to policy-rate statements to uncover prevailing themes.
  - Follows best practices: tokenization, lemmatization, POS-filtering, collocation handling, and document-feature matrix construction.
  - Widely used in central bank communication research (e.g., Klejdysz & Lumsdaine, 2023).
- *Key findings*:
  - Substantial cross-country heterogeneity in dominant topics, reflecting different mandates and policy frameworks.
  - Political turmoil appears as a distinct topic only in: *Azerbaijan, Bangladesh, Lebanon, and Ukraine*.
  - Elsewhere, conflict references are typically embedded within broader macroeconomic themes, not surfaced as standalone topics.
  - No sharp separation between local vs. geopolitical conflicts in language use.
- *Interpretation*: Even during periods of instability, central banks rarely foreground conflict, preferring to maintain a focus on economic fundamentals (See Figure A1).

# Data sample creation

- *Statement-Level Aggregation by Turmoil- and Non-Turmoil-Related Sentences*: Aggregate turmoil & non-turmoil metrics per country–date.
- *Construction of Conflict Proximity Variables*: Merge UCDP 30-day rolling conflict measures (events, fatalities; by type).
- *Event-Window Market Response*: Realized FX Volatility: Compute realized FX volatility over $[t-1, t+h]$ business-day windows, $h \in \{1,2,3,5,10\}$; annualized SD of daily log-returns.
- *Add predetermined controls*: policy rate, term spread, ICRG, reserves/GDP, real GDP growth (monthly last-in-month; quarterly mapped with release lag, then lagged one more month).

**Table 4. Summary Statistics**

| Variables | N | Missing Pct. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| **Dependent variables** | | | | | | |
| vol_fx_1d | 1,257 | 0.00 | 0.05 | 0.10 | 0.00 | 2.05 |
| vol_fx_2d | 1,257 | 0.00 | 0.05 | 0.09 | 0.00 | 1.77 |
| vol_fx_3d | 1,257 | 0.00 | 0.06 | 0.11 | 0.00 | 2.47 |
| vol_fx_5d | 1,257 | 0.00 | 0.06 | 0.10 | 0.00 | 2.06 |
| vol_fx_10d | 1,257 | 0.00 | 0.06 | 0.09 | 0.00 | 1.62 |
| **Independent variables** | | | | | | |
| sentiment_polarity_score_pt | 468 | 0.63 | -0.23 | 0.59 | -0.96 | 0.94 |
| token_count_pt | 1,257 | 0.00 | 29.95 | 9.50 | 11.00 | 69.00 |
| avg_dependency_length_pt | 1,257 | 0.00 | 2.66 | 0.48 | 1.52 | 5.14 |
| parse_tree_depth_pt | 1,257 | 0.00 | 7.52 | 2.02 | 3.00 | 15.00 |
| avg_wordfreq_pt | 1,257 | 0.00 | 0.01 | 0.00 | 0.00 | 0.02 |
| pll_surprisal_contextual_pt | 1,257 | 0.00 | 6.73 | 1.26 | 1.47 | 9.54 |
| sentences_npt | 1,257 | 0.00 | 56.78 | 111.35 | 1.00 | 977.00 |
| sentiment_polarity_score_ npt | 1,257 | 0.00 | 0.18 | 0.21 | -0.50 | 0.81 |
| token_count_ npt | 1,257 | 0.00 | 25.13 | 3.90 | 15.69 | 59.00 |
| avg_dependency_length_ npt | 1,257 | 0.00 | 2.50 | 0.17 | 1.91 | 3.54 |
| parse_tree_depth_ npt | 1,257 | 0.00 | 6.42 | 0.75 | 4.45 | 10.67 |
| avg_wordfreq_ npt | 1,257 | 0.00 | 0.01 | 0.00 | 0.01 | 0.01 |
| pll_surprisal_contextual_ npt | 1,257 | 0.00 | 6.02 | 0.74 | 2.34 | 7.18 |
| num_conflict_events_30d | 1,257 | 0.00 | 27.68 | 113.16 | 0.00 | 1,352.00 |
| fatalities_best_30d | 1,257 | 0.00 | 315.31 | 2,165.70 | 0.00 | 37,834.00 |
| **Control variables** | | | | | | |
| Central bank policy rate | 1,251 | 0.00 | 7.96 | 6.81 | 0.50 | 47.00 |
| Spread of long over short interest rate | 1,023 | 0.19 | 1.85 | 6.23 | -23.10 | 40.53 |
| International Reserves Excluding Gold, % of GDP | 1,169 | 0.07 | 17.88 | 12.67 | 1.81 | 141.83 |
| Real $ GDP, Growth Rate, Year-on-Year | 1,257 | 0.00 | 4.13 | 4.98 | -36.80 | 26.08 |
| Composite Risk Rating | 1,253 | 0.00 | 66.19 | 5.81 | 34.25 | 77.00 |
| Economic Risk Rating | 1,257 | 0.00 | 34.61 | 4.52 | 8.00 | 42.50 |
| Financial Risk Rating | 1,257 | 0.00 | 38.99 | 4.80 | 14.00 | 49.00 |
| Political Risk Rating | 1,257 | 0.00 | 58.74 | 5.64 | 43.00 | 73.00 |
| **Robustness check variables** | | | | | | |
| state_based_30d | 1,257 | 0.00 | 24.95 | 112.37 | 0.00 | 1,350.00 |
| non_state_30d | 1,257 | 0.00 | 0.25 | 1.31 | 0.00 | 23.00 |
| one_sided_30d | 1,257 | 0.00 | 2.48 | 5.61 | 0.00 | 47.00 |
| war_label dummy | 1,257 | 0.00 | 0.37 | 0.48 | 0.00 | 1.00 |
| sentences_pt | 1,257 | 0.00 | 2.93 | 3.82 | 1.00 | 35.00 |
| sentences_npt | 1,257 | 0.00 | 56.78 | 111.35 | 1.00 | 977.00 |

# Descriptive Statistics

Before estimation, we run standard panel diagnostics:
- pairwise correlation matrices,
- unit-root/stationarity tests,
- multicollinearity checks (VIF)

Summary statistics for all variables entering the regressions are shown in Table 4.

# Methodology

- *Paired*: turmoil feature with matched non-turmoil analogue (holds style/volume constant).

$$Y_{it}^{(h)} = \beta W_{it} + \gamma N_{it} + Z'_{i,t-1}\phi + \mu_i + \lambda_{m(t)} + u_{it}.$$

- *Difference*: turmoil minus non-turmoil (nets out generic communication intensity/style).

$$Y_{it}^{(h)} = \theta(W_{it} - N_{it}) + Z'_{i,t-1}\delta + \mu_i + \lambda_{m(t)} + u_{it}.$$

- *FE & sample*: Country FE + year-month FE; horizon-specific common sample for apples-to-apples coefficients.
- *Inference*: Driscoll–Kraay SEs (Bartlett; bandwidth tied to h) to handle heteroskedasticity, overlap, cross-sectional dependence.
- *Moderation (interactions)*: Lagged 30-day conflict intensity × turmoil language (country-mean centered products).

$$Y_{it}^{(h)} = \beta W_{it} + \gamma N_{it} + \phi M_{i,t-1} + \kappa(\widetilde{\Delta W_{it}} * \widetilde{\Delta M_{i,t-1}}) + Z'_{i,t-1}\delta + \mu_i + \lambda_{m(t)} + u_{it},$$

- *Robustness*: Alt. lags, conflict-type controls, two-way clustering, LOCO jackknife, control-set variants, turmoil-only subsample.
- Our estimates should be interpreted as conditional, within-country associations rather than causal effects.

# Methodology

- Outcome is the realized FX volatility $Y_{it}^{(h)} = logVol_{it}^{(h)}$ computed over business days $[\mathrm{t}-1, t+h]$;
- a turmoil–specific textual feature $W_{it}$ and its non-turmoil analogue $N_{it}$;
- $Z_{i,t-1}$ collects lagged macro/ratings controls (policy rate, reserves/GDP, real GDP growth, term spread, an d ICRG risk indices);
- $\beta$ and $\gamma$ are the slopes on the turmoil and non-turmoil text measures in the paired spec;
- $\theta$ is the slope on their difference in the Δ spec;
- $\mu_i$ are country fixed effects, and $\lambda_{m(t)}$ are year-month fixed effects (one common intercept per calendar y ear-month);
- $u_{it}$ is the error term;
- $\kappa$ is the within-country moderation effect;
- $M_{i,t-1}$ a predetermined conflict-intensity moderator (either fatalities in the prior 30 days or event counts i n the prior 30 days);
- Tildes denote country-mean deviations (e.g., $\widetilde{W_{it}} = W_{it} - \overline{W_i}$)

## Table 5. Baseline “paired” model results

# Baseline model

| Y | Model | X | coef | se | N | R2 |
|---|---|---|---|---|---|---|
| log_vol_fx_1d | 1 | log_avg_dependency_length_npt | 0.036 | 0.047 | 861 | 0.051 |
| | | log_avg_dependency_length_pt | -0.011** | 0.004 | 861 | 0.051 |
| | 2 | log_avg_wordfreq_npt | -0.004 | 3.486 | 861 | 0.048 |
| | | log_avg_wordfreq_pt | -1.456** | 0.650 | 861 | 0.048 |
| | 3 | log_parse_tree_depth_npt | -0.001 | 0.036 | 861 | 0.050 |
| | | log_parse_tree_depth_pt | -0.006** | 0.003 | 861 | 0.050 |
| | 4 | log_pll_surprisal_contextual_npt | -0.008 | 0.039 | 861 | 0.049 |
| | | log_pll_surprisal_contextual_pt | -0.006** | 0.003 | 861 | 0.049 |
| | 5 | log_token_count_npt | 0.003 | 0.017 | 861 | 0.051 |
| | | log_token_count_pt | -0.004** | 0.002 | 861 | 0.051 |
| | 6 | sentiment_polarity_score_npt | -0.021 | 0.038 | 250 | -0.090 |
| | | sentiment_polarity_score_pt | -0.001 | 0.008 | 250 | -0.090 |
| log_vol_fx_2d | 1 | log_avg_dependency_length_npt | -0.006 | 0.046 | 861 | 0.046 |
| | | log_avg_dependency_length_pt | -0.012** | 0.005 | 861 | 0.046 |
| | 2 | log_avg_wordfreq_npt | -2.067 | 3.486 | 861 | 0.042 |
| | | log_avg_wordfreq_pt | -1.517** | 0.695 | 861 | 0.042 |
| | 3 | log_parse_tree_depth_npt | -0.024 | 0.036 | 861 | 0.044 |
| | | log_parse_tree_depth_pt | -0.006** | 0.003 | 861 | 0.044 |
| | 4 | log_pll_surprisal_contextual_npt | 0.005 | 0.036 | 861 | 0.042 |
| | | log_pll_surprisal_contextual_pt | -0.006** | 0.003 | 861 | 0.042 |
| | 5 | log_token_count_npt | -0.014 | 0.018 | 861 | 0.044 |
| | | log_token_count_pt | -0.004** | 0.002 | 861 | 0.044 |
| | 6 | sentiment_polarity_score_npt | -0.022 | 0.035 | 250 | -0.171 |
| | | sentiment_polarity_score_pt | -0.002 | 0.010 | 250 | -0.171 |
| log_vol_fx_3d | 1 | log_avg_dependency_length_npt | 0.052 | 0.101 | 861 | 0.047 |
| | | log_avg_dependency_length_pt | -0.016** | 0.007 | 861 | 0.047 |
| | 2 | log_avg_wordfreq_npt | 0.188 | 3.533 | 861 | 0.042 |
| | | log_avg_wordfreq_pt | -2.098** | 0.961 | 861 | 0.042 |
| | 3 | log_parse_tree_depth_npt | 0.031 | 0.071 | 861 | 0.049 |
| | | log_parse_tree_depth_pt | -0.009** | 0.004 | 861 | 0.049 |
| | 4 | log_pll_surprisal_contextual_npt | -0.006 | 0.038 | 861 | 0.044 |
| | | log_pll_surprisal_contextual_pt | -0.008** | 0.003 | 861 | 0.044 |
| | 5 | log_token_count_npt | 0.015 | 0.037 | 861 | 0.047 |
| | | log_token_count_pt | -0.006** | 0.003 | 861 | 0.047 |
| | 6 | sentiment_polarity_score_npt | -0.015 | 0.032 | 250 | -0.063 |
| | | sentiment_polarity_score_pt | 0.002 | 0.010 | 250 | -0.063 |

| Y | Model | X | coef | se | N | R2 |
|---|---|---|---|---|---|---|
| log_vol_fx_5d | 1 | log_avg_dependency_length_npt | 0.051 | 0.099 | 861 | 0.059 |
| | | log_avg_dependency_length_pt | -0.015** | 0.007 | 861 | 0.059 |
| | 2 | log_avg_wordfreq_npt | 1.314 | 3.342 | 861 | 0.055 |
| | | log_avg_wordfreq_pt | -1.879** | 0.934 | 861 | 0.055 |
| | 3 | log_parse_tree_depth_npt | 0.041 | 0.067 | 861 | 0.062 |
| | | log_parse_tree_depth_pt | -0.008** | 0.004 | 861 | 0.062 |
| | 4 | log_pll_surprisal_contextual_npt | -0.030 | 0.034 | 861 | 0.052 |
| | | log_pll_surprisal_contextual_pt | -0.007* | 0.003 | 861 | 0.052 |
| | 5 | log_token_count_npt | 0.019 | 0.035 | 861 | 0.060 |
| | | log_token_count_pt | -0.006** | 0.003 | 861 | 0.060 |
| | 6 | sentiment_polarity_score_npt | -0.007 | 0.034 | 250 | -0.015 |
| | | sentiment_polarity_score_pt | 0.006 | 0.012 | 250 | -0.015 |
| log_vol_fx_10d | 1 | log_avg_dependency_length_npt | 0.013 | 0.096 | 861 | 0.037 |
| | | log_avg_dependency_length_pt | -0.008 | 0.007 | 861 | 0.037 |
| | 2 | log_avg_wordfreq_npt | 1.646 | 3.450 | 861 | 0.037 |
| | | log_avg_wordfreq_pt | -0.782 | 1.179 | 861 | 0.037 |
| | 3 | log_parse_tree_depth_npt | 0.026 | 0.058 | 861 | 0.039 |
| | | log_parse_tree_depth_pt | -0.004 | 0.005 | 861 | 0.039 |
| | 4 | log_pll_surprisal_contextual_npt | -0.003 | 0.029 | 861 | 0.036 |
| | | log_pll_surprisal_contextual_pt | -0.002 | 0.004 | 861 | 0.036 |
| | 5 | log_token_count_npt | 0.007 | 0.031 | 861 | 0.037 |
| | | log_token_count_pt | -0.003 | 0.003 | 861 | 0.037 |
| | 6 | sentiment_polarity_score_npt | -0.019 | 0.031 | 250 | 0.051 |
| | | sentiment_polarity_score_pt | 0.003 | 0.009 | 250 | 0.051 |

# Baseline model

- *Question*: Does the form of political-turmoil communication relate to near-term FX risk?
- *Answer*: **Yes**. Within countries and months—and holding non-turmoil language and lagged fundamentals fixed—more structured, information-dense turmoil passages are associated with lower 1–5-day FX volatility; effects fade by day 10.
- *Consistent pattern across four cores*:
  - Syntactic chaining (↑ avg. dependency length) → volatility ↓
  - Syntactic depth (↑ parse-tree depth) → volatility ↓
  - Information content (↑ contextual surprisal) → volatility ↓
  - Message detail (↑ token count) → volatility ↓
  - (Lexical frequency points the same way; sentiment adds little once structure/density are controlled.)
- *Economic logic*: Clearer, better-scaffolded turmoil passages narrow scenarios, reduce disagreement, and compress announcement-window volatility.
- *Fit & robustness*: Within-$R^2 \approx$ 3–6% (typical for high-freq FX). Results survive Δ (turmoil–non-turmoil) spec, LOCO, alt. control sets, DK vs. 2-way clustering, moderator controls, and timing shifts. Core coefficients remain negative and stable.

## Table 6. Interaction “paired” model results

# Interaction Model

| Y | Model | term | coef | se | N | R2 | coef | se | N | R2 |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | log_fatalities_best_30d_L1 | | | | log_num_conflict_events_30d_L1 | | | |
| log_vol_fx_1d | 1 | log_avg_dependency_length_pt__x__log_fatalities_best_30d_L1__cwc | 0.004 | 0.003 | 861 | 0.051 | 0.004 | 0.004 | 861 | 0.052 |
| | | log_avg_dependency_length_pt | -0.011** | 0.005 | 861 | 0.051 | -0.011** | 0.005 | 861 | 0.052 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.000 | 0.002 | 861 | 0.051 | 0.001 | 0.004 | 861 | 0.052 |
| | 2 | log_avg_wordfreq_pt__x__log_fatalities_best_30d_L1__cwc | 0.250 | 0.410 | 861 | 0.048 | 0.201 | 0.542 | 861 | 0.050 |
| | | log_avg_wordfreq_pt | -1.405** | 0.654 | 861 | 0.048 | -1.438** | 0.655 | 861 | 0.050 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.000 | 0.002 | 861 | 0.048 | 0.001 | 0.003 | 861 | 0.050 |
| | 3 | log_parse_tree_depth_pt__x__log_fatalities_best_30d_L1__cwc | 0.002 | 0.002 | 861 | 0.050 | 0.003 | 0.002 | 861 | 0.050 |
| | | log_parse_tree_depth_pt | -0.006** | 0.003 | 861 | 0.050 | -0.006** | 0.003 | 861 | 0.050 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.002 | 861 | 0.050 | 0.001 | 0.003 | 861 | 0.050 |
| | 4 | log_pll_surprisal_contextual_pt__x__log_fatalities_best_30d_L1__cwc | 0.002 | 0.002 | 861 | 0.049 | 0.002 | 0.002 | 861 | 0.050 |
| | | log_pll_surprisal_contextual_pt | -0.006** | 0.003 | 861 | 0.049 | -0.006** | 0.003 | 861 | 0.050 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.002 | 861 | 0.049 | 0.001 | 0.003 | 861 | 0.050 |
| | 5 | log_token_count_pt__x__log_fatalities_best_30d_L1__cwc | 0.001 | 0.001 | 861 | 0.051 | 0.002 | 0.002 | 861 | 0.051 |
| | | log_token_count_pt | -0.004** | 0.002 | 861 | 0.051 | -0.004** | 0.002 | 861 | 0.051 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.002 | 861 | 0.051 | 0.001 | 0.004 | 861 | 0.051 |
| | 6 | sentiment_polarity_score_pt__x__log_fatalities_best_30d_L1__cwc | -0.007 | 0.009 | 250 | -0.134 | -0.008 | 0.015 | 250 | -0.115 |
| | | sentiment_polarity_score_pt | -0.001 | 0.008 | 250 | -0.134 | -0.001 | 0.008 | 250 | -0.115 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.004 | 0.006 | 250 | -0.134 | -0.004 | 0.010 | 250 | -0.115 |
| log_vol_fx_2d | 1 | log_avg_dependency_length_pt__x__log_fatalities_best_30d_L1__cwc | 0.004 | 0.003 | 861 | 0.047 | 0.006 | 0.004 | 861 | 0.046 |
| | | log_avg_dependency_length_pt | -0.011** | 0.005 | 861 | 0.047 | -0.012** | 0.005 | 861 | 0.046 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.000 | 0.003 | 861 | 0.047 | -0.000 | 0.004 | 861 | 0.046 |
| | 2 | log_avg_wordfreq_pt__x__log_fatalities_best_30d_L1__cwc | 0.503 | 0.490 | 861 | 0.042 | 0.633 | 0.645 | 861 | 0.042 |
| | | log_avg_wordfreq_pt | -1.418** | 0.711 | 861 | 0.042 | -1.465** | 0.708 | 861 | 0.042 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.000 | 0.002 | 861 | 0.042 | -0.000 | 0.004 | 861 | 0.042 |
| | 3 | log_parse_tree_depth_pt__x__log_fatalities_best_30d_L1__cwc | 0.003 | 0.002 | 861 | 0.045 | 0.004 | 0.003 | 861 | 0.044 |
| | | log_parse_tree_depth_pt | -0.006** | 0.003 | 861 | 0.045 | -0.006** | 0.003 | 861 | 0.044 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.000 | 0.002 | 861 | 0.045 | -0.000 | 0.004 | 861 | 0.044 |
| | 4 | log_pll_surprisal_contextual_pt__x__log_fatalities_best_30d_L1__cwc | 0.002 | 0.002 | 861 | 0.042 | 0.003 | 0.003 | 861 | 0.041 |
| | | log_pll_surprisal_contextual_pt | -0.006* | 0.003 | 861 | 0.042 | -0.006* | 0.003 | 861 | 0.041 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.000 | 0.002 | 861 | 0.042 | -0.000 | 0.004 | 861 | 0.041 |
| | 5 | log_token_count_pt__x__log_fatalities_best_30d_L1__cwc | 0.002 | 0.001 | 861 | 0.045 | 0.002 | 0.002 | 861 | 0.044 |
| | | log_token_count_pt | -0.004** | 0.002 | 861 | 0.045 | -0.004** | 0.002 | 861 | 0.044 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.003 | 861 | 0.045 | 0.000 | 0.004 | 861 | 0.044 |
| | 6 | sentiment_polarity_score_pt__x__log_fatalities_best_30d_L1__cwc | -0.002 | 0.008 | 250 | -0.160 | -0.005 | 0.012 | 250 | -0.162 |
| | | sentiment_polarity_score_pt | -0.002 | 0.009 | 250 | -0.160 | -0.002 | 0.009 | 250 | -0.162 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.004 | 0.006 | 250 | -0.160 | -0.003 | 0.010 | 250 | -0.162 |
| log_vol_fx_3d | 1 | log_avg_dependency_length_pt__x__log_fatalities_best_30d_L1__cwc | 0.006 | 0.004 | 861 | 0.047 | 0.006 | 0.005 | 861 | 0.047 |
| | | log_avg_dependency_length_pt | -0.016** | 0.007 | 861 | 0.047 | -0.016** | 0.007 | 861 | 0.047 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.003 | 861 | 0.047 | 0.001 | 0.004 | 861 | 0.047 |
| | 2 | log_avg_wordfreq_pt__x__log_fatalities_best_30d_L1__cwc | 0.625 | 0.559 | 861 | 0.043 | 0.507 | 0.732 | 861 | 0.042 |
| | | log_avg_wordfreq_pt | -1.968** | 0.960 | 861 | 0.043 | -2.054** | 0.977 | 861 | 0.042 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.002 | 861 | 0.043 | 0.002 | 0.004 | 861 | 0.042 |
| | 3 | log_parse_tree_depth_pt__x__log_fatalities_best_30d_L1__cwc | 0.004 | 0.003 | 861 | 0.049 | 0.004 | 0.003 | 861 | 0.048 |
| | | log_parse_tree_depth_pt | -0.009** | 0.004 | 861 | 0.049 | -0.009** | 0.004 | 861 | 0.048 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.001 | 0.003 | 861 | 0.049 | 0.002 | 0.004 | 861 | 0.048 |
| | 4 | log_pll_surprisal_contextual_pt__x__log_fatalities_best_30d_L1__cwc | 0.003 | 0.002 | 861 | 0.045 | 0.003 | 0.003 | 861 | 0.044 |
| | | log_pll_surprisal_contextual_pt | -0.008** | 0.004 | 861 | 0.045 | -0.008** | 0.004 | 861 | 0.044 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.001 | 0.002 | 861 | 0.045 | 0.002 | 0.004 | 861 | 0.044 |
| | 5 | log_token_count_pt__x__log_fatalities_best_30d_L1__cwc | 0.003 | 0.002 | 861 | 0.047 | 0.002 | 0.002 | 861 | 0.046 |
| | | log_token_count_pt | -0.006** | 0.003 | 861 | 0.047 | -0.006** | 0.003 | 861 | 0.046 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.003 | 861 | 0.047 | 0.002 | 0.004 | 861 | 0.046 |
| | 6 | sentiment_polarity_score_pt__x__log_fatalities_best_30d_L1__cwc | -0.006 | 0.009 | 250 | -0.080 | -0.012 | 0.013 | 250 | -0.081 |
| | | sentiment_polarity_score_pt | 0.001 | 0.010 | 250 | -0.080 | 0.002 | 0.010 | 250 | -0.081 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.003 | 0.006 | 250 | -0.080 | -0.001 | 0.010 | 250 | -0.081 |

| Y | Model | term | coef | se | N | R2 | coef | se | N | R2 |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | log_fatalities_best_30d_L1 | | | | log_num_conflict_events_30d_L1 | | | |
| log_vol_fx_5d | 1 | log_avg_dependency_length_pt__x__log_fatalities_best_30d_L1__cwc | 0.006 | 0.004 | 861 | 0.060 | 0.005 | 0.005 | 861 | 0.059 |
| | | log_avg_dependency_length_pt | -0.014** | 0.007 | 861 | 0.060 | -0.015** | 0.007 | 861 | 0.059 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.000 | 0.003 | 861 | 0.060 | 0.001 | 0.004 | 861 | 0.059 |
| | 2 | log_avg_wordfreq_pt__x__log_fatalities_best_30d_L1__cwc | 0.546 | 0.537 | 861 | 0.056 | 0.300 | 0.719 | 861 | 0.054 |
| | | log_avg_wordfreq_pt | -1.768* | 0.941 | 861 | 0.056 | -1.853* | 0.952 | 861 | 0.054 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.002 | 861 | 0.056 | 0.001 | 0.004 | 861 | 0.054 |
| | 3 | log_parse_tree_depth_pt__x__log_fatalities_best_30d_L1__cwc | 0.004 | 0.002 | 861 | 0.063 | 0.003 | 0.003 | 861 | 0.061 |
| | | log_parse_tree_depth_pt | -0.008* | 0.004 | 861 | 0.063 | -0.008** | 0.004 | 861 | 0.061 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.003 | 861 | 0.063 | 0.002 | 0.004 | 861 | 0.061 |
| | 4 | log_pll_surprisal_contextual_pt__x__log_fatalities_best_30d_L1__cwc | 0.003 | 0.002 | 861 | 0.054 | 0.002 | 0.003 | 861 | 0.052 |
| | | log_pll_surprisal_contextual_pt | -0.007* | 0.004 | 861 | 0.054 | -0.007* | 0.004 | 861 | 0.052 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.002 | 861 | 0.054 | 0.001 | 0.004 | 861 | 0.052 |
| | 5 | log_token_count_pt__x__log_fatalities_best_30d_L1__cwc | 0.002 | 0.002 | 861 | 0.061 | 0.002 | 0.002 | 861 | 0.059 |
| | | log_token_count_pt | -0.005** | 0.003 | 861 | 0.061 | -0.006** | 0.003 | 861 | 0.059 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | 0.000 | 0.003 | 861 | 0.061 | 0.001 | 0.004 | 861 | 0.059 |
| | 6 | sentiment_polarity_score_pt__x__log_fatalities_best_30d_L1__cwc | -0.007 | 0.011 | 250 | -0.051 | -0.012 | 0.014 | 250 | -0.052 |
| | | sentiment_polarity_score_pt | 0.006 | 0.011 | 250 | -0.051 | 0.006 | 0.011 | 250 | -0.052 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.003 | 0.007 | 250 | -0.051 | -0.001 | 0.012 | 250 | -0.052 |
| log_vol_fx_10d | 1 | log_avg_dependency_length_pt__x__log_fatalities_best_30d_L1__cwc | 0.004 | 0.004 | 861 | 0.040 | 0.003 | 0.005 | 861 | 0.039 |
| | | log_avg_dependency_length_pt | -0.007 | 0.007 | 861 | 0.040 | -0.008 | 0.007 | 861 | 0.039 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.002 | 0.003 | 861 | 0.040 | -0.003 | 0.004 | 861 | 0.039 |
| | 2 | log_avg_wordfreq_pt__x__log_fatalities_best_30d_L1__cwc | 0.217 | 0.608 | 861 | 0.040 | -0.049 | 0.778 | 861 | 0.039 |
| | | log_avg_wordfreq_pt | -0.758 | 1.122 | 861 | 0.040 | -0.788 | 1.158 | 861 | 0.039 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.002 | 0.002 | 861 | 0.040 | -0.003 | 0.004 | 861 | 0.039 |
| | 3 | log_parse_tree_depth_pt__x__log_fatalities_best_30d_L1__cwc | 0.002 | 0.003 | 861 | 0.041 | 0.001 | 0.004 | 861 | 0.040 |
| | | log_parse_tree_depth_pt | -0.004 | 0.005 | 861 | 0.041 | -0.004 | 0.005 | 861 | 0.040 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.002 | 0.002 | 861 | 0.041 | -0.003 | 0.004 | 861 | 0.040 |
| | 4 | log_pll_surprisal_contextual_pt__x__log_fatalities_best_30d_L1__cwc | 0.002 | 0.002 | 861 | 0.038 | 0.001 | 0.003 | 861 | 0.037 |
| | | log_pll_surprisal_contextual_pt | -0.002 | 0.004 | 861 | 0.038 | -0.002 | 0.004 | 861 | 0.037 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.002 | 0.002 | 861 | 0.038 | -0.002 | 0.004 | 861 | 0.037 |
| | 5 | log_token_count_pt__x__log_fatalities_best_30d_L1__cwc | 0.002 | 0.002 | 861 | 0.040 | 0.001 | 0.002 | 861 | 0.039 |
| | | log_token_count_pt | -0.003 | 0.003 | 861 | 0.040 | -0.003 | 0.003 | 861 | 0.039 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.002 | 0.002 | 861 | 0.040 | -0.003 | 0.004 | 861 | 0.039 |
| | 6 | sentiment_polarity_score_pt__x__log_fatalities_best_30d_L1__cwc | -0.009 | 0.011 | 250 | 0.056 | -0.022 | 0.020 | 250 | 0.044 |
| | | sentiment_polarity_score_pt | 0.002 | 0.008 | 250 | 0.056 | 0.002 | 0.008 | 250 | 0.044 |
| | | log_fatalities_best_30d_L1 \| log_num_conflict_events_30d_L1 | -0.003 | 0.005 | 250 | 0.056 | 0.000 | 0.008 | 250 | 0.044 |

# Interaction Model

- *Findings*:
  - *Baseline effects survive*: Across $h = 1, 2, 3, 5$, turmoil-specific language retains negative main effects, similar in magnitude to baseline, in both paired and Δ models.
  - *No systematic moderation*: Interaction coefficients are small and statistically indistinguishable from zero across features and horizons; level effects of the moderators themselves are also imprecise.
- *Robustness*: Results unchanged under:
  - alternative moderator timing (contemporaneous, +1–2 months lags),
  - adding conflict-type controls,
  - leave-one-country-out (LOCO) checks.
- *Interpretation / Takeaway*:
  - The volatility-reducing impact of structured, information-dense turmoil language is broadly level-invariant to measured conflict intensity.
  - Given null interactions, we do not report marginal effects at low/median/high intensity in the main text.

# Summary

- *Measures*: Language structure & information-density proxies (parse-tree depth, dependency length, contextual surprisal, work frequency, token count); Sentiment.
- *Findings*: Richer, more structured turmoil language is consistently associated with lower 1–5-day FX volatility; effects fade by day 10; not driven by generic wordiness or conflict severity; weak moderation.
- *Interpretation*: Clearer, better-organized, context-specific language narrows belief dispersion, trimming announcement-window volatility.
- Results support a clarity-and-information channel; better communication lowers market risk at the time of announcements
- *Policy*: Structured, context-rich turmoil passages can stabilize near-term FX in politically noisy periods.

# Policy Suggestion

- Speak better, not less.
- *Structure*: Use explicit linkages/if-then contingencies; coherent clause scaffolding.
- *Elaboration*: Allocate adequate space to the turmoil section (message detail).
- *Information density*: Add new, situation-specific facts (higher surprisal) to resolve uncertainty.
- *Delivery*: Front-load clarity at release; align pressers/FAQs; ensure translations preserve structure rather than just vocabulary.

# Further work

- Extend to rates/equities/CDS and intraday;
- test audience segmentation and localization;
- strengthen identification with narrative/experimental designs;
- integrate topics/stance/uncertainty with structure & surprisal in a unified model

# Q & A

Thank you.

# Acknowledgments

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This research would not have been possible without their funding and institutional backing.

# Appendices

**Table AVII. Description of sample**

| | Country | Number of statements released | First | Last | Statement Type | Name of Committee | Source |
|---|---|---|---|---|---|---|---|
| 1 | Azerbaijan | 85 | April 2007 | April 2025 | Press Release | Management Board | Central Bank of the Republic of Azerbaijan |
| 2 | Bangladesh | 36 | January 2006 | January 2025 | Monetary Policy Statement | Monetary Policy Committee | Bangladesh Bank |
| 3 | India | 116 | April 1998 | April 2025 | The Statement on Mid-term Review of Monetary and Credit Policy, Press Release | Monetary Policy Committee | Reserve Bank of India |
| 4 | Indonesia | 186 | August 2005 | April 2025 | Press Release | Board of Governors | Bank Indonesia |
| 5 | Lebanon | 23 | March 2002 | September 2024 | Monetary Overview | — | Banque du Liban |
| 6 | Pakistan | 84 | December 2005 | March 2025 | Monetary Policy Statement | Monetary Policy Committee | State Bank of Pakistan |
| 7 | Philippines | 220 | December 2001 | April 2025 | Press Release | Monetary Board | Bangko Sentral ng Pilipinas |
| 8 | Thailand | 196 | May 2000 | April 2025 | Press Release | Monetary Policy Committee | Bank of Thailand |
| 9 | Turkey | 223 | January 2006 | April 2025 | Press Release | Monetary Policy Committee | Central Bank of the Republic of Türkiye |
| 10 | Ukraine | 88 | April 2014 | January 2025 | Press Release | Monetary Policy Committee | National Bank of Ukraine |

# Appendices

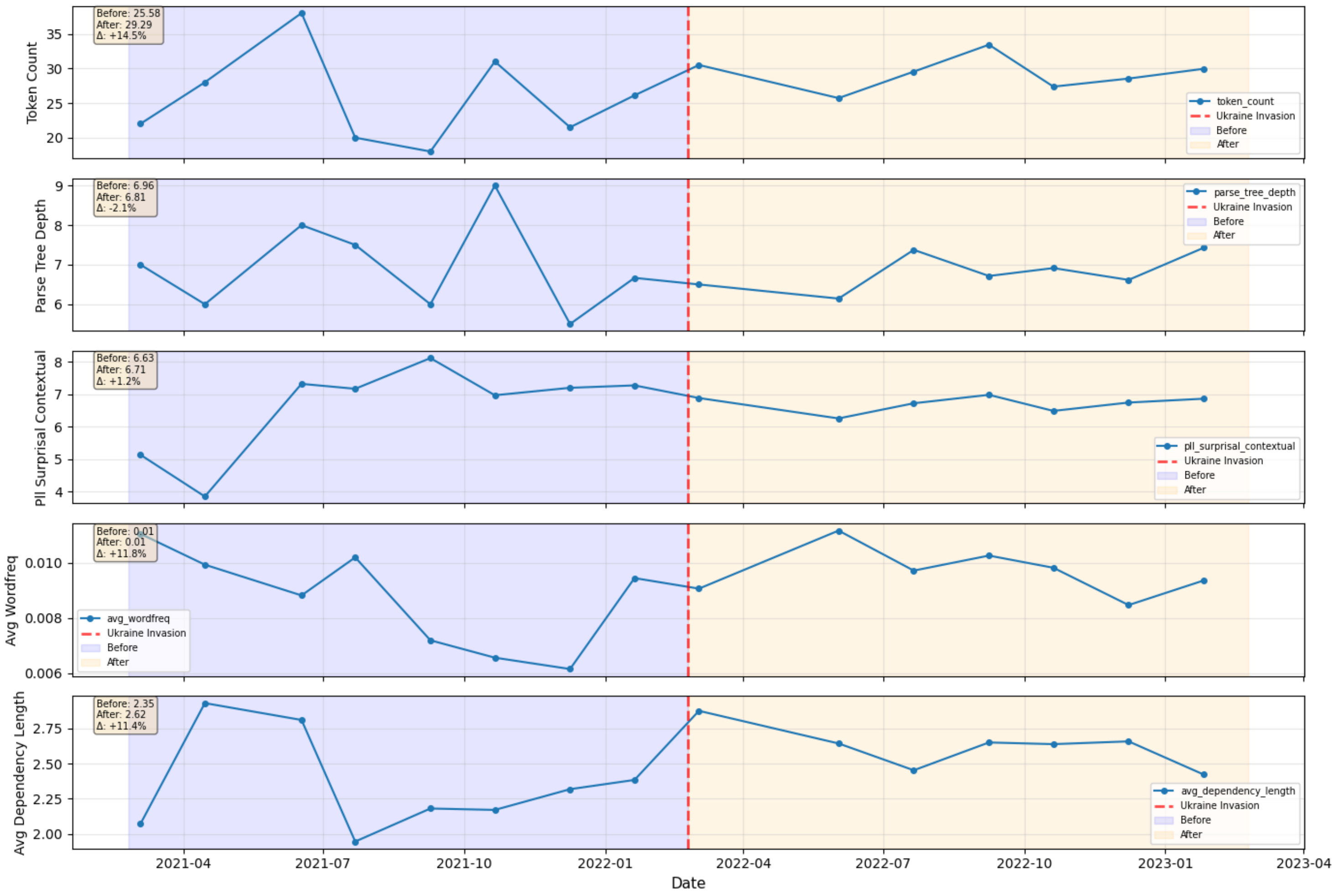
## Table AIX. Definition of variables.

| Variable | Definition |
|---|---|
| Dependent variables | |
| vol_fx_1d | Realized domestic-currency exchange-rate volatility over the prior 1 trading day. |
| vol_fx_2d | Realized domestic-currency exchange-rate volatility over the prior 2 trading days. |
| vol_fx_3d | Realized domestic-currency exchange-rate volatility over the prior 3 trading days. |
| vol_fx_5d | Realized domestic-currency exchange-rate volatility over the prior 5 trading days. |
| vol_fx_10d | Realized domestic-currency exchange-rate volatility over the prior 10 trading days. |
| Independent variables | |
| sentiment_polarity_score_pt | Sentiment score of turmoil–related sentences. |
| token_count_pt | Total tokens across turmoil–related sentences. |
| avg_dependency_length_pt | Mean dependency distance in turmoil–related sentences. |
| parse_tree_depth_pt | Mean parse-tree depth of turmoil–related sentences. |
| avg_wordfreq_pt | Average corpus word frequency of turmoil–related sentences. |
| pll_surprisal_contextual_pt | Pseudo-log-likelihood surprisal of turmoil–related sentences. |
| sentiment_polarity_score_ npt | Sentiment score of non-turmoil–related sentences. |
| token_count_ npt | Total tokens across non-turmoil–related sentences. |
| avg_dependency_length_ npt | Mean dependency distance in non-turmoil–related sentences. |
| parse_tree_depth_ npt | Mean parse-tree depth of non-turmoil–related sentences. |
| avg_wordfreq_ npt | Average corpus word frequency of non-turmoil–related sentences. |
| pll_surprisal_contextual_ npt | Pseudo-log-likelihood surprisal of non-turmoil–related sentences. |
| num_conflict_events_30d | Total conflict events in the past 30 days. |
| fatalities_best_30d | Cumulative fatalities (best estimate) in the past 30 days. |
| Control variables | |
| Central bank policy rate | Main policy interest rate (%). |
| Spread of long over short interest rate | Long-term government yield minus short-term rate (percentage points). |
| International Reserves Excluding Gold, % of GDP | Official FX reserves (ex-gold) as a share of GDP (%). |
| Real $ GDP, Growth Rate, Year-on-Year | Annual growth rate of real GDP (% y/y). |
| Composite Risk Rating | Overall country-risk index level. |
| Economic Risk Rating | Macroeconomic risk index level. |
| Financial Risk Rating | Financial-sector/external risk index level. |
| Political Risk Rating | Political-environment risk index level. |
| Robustness check variables | |
| state_based_30d | Number of state-based conflict events in the past 30 days. |
| non_state_30d | Number of non-state conflict events in the past 30 days. |
| one_sided_30d | Number of one-sided violence events in the past 30 days. |
| war_label dummy | Dummy indicator that a sentence is turmoil–related. |
| sentences_pt | Count of turmoil–related sentences in the statement. |
| sentences_npt | Count of non-turmoil–related sentences. |

Notes: ‘pt’ stands for political-turmoil specific textual measures whereas ‘npt’ stands for non-political-turmoil ones.

# Appendices

## Figure 3. Political turmoil metrics around russian full-scale invasion of Ukraine in 2022



# Appendices

**Figure A1. Topic evolution in central bank policy rate statements**