Central Bank Communication in Time of Crisis: Different Aspects of Linguistic Complexity

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Abstract

Central banks' communication strategies can change to fit the need to be clearer or to retain more flexibility. For example, they may wish to stimulate the economy with a clear indication that interest rates will be kept low for an extended period. At the same time, this can restrict their freedom to make future decisions appropriately, to deal with the unexpected. In this context, textual complexity can reflect an intentional effort to avoid overly rigid commitments, allowing central banks to maintain flexibility while still communicating policy direction. These trade-offs can vary according to economic conditions, especially during crisis versus normal times. This paper utilizes natural language tools to examine the textual complexity of policy statements from various central banks to derive not only conventional measurements of textual properties such as readability, but also other features, including abstractness, informativeness, and disunity. We find patterns showing that complexity intensifies during extremely low-growth periods or when economic stimulus is needed. Furthermore, the results reveal significant geographic variation, with differences driven more by regional context than by language. There is also evidence that statements targeting households and firms are far from negligible, underscoring the importance of communicating effectively with the general public. By mapping these patterns, the study provides a deeper understanding of how central banks adapt their communication strategy in times of crisis, contributing to the broader investigation of central bank communication and credibility.

Keywords:

1 Introduction

Central banks are indispensable to the functioning of an efficient economy: by regulating the money supply and setting interest rates, they guide the monetary policy and stabilize the economy. A key instrument in achieving this is the central bank's communication strategy, which shapes market expectations and influences the savings and investment decisions of economic agents – including financial institutions, households, and businesses.

For this reason, numerous studies have examined the impact of various communication tools on the market. However, the reverse can also be true: central banks' communication strategies may be influenced by prevailing economic conditions – a dynamic that has unfortunately received comparatively less attention, particularly in terms of textual complexity. Historically, the style of communication was largely shaped by central bankers' preferences. A widely famous quote from Chairman Alan Greenspan – "I guess I should warn you, if I turn out to be particularly clear, you've probably misunderstood what I've said" (as quoted in Floyd Norris, "What if the Fed Chief Speaks Plainly?", New York Times, October 28, 2005) – reflects his philosophy of managing expectations and avoiding overreaction. On the other hand, during Greenspan's tenure, the Federal Open Market Committee (FOMC) faced increasing pressure from Congress to enhance transparency, leading to the release of meeting transcripts beginning in 1993. This shift was driven by growing public scrutiny of the FOMC's expanding influence, necessitating clearer and more accessible communication. Similar developments occurred during the COVID-19 pandemic, when both the Federal Reserve and the European Central Bank (ECB) launched public outreach initiatives such as "Fed Listens." The ECB has even explicitly included reducing complexity as one of its communication goals. In times of crisis, central bankers seem to adopt more concise and direct language to persuade the public and enhance the effectiveness of their messaging.

On the other hand, excessive clarity can constrain policy flexibility. If promises are broken, it can severely damage a central bank's credibility – an asset of vital importance. In 2011, ECB President Jean-Claude Trichet clearly signaled rate hikes to combat inflation, raising interest rates twice despite growing signs of a eurozone debt crisis. The move worsened economic conditions and was quickly reversed, undermining the ECB's credibility. Thus, central bankers face a trade-off, and economic conditions can shape and alter their communicative behavior.

This paper aims to study the trade-off between clarity and flexibility in central bank communication by analyzing policy statements from institutions around the world, with a particular focus on textual ambiguity. Intuitively, textual complexity, often seen as the inverse of clarity, can also serve as a strategic instrument for enhancing flexibility in central bank communication, allowing policymakers to signal optionality and preserve interpretive space. However, attributing increased complexity during crises solely to higher volumes – such as word counts or speech frequency used in many studies—is unreliable. This paper seeks to broaden the understanding of communication complexity beyond conventional metrics, including those mentioned above and readability scores like the Flesch Reading Ease. Our analysis incorporates additional dimensions such as abstractness/concreteness (defined by specificity, tangibility, and vividness), informativeness, and disunity.

We examine central bank statements from around the world, including both major central banks and those operating under inflation-targeting regimes. The objective is to identify and contextualize international patterns in central bank ambiguity language during periods of crisis or extreme events. By uncovering these patterns, we aim to enhance the interpretation of future central bank communications in a more nuanced and comprehensive manner. Specifically, we seek to address the following questions:

1. Are there consistent correlations between various dimensions of textual complexity in central bank statements and policy rates or national economic conditions over time, particularly during periods of acute crisis?
2. How do these correlations differ across individual countries or regional/linguistic subgroups?
3. Do observable patterns vary when statements are directed toward specific economic agents – especially households and firms – and how does textual complexity relate to sentiment variables commonly employed in the literature?
4. Have the thematic focuses of central bank statements evolved over time?

The first and second research questions aim to statistically examine fluctuations in various aspects of statement complexity during periods of economic turbulence, particularly crises. Communication complexity can evolve in different directions during downturns. On one hand, central banks may seek to articulate their decisions with greater clarity to reassure the public, though this approach risks undermining credibility if promises are not fulfilled. On the other hand, they may opt for vaguer language to allow for broader interpretation and increased policy flexibility – albeit at the expense of communicative effectiveness.

Importantly, not all increases in complexity are inherently negative. For instance, a rise in word count following the ELB period may reflect the inclusion of more concrete information. Simple metrics – such as word count or sentence length – often interpret such changes as a rise in textual complexity, potentially leading to misleading conclusions. In contrast, by applying more refined metrics that account for dimensions like specificity and abstraction, we may find that complexity does not increase uniformly. Instead, we can isolate which aspects have shifted – for example, an increase in informational content accompanied by a decrease in abstract language. This distinction allows for a more accurate assessment of whether the communication has become more or less effective. Careful analysis of these dynamics can lay the groundwork for developing more precise metrics to evaluate the effectiveness of central bank communication.

This leads to the significance of the third question. If the goal is to stimulate the economy not only through financial institutions and investors but also by reaching the general public, overly complex language and structure may alienate certain audiences, thereby reducing policy effectiveness. Households – and potentially some firms – may be especially vulnerable to this weakness. Identifying whether excessive complexity disproportionately affects these groups could offer valuable insights. Finally, the fourth question addresses whether the thematic content of central bank statements has shifted over time. Understanding these shifts may reveal broader trends in institutional priorities and public engagement strategies.

Preliminary findings indicate substantial variation in how complexity metrics respond to policy rates and macroeconomic variables. Notably, linguistic complexity in central bank statements appears to correlate more strongly with periods of extremely low economic growth than with conventional indicators of downturns. In many cases, these statements become more difficult to read, convey greater informational content, and exhibit reduced cohesion across sentence transitions. Furthermore, irrespective of growth levels, when there is a need to stimulate the economy, statements tend to adopt more abstract language as interest rates decline. These results complement recent work using large language models to assess semantic clarity and explanatory depth in central bank communication, which finds increased complexity during periods of uncertainty (Silva et al., 2025). We also observe persistent regional differences in communication style that align more closely with geographic location – specifically, between Eastern and Western countries – than with linguistic factors (e.g., English vs. non-English-speaking nations).

Descriptive evidence also suggests that households constitute a relevant audience for central bank communications. Generally, when statements explicitly target households and firms, they tend to show little to no increase in complexity—and in some cases, even a slight reduction—indicating that communicative clarity is not a major concern when addressing these audiences, at least on average. Moreover, linguistic complexity tends to be higher in countries where central banks consistently adopt more hawkish or optimistic tones in their policy statements. Further analysis reveals that inflation has remained a dominant concern throughout the period from 2000 to 2024. Although economic growth gained prominence in recent years, this trend reversed following the onset of the pandemic. The inflation topic also shows a modest positive correlation with abstractness (0.38), aligning partially with the broader pattern of central banks favoring more abstract communication when emphasizing inflation-fighting priorities.

This paper starts with a brief literature review surveying studies that leverage textual data to analyze central bank statements and their correlations with macroeconomic indicators and financial instruments. The analysis then proceeds with a detailed description of the dataset, the techniques used to quantify and identify various aspects of linguistic complexity within these statements, followed by the introduction of a basic framework and the regression models employed to address the research questions. Next, we present and discuss our results. Finally, the paper concludes by summarizing key findings and proposing promising directions for future research in this evolving domain.

2 Literature Review

This paper primarily focuses on the literature surrounding central bank communications, particularly studies that leverage textual data to examine the nuanced relationship between communication characteristics—either in isolation or in conjunction with other factors—and key economic outcomes such as policy rates and macroeconomic indicators.

2.1 The Effects of Central Bank Communication on the Economy

In recent years, the literature analyzing central bank communications through textual data has expanded considerably. This analytical shift has moved away from labor-intensive manual labeling toward more efficient automated textual analysis tools, enabling the processing of substantially larger datasets. The most prominent examples of this trend are sentiment analysis and hawkish/dovish identifications.

Sentiment analysis in central bank communications typically centers on several key categories, with positivity/negativity and dissent being the most prevalent. A positive tone in policy statements generally signals optimistic economic conditions, while a negative tone may encourage saving and dampen spending. These studies often vary in the types of communication analyzed (e.g., policy statements, speeches) and the specific central banks examined, exploring relationships between positive tone and outcomes such as policy uncertainty and volatility (Baranowski et al., 2021; Tillmann and Walter, 2019; Gu et al., 2022), unemployment, output growth, inflation (Bohl et al., 2023; Clements and Reade, 2020; Eugster and Uhl, 2024), interest rates (Astuti et al.), and financial markets (Picault and Renault, 2017; Ehrmann and Talmi, 2020; Schmeling and Wagner, 2023; Hayo et al., 2022). Dissent, another critical dimension of interest, reflects internal disagreements during policy deliberations. Its presence signals ongoing debates over economic risks and can offer valuable insights into future monetary policy directions, thereby influencing market expectations and contributing to policy uncertainty. However, the analysis of dissent falls outside the scope of this paper, as we treat each central bank as a unified entity, represented by its aggregated policy statements rather than individual member speeches, interviews, or transcripts.

Another aspect of particular interest to economists and policymakers is the distinction between hawkishness and dovishness in central bank communication. "Hawks" are typically characterized by a willingness to tolerate higher interest rates in order to control inflation, even at the potential expense of economic growth, consumer spending, and employment. In contrast, "doves" prioritize economic growth and employment, potentially accepting higher inflation as a trade-off. These two orientations serve as vital indicators of the policy stance and implicit signals embedded within monetary policy statements. For example, Parle (2022) identified a statistically significant positive effect on stock prices resulting from a more hawkish tone in ECB press conference transcripts. Similarly, Dossani (2021) examined transcripts from five central banks—including the ECB and the Federal Reserve—and found that increased hawkishness was associated with a decline in the variance risk premium and variance swap returns, as well as an increase in option-implied risk aversion.

However, the assessment of ambiguity in central bank communications has not yet received the same depth of measurement and research as other facets of textual analysis. The most widely adopted approach to this dimension of complexity is readability—a particularly popular metric due to its intuitive appeal, its direct impact on financial markets and its central role in shaping the effectiveness of central bank messaging. The underlying rationale is that overly opaque policy statements can be detrimental: households may struggle to interpret them, and businesses may be forced to rely on external interpretations—often from news outlets—which can be subjective, potentially biased, and costly if access requires subscription fees. Although the general public has traditionally paid limited attention to central bank actions outside of major policy decisions or leadership changes, public awareness has likely increased in recent years due to events such as the COVID-19 pandemic. The unexpected surge in inflation, accompanied by disruptions in unemployment, wages, and living costs, has made the tangible effects of monetary policy more visible to everyday citizens. Both the emotional tone and linguistic complexity of central bank communications have proven to be valuable indicators of financial activity, particularly in relation to signals from the Federal Reserve and the European Central Bank. The most established readability metric is the Flesch-Kincaid score. Studies have shown that this score has increased significantly over time for both the Fed and the ECB (T. Hughes and Kesting (2014)), although the ECB has implemented reforms in recent years aimed at lowering its score to improve accessibility. Numerous studies have employed readability metrics to examine their economic implications—specifically, the impact on trading volume, return volatility (Smales and Apergis, 2017), contemporaneous trading activity under unconventional monetary policy (Hayo et al., 2022), and interactions with other sentiment measures (Celler).

Beyond the major central banks, existing studies have also examined smaller or less prominent institutions, typically on an individual basis rather than as part of a comparative framework (Binette and Tchebotarev, 2019; Doan et al., 2023). In contrast, our research adopts a broader analytical scope, examining cross-country differences and incorporating a selection of developing economies. This distinct focus naturally leads to our involvement with the existing cross-national literature.

This area of research remains relatively limited in scope, often lacking recent textual data and frequently confined to analyses focused on the United States and Europe. For instance, Born et al. (2014) employed a comprehensive set of Financial Stability Reports (FSRs) from 37 countries spanning 1996 to 2009, with a primary focus on the relationship between extracted positivity and financial market outcomes such as stock prices and volatility. In contrast, our research focuses more on textual complexity and its relationship with key macroeconomic variables—such as growth and inflation—particularly in connection with recessions, thereby extending beyond the scope of financial stability analysis.

Moreover, the temporal scope of Born et al. (2014) excludes several critical recent developments, including the Effective Lower Bound (ELB) periods and the COVID-19 pandemic. The study most closely aligned with our approach is arguably Luangaram and Wongwachara (2017), which analyzed monetary policy statements from 22 central banks between 2000 and 2015 using a range of linguistic tools, including topic modeling, sentiment analysis, readability metrics, and text similarity. However, this work does not explicitly address the ELB period and, once again, omits the pandemic era from its dataset. Additionally, the computational tools employed in Luangaram and Wongwachara (2017) rely on standard techniques for assessing textual ambiguity, underscoring a clear opportunity for methodological advancement.

In conclusion, one of the key challenges associated with these models lies in the limited availability and accessibility of the required variables. More importantly, my primary interest does not lie in how central bank statements influence financial markets, but rather in understanding the intrinsic characteristics of the texts themselves—how they are constructed and evolve over time. In this regard, much of the literature adopts a reverse approach, regressing textual features against macroeconomic indicators such as real GDP growth, unemployment rates, and inflation (Bohl et al., 2023), often incorporating lag structures to capture temporal dynamics (Hayo and Zahner, 2023). A recent contribution by the IMF (Silva et al., 2025) takes this further by using large language models to classify central bank statements according to semantic clarity and explanatory depth, showing that complexity increases during periods of uncertainty. While their focus is on communicative intent and audience segmentation, my approach centers on linguistic structure—readability, abstractness, informativeness, and coherence—offering a complementary perspective on how complexity manifests in response to economic conditions, particularly during periods of crisis.

2.2 Target Audiences and Speakers Heterogeneity

The intuitive premise that greater public knowledge of economic conditions fosters more informed decision-making underscores a fundamental requirement for effective central bank communication: economic agents must possess a sound understanding of monetary policy goals and strategies. This principle readily applies to financial market participants and professional forecasters, who are typically well-equipped with the expertise to interpret and respond to policy statements. However, this may not hold true for the general public, where both the motivation to engage with complex economic information and the foundational knowledge needed to interpret it effectively may be limited (van der Cruijsen et al., 2015)

Regarding public engagement, Gros and Capolongo (2020) aptly conclude that "the interest of the wider public for monetary policy is intermittent, linked to major decision points and/or personnel changes." This phenomenon was particularly evident during major events such as the COVID-19 pandemic and the global financial crisis, when public scrutiny of central bank actions intensified. As for the knowledge barrier, Dräger et al. (2016) demonstrates that increased transparency in monetary policy—combined with media coverage—can enhance public understanding of key economic concepts, thereby improving forecast accuracy among non-expert audiences.

Beyond these considerations, a substantial body of theoretical literature strongly supports the notion of audience heterogeneity in central bank communication (Blinder et al., 2022). For instance, Binder (2017) and Coibion and Gorodnichenko (2015) argue that inflation expectations are formed differently across households, firms, and financial markets, thereby necessitating more audience-specific messaging from central banks. While this awareness has gained considerable theoretical traction, it has yet to be fully realized in empirical research. As Blinder et al. (2008) observed, "virtually all the research to date has focused on central bank communication with the financial markets" (p. 941). In this paper, we aim to help bridge this empirical gap in part by applying the model developed by Pfeifer and Marohl (2023) to infer the intended economic agents for specific pieces of central bank communication, enabling us to briefly explore this crucial dimension within our dataset.

Moreover, heterogeneity may arise not only from the audience but also from the speakers themselves, who may tailor their language depending on the target group—potentially introducing inconsistencies. For example, Bennani and Neuenkirch (2016) found evidence that central bankers adjust their speeches depending on whether they are addressing domestic or international audiences, or whether the speech occurs before or after a Governing Council meeting. In contrast, other studies, such as Jansen and de Haan (2013), suggest that the ECB's overall communication has remained consistent over time, highlighting an area of ongoing debate and empirical inquiry. To account for this potential variation, our research leverages panel data and employs a Fixed Effects model to control for unobserved heterogeneity across institutions.

3 Data

This section details the primary datasets utilized in this research: a comprehensive collection of central bank policy statements and a compilation of relevant country-specific characteristics.

3.1 Central Bank Statements

The textual data consists of English-language policy statements collected from the public websites of 18 central banks. The sample includes three major institutions—the Federal Reserve (Fed), the European Central Bank (ECB), and the Bank of Japan (BoJ)—as well as a diverse set of central banks operating under inflation-targeting regimes across both advanced and emerging market economies.

Covering the period from 2000 to 2024, the dataset spans several pivotal economic episodes, including the pre- and post-Great Financial Crisis (GFC), periods of the effective lower bound (where applicable), and the pre- and post-COVID-19 pandemic eras. While the overall timeframe is extensive, the availability of statements varies by country (see Table 11 in the Appendix for details). It is also important to note that the timing of statement releases differs significantly across countries—and occasionally within countries—due to variations in meeting schedules and the need for ongoing adjustments in response to evolving economic conditions and interest rate changes.

The initial dataset comprises 3,809 individual statements. To ensure temporal consistency and facilitate regression analysis, these observations are aggregated to the quarterly level, resulting in a condensed dataset of 1,592 observations.

Given the variability in naming conventions for "policy statements" across central banks, the "press release" version was consistently selected [1]. This choice promotes uniformity in both length

[1]In the case of the ECB, the introductory statement from its press conferences was chosen for three key consid-

and communicative intent across the dataset, aligning particularly well with the paper's emphasis on central bank communication directed toward the broader public, including households.

During the data collection process, careful attention was paid to excluding extraneous elements such as dates, timestamps, and administrative details (e.g., signatures, notices of future meetings) that appear on the source webpages. This targeted preprocessing ensures that the textual analysis focuses exclusively on the substantive content of the policy statements, preserving the stylistic integrity of each central bank's communication.

3.2 Country Characteristics

For the international comparative analysis, this study incorporates a comprehensive set of macroeconomic variables: real GDP (and its growth rate), the Consumer Price Index (CPI) (and derived inflation rates), the unemployment rate, recession indicators, and the policy rate. Wherever possible, data span the period from 2000 to 2024.

Real GDP: The majority of real GDP data is sourced from the Federal Reserve Bank of St. Louis (FRED). While quarterly data are available for some countries, others provide only annual data, with no monthly GDP figures. For countries lacking quarterly data on FRED, supplementary data were retrieved directly from the official websites of their respective central banks. Although some of these sources are not in English, careful translation efforts were undertaken to minimize potential errors.

The primary measure used in this analysis is the quarter-to-quarter change in real GDP growth, which helps mitigate cross-country differences in national currencies. To identify periods of "extreme crisis," binary variables are constructed to flag instances when real GDP growth falls within the lowest percentiles for each country. The 2nd percentile is used for the main analysis, while the 5th and 10th percentiles are included in the Appendix for robustness checks.

Another approach to capturing extreme economic events involves the use of conventional **recession indicators**. For countries outside the United States, the OECD midpoint method is employed to ensure consistency. For the United States specifically, we additionally incorporate the National Bureau of Economic Research (NBER) recession indicator, which provides a fourth interpretation alongside the OECD-based methods. The NBER definition typically reflects a more stringent threshold for recession, identifying fewer periods than the OECD-based measures.

To complement our analysis, we distinguish between two approaches to identifying recessionary periods: quantile recession indicators and 3D recession indicators. The former flags episodes of extreme economic contraction based solely on the bottom percentiles of real GDP growth, offering a data-driven method for capturing sharp downturns. In contrast, 3D recession indicators—taken from conventional frameworks such as those used by the OECD and NBER—incorporate three dimensions: depth, diffusion, and duration. These expert-defined measures provide a broader per-

erations: (i) it is more directly comparable to other central banks for public-facing communication; (ii) alternative ECB statements were less informative, particularly in earlier periods; and (iii) the ECB has historically emphasized its press conferences as a primary channel of communication (Bernoth and Dany-Knedlik, 2020).

spective on economic distress but may overlook short-lived or narrowly concentrated contractions. A detailed comparison of these approaches, including visual illustrations and methodological nuances, is provided in the Appendix 8.2.

The **Consumer Price Index (CPI)** and **policy rate** data are both obtained from the Bank for International Settlements (BIS) data repository. To enable cross-country comparability, CPI data are normalized to an index of 100 in the year 2007 for all countries. Inflation is calculated as the simple growth rate of the CPI. For the policy rate, we use its first difference to effectively capture both the direction and magnitude of monetary policy adjustments. We also leverage a binary indicator to denote whether the policy rate changed or remained constant, which allows us to evaluate the behavior of textual complexity in relation to policy inertia—these results are detailed in the Appendix.

The **unemployment rate** data are sourced from the OECD database and presented as monthly, seasonally adjusted figures. This dataset primarily covers OECD member countries, with the exception of Indonesia, Peru, the Philippines, and Thailand. We specifically use the total unemployment rate for individuals aged 15 and above, rather than disaggregated male/female rates. The exclusion of gender-specific rates is justified by their high correlation with the total rate (correlation coefficients typically exceeding 0.95), which helps maintain analytical focus and avoid multicollinearity. For countries not covered by the OECD database, the same data collection strategy used for real GDP was applied—namely, sourcing from national central bank websites. While minor discrepancies in age definitions exist (e.g., Peru defines unemployment starting at age 14), these differences are considered acceptable for the purposes of this study, as they reflect the official metrics used by national economic authorities.

Table 1 presents the mean and standard deviation for each economic variable across the included countries. The following notations are used: i denotes the policy rate, Δi its first difference (i.e., change in policy rate), u the unemployment rate, RI the 3D recession indicator, g_y the growth rate of real GDP, and π the inflation rate. The summary statistics reveal a considerable degree of heterogeneity across countries, both in levels and volatility. This underscores the importance of accounting for country-specific characteristics—particularly through the inclusion of country fixed effects—wherever possible in the empirical analysis.

4 Quantifying Central Banks' Statements

This section outlines the methodological algorithm used to extract textual variables from central bank policy statements. The discussion begins with the construction of textual ambiguity metrics, followed by the application of topic modeling algorithms to uncover latent themes. Next, we describe the procedure for inferring each statement's relevance to different economic agents. Finally, we detail the extraction of widely used sentiment indicators, including hawkish versus dovish tones and classifications of positive versus negative sentiment.

Table 1: Average economic figures across countries

Country	i mean	i std	Δi mean	Δi std	u mean	u std	RI mean	RI std	g_y mean	g_y std	π mean	π std
Australia	3.265	1.973	-0.014	0.435	5.297	0.901	0.443	0.481	0.783	1.297	2.915	1.618
Canada	2.101	1.621	-0.014	0.419	6.959	1.106	0.361	0.456	0.492	1.604	2.235	1.356
Chile	4.147	2.447	-0.001	0.913	8.172	1.432	0.485	0.484	0.827	1.890	3.832	2.642
Colombia	6.413	3.701	0.152	0.962	10.964	2.394	0.022	0.096	0.652	3.623	5.901	3.255
ECB	1.683	1.615	-0.001	0.348	8.992	1.575	0.366	0.474	0.314	1.773	2.142	1.801
Fed	1.943	2.034	-0.013	0.479	5.695	1.956	0.107	0.290	0.537	1.278	2.588	1.729
Hungary	5.462	3.809	-0.023	1.069	6.505	2.528	0.369	0.470	0.523	2.263	4.829	4.566
Iceland	5.344	2.814	-0.139	1.070	5.209	1.786	0.361	0.471	0.667	2.918	4.585	3.106
Indonesia	6.464	2.047	-0.086	0.472	–	–	0.274	0.434	1.182	1.064	5.286	3.543
Japan	0.052	0.187	0.005	0.059	3.819	1.006	0.370	0.464	0.163	1.371	0.411	1.290
Korea	2.855	1.339	-0.018	0.302	3.502	0.444	0.385	0.476	0.871	0.926	2.497	1.339
New Zealand	3.915	2.288	-0.015	0.483	4.831	0.968	0.408	0.495	0.650	1.965	2.564	1.658
Norway	2.565	2.085	-0.010	0.465	3.863	0.594	0.467	0.493	0.389	1.166	2.445	1.451
Peru	3.746	1.721	0.027	0.602	8.071	1.968	0.109	0.294	1.295	7.082	3.025	1.887
Philippines	4.823	1.705	-0.020	0.397	6.689	1.903	0.542	0.484	1.276	3.395	3.885	1.975
Poland	4.249	3.197	-0.132	0.676	9.388	5.825	0.412	0.471	0.881	1.480	3.349	3.618
Thailand	2.047	1.055	0.003	0.315	1.102	0.400	0.542	0.483	0.802	2.038	1.950	2.242

4.1 Textual Complexity Measurements

The following measurements of textual complexity primarily focus on the precise definition and algorithmic implementation of each aspect. Due to the length of the actual data, which spans multiple pages, we present two simplified examples resembling monetary policy statements. A statement that clearly anchors expectations might read: "The Committee will set the rate at 0.25 percent until inflation reaches 2 percent and unemployment falls below 5 percent. We expect these conditions to be met by mid-2026." In contrast, a more flexible—and therefore more textually complex—version could be: "The Committee anticipates that maintaining the current policy rate may be appropriate as long as inflation trends toward 2 percent and labor market indicators improve. These conditions could potentially be met by mid-2026, although considerable uncertainty remains". Although both statements convey the same policy decision, the use of modal verbs such as "may" and phrases like "considerable uncertainty remains" introduce a degree of flexibility. These elements also contribute to increased textual complexity: "may" is a modal verb that signals uncertainty, and the phrase "although considerable uncertainty remains" reduces the relative coherence between sentences compared to the clearer version. Further explanation tailored to each linguistic complexity dimension is provided in Appendix 8.1.

4.1.1 Readability

Readability refers to the estimated educational level required for an audience to comprehend a given text. To assess the complexity of central bank communications, this study employs a comprehensive set of established readability metrics. These include: Gunning-Fog Index, SMOG Index, Flesch Reading Ease (a widely used metric in the literature), Flesch-Kincaid Grade Level, Automated Readability Index (ARI), Coleman-Liau Index, LIX, and RIX. Each of these metrics captures different aspects of textual complexity, such as sentence length, syllable count, and word frequency. Detailed descriptions of these measures are provided in the Appendix 8.3.

Although these readability metrics differ in name and calculation, they share substantial underlying similarity due to common linguistic components. Most metrics are derived from factors such as word count, sentence length, and the frequency of "hard" or polysyllabic words, often through various transformations. Given the resulting multicollinearity among these variables, we apply Principal Component Analysis (PCA) to reduce dimensionality and extract a single composite indicator of textual complexity. Specifically, the first principal component is retained and used as the unified readability variable. [2]

The correlation matrix reveals positive relationships among all metrics, with the notable exception of the Flesch Reading Ease score. While higher values for most readability indices (e.g., Gunning-Fog, SMOG) indicate greater difficulty in comprehension, the Flesch Reading Ease score operates inversely—higher values reflect simpler, more accessible text. Accordingly, the first principal component is interpreted so that higher values indicate greater textual complexity.

4.1.2 Abstractness

Concretenessis often inversely related to textual complexity, owing to its strong association with the ease of mental imagery and the tangibility of words and concepts. More concrete texts tend to be easier to comprehend and process cognitively. A substantial body of research links concreteness to cognitive performance, largely through a mechanism known as the concreteness effect. This effect is commonly explained by three foundational theories:

- (i) Dual-Coding Theory: Concrete terms activate both the verbal and imagery systems in the brain, with a stronger association to the latter. In contrast, abstract words typically engage only the verbal system, thus impeding memorability and cognitive processing.
- (ii) Age of Acquisition Hypothesis: Abstract terms are generally acquired later in linguistic development than concrete terms. This delayed acquisition contributes to greater difficulty in understanding and retaining abstract concepts.
- (iii) Context Availability Model: Abstract terms are harder to retrieve because they are less strongly associated with contextual knowledge.

The semantic counterpart to concreteness is **abstractness**, which typically signals higher cognitive demand and greater linguistic complexity.

To quantify concreteness for each word within a document, values are assigned—where available—using three established sources: the Brysbaert dataset (Brysbaert et al., 2013), the Glasgow

[2] Bartlett's test yields a p-value of 0, confirming the suitability of PCA. Correlations among the components are also notably high, ranging from 0.73 to 0.98, with most values exceeding 0.90. These patterns hold consistently across all other complexity metrics discussed in the subsequent subsections.

Norms (Scott et al., 2019), and the MRC Psycholinguistic Database (Coltheart, 1981). These concreteness scores typically range from 1 to 5, with 5 indicating the highest level of concreteness and 1 representing the highest level of abstractness.

The average concreteness of a document is calculated either as the mean of all assigned values or as the ratio of total concrete words to abstract words. Two variants of the former measure are considered, depending on whether words without a concreteness score (and not classified as stop words) are included in the denominator. In cases where a document contains no words with available concreteness ratings, a fallback value is assigned—either the mean of all concreteness scores across the dataset or a default midpoint value of 2.5.

The final concreteness metric used in this study is the ratio of concrete to abstract words. To ensure that all textual ambiguity indicators are directionally consistent—i.e., higher values reflect greater complexity—we invert the concreteness measures to derive abstractness. Specifically, we compute 6 − concreteness for mean-based metrics and 1/concrete ratio for ratio-based metrics

All derived variants of abstractness are then combined using Principal Component Analysis (PCA), following the same methodology applied to readability. The first principal component serves as the composite abstractness variable. A higher value of this composite score indicates greater difficulty of comprehension, reflecting increased complexity in central bank statements.

4.1.3 Informativeness

Under information theory, **informativeness** refers to the amount of information conveyed by a text, commonly quantified using Shannon entropy. Entropy is defined as:

$$H(X) = -\sum_{i=1}^{n} p(x_i) log_e p(x_i)$$

where $p(x_i)$ represents the probability of the token x_i. A higher entropy value indicates greater token diversity, suggesting that the text contains a broader range of vocabulary and, by extension, more informational content.

This measure is frequently used to assess the richness of textual data and, to some extent, can be interpreted as a proxy for complexity. However, it is important to note that lexical diversity does not always equate to cognitive difficulty. In fact, a varied vocabulary can improve clarity rather than hinder it. For this reason, we adopt the term informativeness to describe this characteristic specifically, distinguishing it from other dimensions of textual complexity.

To ensure consistency with other variables subjected to principal component transformation, the informativeness metric is normalized prior to inclusion in the analysis.

4.1.4 Disunity

The variable termed **disunity** in this study corresponds to what is conventionally referred to as document coherence. It is operationalized using cosine similarity between sentence-level word embeddings, which capture semantic relationships within the text.

Two versions of coherence are implemented: **first-order coherence**, calculated as the cosine similarity between consecutive sentences (Bedi et al., 2015), and **second-order coherence**, which measures similarity between sentences separated by one intervening sentence (Parola et al., 2023). In both cases, higher similarity scores indicate greater semantic distance between sentences—implying lower cohesion and, therefore, higher disunity.

The term disunity is adopted in place of coherence to clarify the directional interpretation of the metric. While coherence typically carries a positive connotation, the numerical values derived here reflect an inverse relationship to ease of comprehension: higher scores denote less semantic cohesion.

Following the methodology used for readability, disunity is summarized using Principal Component Analysis (PCA). The first principal component of both first-order and second-order coherence scores is extracted to form a single composite measure of textual disunity.

4.1.5 Others

Several additional textual metrics, while potentially informative, have been excluded from the primary analysis due to ambiguities in interpretation or high correlation with previously defined variables.

One such omitted variable is dependency distance, a syntactic complexity measure based on the distance between each token and its syntactic head or dependent within a sentence (**??**). This metric allows for the calculation of both the mean and standard deviation of dependency distances across a document. To illustrate, consider the sentence "The central bank unexpectedly raised interest rates." In this example, "raised" is the head of the clause; "bank" is its subject (a dependent of "raised"), modified by "central"; "rates" is the object of "raised", modified by "interest"; and "unexpectedly" is an adverbial modifier of "raised." Longer dependency distances imply that readers must retain earlier sentence elements in working memory to integrate them with later components, thereby increasing cognitive load and reducing reading ease. While this metric aligns conceptually with syntactic complexity, its dual reliance on both mean and variance makes interpretation less straightforward. Relying solely on the mean may obscure important structural nuances.

Other basic metrics—such as average words per sentence or average word length—are also excluded from the core analysis. Although they offer surface-level insights, they lack the depth and multidimensionality of the composite readability measures already employed. Additionally, dictionary-based metrics, which depend on predefined vocabularies, tend to be less reliable when applied to domain-specific corpora like central bank communications, where specialized terminology is prevalent and often absent from general-purpose lexicons.

Another category of relevant variables is derived from information theory. In addition to Shannon entropy (used to measure Informativeness), two related metrics—**perplexity** and its normalized variant—are considered:

- Perplexity quantifies how well a probability distribution or language model predicts a given text sample. It is defined as:

$$PPL(X) = e^{-H(X)}$$

where $H(X)$ is the entropy of the text.

- The length-normalized perplexity is calculated by dividing the perplexity score by the number of words in the document.

However, due to the irregular distribution of perplexity scores—and by extension, length-normalized perplexity—these metrics are excluded from the main analysis. Their limited interpretability within an economic context further limits their practical utility, making them less suitable for the current framework.

Finally, to provide a comprehensive overview, Table 2 in the Appendix presents the average values of all ambiguity-related metrics—**Readability**, **Abstractness**, **Informativeness**, and **Disunity**—for each country. All values are normalized to have a mean of 0 and a standard deviation of 1 to ensure comparability across countries.

Table 2: Average of ambiguity measurements across countries

Country	**Readability**	**Abstractness**	**Informativeness**	**Disunity**
Australia	-2.839	0.534	0.011	-0.135
Canada	-1.408	-1.574	-0.319	0.281
Chile	-0.203	0.619	-0.451	-0.253
Colombia	-0.241	1.441	-0.315	0.581
ECB	1.096	1.461	2.072	0.936
Fed	2.968	0.371	-0.418	-0.133
Hungary	0.538	0.154	0.706	0.943
Iceland	-2.15	1.015	-0.48	-0.582
Indonesia	2.831	-0.224	1.751	0.89
Japan	-0.09	-4.488	-0.242	-1.366
Korea	2.234	-1.082	-0.383	0.817
NewZealand	-1.463	0.479	-0.485	-0.2
Norway	-3.769	-2.254	-0.35	-0.789
Peru	-1.861	0.452	-0.403	-2.239
Philippines	2.864	0.918	-0.572	0.882
Poland	0.197	1.643	0.324	0.87
Thailand	0.788	2.148	-0.415	-0.25

As observed, a high score in one dimension of textual complexity—such as elevated readability (indicating greater difficulty)—does not necessarily correspond to a high score in another, such as abstractness. This highlights the nonlinear behavior of different facets of textual ambiguity across countries. In other words, central bank statements may exhibit varying combinations of complexity traits that do not move uniformly together. Nevertheless, a general directional pattern emerges: overall textual complexity tends to be associated with higher readability scores (i.e., harder to read), greater abstractness, increased informativeness (reflecting more diverse vocabulary), and elevated disunity (indicating lower semantic cohesion).

4.2 Topic modeling

Topic modeling is an unsupervised machine learning technique in Natural Language Processing (NLP) used to uncover abstract "topics" or thematic structures within a collection of documents. Unlike traditional classification methods, which rely on predefined categories and labeled data, topic modeling autonomously identifies latent semantic patterns without prior knowledge of the underlying topics. The foundational assumption is that each document comprises a mixture of topics, and each topic is characterized by a distinct distribution of words. For instance, a document centered on "sports" may include terms such as "game," "team," "player," and "score," whereas a document focused on "finance" might feature words like "stock," "market," "economy," and "investment." Topic modeling seeks to reverse-engineer these associations by detecting word co-occurrence patterns and clustering them into interpretable topics.

One of the most widely adopted algorithms for topic modeling is **Latent Dirichlet Allocation (LDA)**. LDA is a generative probabilistic model that assumes a latent structure by which documents are composed from a set of topics, and topics are composed from a set of words. Given the observed words in the corpus, the algorithm aims to infer the hidden variables that govern this generative process, thereby revealing the thematic composition of each document. It is important to note that each document is modeled as a mixture of multiple topics and every topic is a mixture of words, defined by a probability distribution over the vocabulary. For instance, a news article might be composed of 70% politics and 30% economics. A topic labeled "politics" might assign high probabilities to words such as "government," "election", "policy", and "parliament", while a topic labeled "economics" might emphasize terms like "inflation", "interest", "market", and "growth".

Before applying LDA, the text data undergoes a series of preprocessing steps, which is detailed in Appendix 8.4.1. The cleaned and processed text is then transformed into a document-term matrix, which records the frequency of each term within each document. The LDA algorithm is implemented through an iterative process, typically using either Gibbs sampling or Variational Inference to approximate the posterior distributions. The intuitive steps of the Gibbs sampling approach are presented in the Appendix 8.4.2 along with the hyperparameter settings.

Once the LDA algorithm converges, it produces two primary outputs:

- **Topic-word distributions**: For each topic, the model generates a list of words along with their associated probabilities of appearing within that topic. These distributions help interpret the semantic meaning of each topic by identifying its most representative keywords.

- **Document-topic distributions**: For each document, the model provides a probability distribution over the set of topics, indicating the extent to which each topic is present. This allows for a nuanced understanding of the thematic composition of individual documents.

Based on these outputs, topics are manually labeled to facilitate interpretation and ensure alignment with the economic context of the corpus, enhancing the relevance and clarity of subsequent analyses.

4.3 Other textual characteristics

Beyond textual ambiguity, this study incorporates additional linguistic features essential for a comprehensive understanding of central bank communication. A substantial body of literature emphasizes the need for clearer messaging from central banks, particularly given that communications directed at non-financial institutions—such as households or small firms—can be significantly more difficult to interpret due to limited domain-specific expertise. Accordingly, it is important to assess whether these diverse economic agents are indeed the intended audience for such communications.

To move beyond traditional bag-of-words approaches—which often fail to capture contextual nuance and audience-specific sentiment—this study employs the deep-learning-based Large Language Model (LLM) **CentralBankRoBERTa**, introduced by Pfeifer and Marohl (2023). This model serves as a state-of-the-art economic agent classifier, capable of estimating the proportion of a document's content directed toward five macroeconomic agents: households, firms, the financial sector, the government, and the central bank itself. In addition, CentralBankRoBERTa functions as a binary sentiment classifier, identifying the emotional tone (positive or negative) of individual sentences within central bank statements.

What distinguishes CentralBankRoBERTa from conventional sentiment classifiers is its ability to address two critical limitations: context insensitivity and lack of audience specificity. This distinction is particularly important in monetary policy communication, where a single policy action—such as lowering interest rates—may elicit divergent reactions across agents. For example, households may interpret the move positively due to reduced borrowing costs, while financial institutions may view it negatively due to compressed interest margins.

In addition to CentralBankRoBERTa's capabilities, we incorporate the **net hawkish** tone metric, as conceptualized by Malmendier et al. (2021), which serves as an indicator of the central bank's stance on inflation versus growth. Complementing this, we analyze the **positive/negative** tone of each document using a distilled version of the RoBERTa-base model. This model has been fine-tuned on a polar sentiment dataset comprising 4,840 sentences from English-language financial news, with sentiment labels annotated by 5–8 independent raters based on inter-annotator agreement.[3] This rigorous training ensures that sentiment classification is well-calibrated to the linguistic nuances of financial discourse.

5 Basic Framework and Regressions

5.1 Basic Framework

Let us consider how the style of a public policy statement is crafted. Specifically, for the purpose of our research question, I focus on linguistic complexity (LC)—that is, how the clarity of such statements is determined.

[3] Details regarding this model can be accessed at: https://huggingface.co/mrm8488/distilroberta-finetuned-financial-news-sentiment-analysis

Decision-makers, particularly central bankers, face motivations and circumstances that compel them to be both clear and vague at the same time. On one hand, they are pressured to communicate policy decisions with greater clarity—especially when implementing measures such as quantitative easing—in order to maintain public confidence. Clarity is also crucial for shaping public behavior toward desirable outcomes, a dynamic I refer to as the "anchoring force". For instance, in the housing market, central bankers may aim to encourage the public to take out mortgages and loans to stimulate economic activity for an extended period of time. If they signal that interest rates will remain low and deliver this message in a concise and unambiguous manner, the operation is likely to succeed. However, if the message is accompanied by ambiguous reasoning or unclear motives, its effectiveness diminishes significantly. This idea can be formalized without loss of generality as:

$$LC_{c,t}(anchoring) = f_a(\mu_c, i_{c,t}, \mathbf{X_{c,t}}) \tag{1}$$

where the degree of textual complexity arising from anchoring is influenced by the speaker (μ_c), the economic conditions at time t for speaker c ($\mathbf{X_{c,t}}$), and the policy decisions made ($i_{c,t}$). The intuition behind incorporating these components into the equation is as follows:

- **Speaker-specific preferences:** Different speakers may exhibit varying inclinations toward anchoring or flexibility. These preferences can be shaped by individual characteristics, institutional roles, or reputational considerations. For example, a central bank governor with a strong public presence may face greater scrutiny, thereby limiting the degree of ambiguity the public is willing to tolerate in their communication.

- **Economic conditions and policy shifts:** The prevailing macroeconomic environment and the magnitude or direction of changes in the target interest rate significantly influence the trade-off between anchoring and flexibility. During periods of deep recession or financial instability, central bankers are often compelled to communicate with heightened clarity and conviction to maintain public confidence and anchor expectations. In such scenarios, anchoring becomes critical, as stakeholders seek reassurance and guidance.

  Conversely, when the interest rate target remains near its long-run neutral level or changes only incrementally, central banks may afford greater ambiguity in their messaging. This allows for strategic flexibility without undermining credibility. However, when policy decisions represent a sharp departure from previous stances—particularly if the rate deviates substantially from its neutral benchmark—greater justification is required to preserve trust. In these cases, the pressure to be persuasive intensifies, even if it constrains future communicative optionality.

  In essence, the more extreme the economic context or policy shift, the stronger the imperative for anchoring, often at the expense of flexibility.

On the other hand, central bankers may choose to keep their statements intentionally vague. This allows for greater flexibility in the face of uncertainty or in preparation for unexpected developments. Flexibility is essential, as breaking promises can erode the central bank's credibility and public trust—both of which are critical for future operations, especially those that rely heavily on trust. The equation for flexibility can be expressed analogously to that of anchoring:

$$LC_{c,t}(flexibility) = f_f(\mu_c, i_{c,t}, \mathbf{X_{c,t}}) \tag{2}$$

Beyond the factors discussed above, additional circumstances may compel central banks to adjust the textual complexity of their statements. Some situations require the transmission of significantly more information than usual, which naturally increases linguistic complexity. Furthermore, the need to explain abstract mechanisms—such as how quantitative easing works—often leads to a heavier reliance on abstract language, exacerbating the complexity problem. However, more comprehensible statements can enhance public understanding of these policies, thereby increasing confidence in the central bank's guidance and communication.

Even under these conditions, trade-offs persist. For instance, central bankers must decide whether to explain an abstract concept or leave it unexplained. If they choose to explain it, anchoring may increase: clear and accessible explanations can foster public understanding, build confidence in the policy, and guide behavior in the intended direction (e.g., encouraging borrowing or investment). Yet if the explanation is too complex, it risks alienating or confusing segments of the audience—particularly non-experts—thereby undermining anchoring, as people may not trust or act on what they do not understand.

If the central bank opts not to explain the concept, anchoring likely decreases, since the public may perceive the policy as opaque or arbitrary. This can erode confidence and reduce the likelihood of behavioral alignment with policy goals. Flexibility, on the other hand, may increase: by avoiding anchored expectations or technical justifications, central bankers retain room to adjust public interpretation even when the policy itself remains fixed. Here, flexibility refers not to the ability to change the decision, but to the ability to adapt its justification, timing, or future direction without being seen as inconsistent.

A similar trade-off arises when deciding how much information to convey. On one hand, providing more information can enhance anchoring by signaling transparency, commitment, and a clear rationale behind the policy decision. On the other hand, a richly detailed statement may also cover a wide range of contingencies, which increases perceived flexibility by allowing the central bank to adjust its narrative or future actions without appearing inconsistent. However, this dual function introduces a subtle trade-off: the more a statement emphasizes commitment and clarity, the more it risks constraining future maneuverability; conversely, the broader and more hedged the message, the more it may dilute its persuasive power.

We then assume linearity [4] for both of the forces and obtain the following for speaker c at time t:

[4] We fully acknowledge the possibility of non-linear specifications—this choice is motivated by the prevalence of linear regressions in recent literature and for the sake of simplicity

$$
\begin{aligned}
-LC_{c,t}(anchoring) &= \gamma_0 + \mu_c + \gamma_1 i_{c,t} + \boldsymbol{\gamma_2}\mathbf{X_{c,t}} + \epsilon_{c,t} \\
LC_{c,t}(flexibility) &= \beta_0 + \mu_c + \beta_1 i_{c,t} + \boldsymbol{\beta_2}\mathbf{X_{c,t}} + \zeta_{c,t}
\end{aligned} \tag{3}
$$

The negative sign is used to represent the opposing nature of anchoring and textual complexity. Additionally, the final linguistic complexity reflects a trade-off between anchoring and flexibility, weighted by α and $1-\alpha$, respectively, with $\alpha \in [0,1]$. For simplicity, I express this trade-off in terms of differences for speaker c at time t:

$$
LC_{c,t} = \alpha LC_{c,t}(flexibility) - (1-\alpha)LC_{c,t}(anchoring) \tag{4}
$$

Here, α represents the weight assigned to the trade-off between anchoring and flexibility in central bank communication. A higher value of α indicates a greater emphasis on flexibility—or, equivalently, a lower emphasis on anchoring—favoring a more complex or ambiguous textual style. Conversely, $(1-\alpha)$ reflects a preference for clarity and directness in communication. Substitute the equations 3 into 4, we have:

$$
\begin{aligned}
LC_{c,t} = & \quad \alpha(\gamma_0 + \mu_c + \gamma_1 i_{c,t} + \boldsymbol{\gamma_2}\mathbf{X_{c,t}} + \epsilon_{c,t}) \\
& -(1-\alpha)(\beta_0 + \mu_c + \beta_1 i_{c,t} + \boldsymbol{\beta_2}\mathbf{X_{c,t}} + \zeta_{c,t}) \\
= & \quad [\alpha(\gamma_0 + \beta_0) - 1] + [2\alpha - 1]\mu_c + [\alpha(\gamma_1 + \beta_1) - 1]i_{c,t} \\
& + [\alpha(\boldsymbol{\gamma_2} + \boldsymbol{\beta_2}) - \mathbf{1}]\mathbf{X_{c,t}} + [\epsilon_{c,t} - \zeta_{c,t}]
\end{aligned} \tag{5}
$$

In reduced form, we can rewrite equation 5 as:

$$
LC_{c,t} = const + \mathbf{A_1}\mu_c + \mathbf{A_2} i_{c,t} + \mathbf{A_3}\mathbf{X_{c,t}} + u_{c,t} \tag{6}
$$

It is valid to estimate equation 6 using ordinary least squares (OLS), provided μ_c is excluded. To account for the presence of μ_c, we can apply a panel fixed effects model, which effectively controls for speaker-specific unobserved heterogeneity. Unfortunately, we cannot identify α within the current framework, as μ_c is extremely difficult to approximate or observe directly. Moreover, there is no strong theoretical basis to assume symmetry between equations 1 and 2—that is, to assume $\gamma_1 = \beta_1$ and $\boldsymbol{\gamma_2} = \boldsymbol{\beta_2}$. Therefore, in this paper, we focus on estimating the predictive power of policy decision rates and economic conditions on textual complexity, that is, estimating the total effect $\mathbf{A_2}$ and $\mathbf{A_3}$.

Hypotheses on the Signs of the Coefficients. Given the multifaceted nature of LC, each component—readability, abstractness, informativeness, and disunity—may respond differently to underlying economic and institutional factors.

1. $\mathbf{A_2}$: This coefficient reflects the effect of prevailing policy rate decision on LC. Its sign is theoretically ambiguous, as no established literature provides a definitive prediction, and it

is plausible that no significant effect may be observed. One hypothesis is that during periods requiring economic stimulus, overall LC may increase. This stems from the need to explain underperformance across sectors and address unemployment concerns. In such contexts, policymakers often convey more information, which can lead to greater disunity and increased abstractness, as a broader vocabulary is employed to deliver compact yet comprehensive messages.

Conversely, when the policy focus shifts toward combating inflation, the discourse tends to narrow around inflation-specific themes. This may reduce disunity and informativeness, as the scope of communication becomes more focused. The effect on abstractness remains unclear: while inflation discussions often involve abstract concepts, the language used may not deviate significantly from that of normal economic periods. Readability may remain relatively stable, as it is more closely tied to structural and stylistic choices—factors likely absorbed by fixed effects in the model. However, it may still respond indirectly to shifts in other LC dimensions, particularly if conveying complex mechanisms necessitates more intricate sentence structures.

2. $\mathbf{A_3}$: This coefficient captures the influence of specific economic indicators—namely, real GDP growth, inflation, and unemployment—on LC. Recessionary periods, in particular, require central bankers to communicate policy intentions with heightened clarity to maintain public confidence, especially when deploying unconventional tools such as quantitative easing. These periods also demand the transmission of more information, which can elevate linguistic complexity. Moreover, the need to explain abstract mechanisms may result in increased abstractness, as central banks articulate policies that deviate from conventional frameworks.

   Conversely, when the focus shifts to tackling inflation, the discourse tends to center primarily on inflation itself. This may result in reduced disunity and informativeness, as the scope narrows. The effect on abstractness remains ambiguous, since discussions around inflation can often involve more abstract concepts, but it could be using a relatively similar set of language to normal economic periods. Again, readability may not be significantly affected, similarly to that in β_1.

From a linguistic complexity standpoint, the imperative to "be clear" does not necessarily result in simpler statements. In practice, this imperative is often outweighed by the volume of information conveyed and the abstract nature of the concepts discussed. Accordingly, we hypothesize a positive sign for $\boldsymbol{\beta_2}$, reflecting the expectation that more challenging economic conditions lead to increased linguistic complexity.

Importantly, the degree of economic downturn may influence this relationship. In cases of mild GDP decline, central bankers may intentionally maintain vagueness in their statements to preserve strategic flexibility, particularly when the trade-off between inflation and growth remains salient. These downturns, often cyclical and familiar, may prompt policymakers to adopt brief and straightforward messaging, thereby reducing the need for detailed clarification.

By contrast, extreme economic downturns—characterized by deep recessions or financial instability—typically demand more persuasive and information-rich communication. In such contexts, central banks must articulate complex policy mechanisms and justify bold or unconventional decisions, which increases the abstractness, informativeness, and overall complexity of their statements.

However, the current regression framework assumes linearity, which limits its ability to fully capture these nuanced dynamics. To address this limitation, we analyze a broad range of quantiles of real GDP growth, enabling a partial exploration of potential nonlinear effects and allowing for a more granular understanding of how linguistic complexity responds to varying degrees of economic stress.

5.2 Regressions

When all countries or a subgroup of countries are considered, the dataset becomes a panel data with entity dimension as countries and time dimension with quarterly frequency. I run the fixed effect models specified as follows with country i at time t:

$$LC_{i,t} = \alpha_0 + \eta_i + \alpha_1 \Delta i_{i,t} + \alpha_2 g^{2p}_{y_{i,t}} + \alpha_3 g^{2p}_{y_{i,t-1}} + \alpha_6 \pi_{i,t} + \alpha_7 \pi_{i,t-1} + \alpha_8 u_{i,t} + \alpha_9 u_{i,t-1} + \epsilon_{i,t} \quad (7)$$

and

$$LC_{i,t} = \alpha_0 + \eta_i + \alpha_1 \Delta i_{i,t} + \alpha_4 RI_{i,t} + \alpha_5 RI_{i,t-1} + \alpha_6 \pi_{i,t} + \alpha_7 \pi_{i,t-1} + \alpha_8 u_{i,t} + \alpha_9 u_{i,t-1} + \epsilon_{i,t} \quad (8)$$

where LC indicating one of the four linguistic complexity measurements (readability, abstractness, informativeness and disunity), η_i as country fixed effect, Δi as policy rate change, g^{2p}_y as the bottom 2 percentile of the real GDP growth, RI as recession indicators, π as inflation rate and u as unemployment rate. The lagged values are added for all economic condition variables to ensure that countries that do not observe the exact economic conditions at time t can still observe them at time $t-1$. It is also necessary to include the inertia in considering past economic conditions in decision-making at time t. Note that the measurement based on the percentile indicator represents a much more extreme crisis compared to the recession indicator counterpart.

The regressions are run on different subsets of countries, listed as follows:

- All countries that have the appropriate data.
- Geography differences - Western: ['Fed', 'ECB', 'Hungary', 'Poland', 'Australia', 'Canada', 'New Zealand', 'Peru', 'Colombia', 'Iceland', 'Chile', 'Norway']
- Geography differences - Eastern: ['Japan', 'Korea', 'Philippines', 'Thailand']
- Language differences - English speaking: ['Fed', 'ECB', 'Australia', 'Canada', 'New Zealand']
- Language difference - non-English speaking: the rest of the countries not included in the English-speaking group.

When considering individual countries, the equations become OLS regressions. For each country i:

$$LC_t = \alpha_0 + \eta_i + \alpha_1 \Delta i_t + \alpha_2 g^{2p}_{yt} + \alpha_3 g^{2p}_{yt-1} + \alpha_4 \pi_t + \alpha_5 \pi_{t-1} + \alpha_6 u_t + \alpha_7 u_{t-1} + \epsilon_t \quad (9)$$

On the flip side, with an extremely high value of inflation (or CPI) instead of the bottom percentile of real GDP growth, I will run the following equation:

$$LC_{i,t} = \alpha_0 + \eta_i + \alpha_1 \Delta i_{i,t} + \alpha_2 \pi^{2p}_{i,t} + \alpha_3 \pi^{2p}_{i,t-1} + \alpha_6 g_{y_{i,t}} + \alpha_7 g_{y_{i,t-1}} + \alpha_8 u_{i,t} + \alpha_9 u_{i,t-1} + \epsilon_{i,t} \quad (10)$$

and

$$LC_{i,t} = \alpha_0 + \eta_i + \alpha_1 \Delta i_{i,t} + \alpha_4 \pi_{i,t} + \alpha_5 \pi_{i,t-1} + \alpha_6 g_{y_{i,t}} + \alpha_7 g_{y_{i,t-1}} + \alpha_8 u_{i,t} + \alpha_9 u_{i,t-1} + \epsilon_{i,t} \quad (11)$$

where LC indicates one of the four linguistic complexity measurements (readability, abstractness, informativeness and disunity), η_i as country fixed effect, Δi as policy rate change, π^{2p} as the top 2 percentile of the inflation, g_y as real GDP growth, and u as unemployment rate.

6 Results and Discussion

6.1 Main Results

6.1.1 Countries and sub-group of countries

The initial findings from the first fixed-effects model are systematically presented in Tables 3 and 4. These tables examine whether policy rate decisions, recession indicators (quantile-based and 3D composite), and broader economic conditions possess predictive power over textual ambiguity in central bank communications. The analysis spans all countries (reported in the first two columns), geographic subgroups (columns 3 to 6), and linguistic subgroups (columns 7 to 10). "Model 1" refers to the specification using the quantile recession indicator (Equation 7), while "Model 2" employs the 3D recession indicator (Equation 8).

We begin with readability (Panel A). A notable and consistent distinction emerges between Model 1 and Model 2 regarding the significance of recession indicators across nearly all specifications—except for Eastern countries. Specifically, only the quantile recession indicator, which captures the depth of GDP contraction, shows a statistically significant positive association with readability. This includes the lagged values for both the full sample and Western countries. In other words, extremely low real GDP growth rates are linked to increased textual complexity (i.e., higher readability scores). This relationship is statistically significant at the 1% level for both the full sample and Western countries, and at the 5% level for both linguistic subgroups.

In contrast, the 3D recession indicator does not exhibit significant predictive power over readability. For Eastern countries, the direction and magnitude of policy rate changes play a more prominent role: a loosening monetary policy is specifically associated with lower readability, suggesting more complex or nuanced messaging during accommodative phases.

Table 3: **Fixed effect models for all and sub-groups of countries (part 1)**

	All		Geography				Language			
			Western		Eastern		English speaking		Non-English speaking	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	A. Readability									
Δi_t	-0.013	0.048	-0.024	-0.012	0.657*	0.562	0.115	-0.411	-0.085	0.042
	(0.101)	(0.104)	(0.113)	(0.142)	(0.360)	(0.390)	(0.136)	(0.286)	(0.118)	(0.078)
$g^{2p}_{y_t}$	1.312***		1.493***		0.824		1.184**		1.351**	
	(0.400)		(0.453)		(0.928)		(0.468)		(0.582)	
$g^{2p}_{y_{t-1}}$	0.627**		0.709**		0.206		0.762		0.445	
	(0.300)		(0.356)		(0.684)		(0.782)		(0.325)	
RI_t		0.043		-0.373		0.693		-0.618		0.376
		(0.342)		(0.360)		(0.590)		(0.644)		(0.385)
RI_{t-1}		0.199		-0.136		0.104		-0.876		0.541**
		(0.304)		(0.368)		(0.323)		(0.559)		(0.272)
π_t	0.008	-0.066	0.078	0.012	-0.011	-0.078	-0.028	-0.222	0.042	-0.017
	(0.061)	(0.081)	(0.070)	(0.109)	(0.143)	(0.131)	(0.151)	(0.172)	(0.059)	(0.089)
π_{t-1}	-0.057	0.020	-0.068	0.005	0.104	0.163	-0.034	0.209***	-0.060	0.011
	(0.045)	(0.071)	(0.045)	(0.055)	(0.216)	(0.226)	(0.108)	(0.080)	(0.051)	(0.088)
u_t	-0.053	0.042	0.038	0.226*	0.083	0.116***	0.062	0.263*	-0.080	-0.012
	(0.070)	(0.097)	(0.069)	(0.118)	(0.055)	(0.021)	(0.121)	(0.159)	(0.071)	(0.085)
u_{t-1}	0.140*	0.048	0.224**	0.033	0.078**	0.036	0.313**	0.145	0.111	0.055
	(0.083)	(0.088)	(0.104)	(0.141)	(0.037)	(0.037)	(0.150)	(0.178)	(0.099)	(0.084)
R^2	0.02	0.01	0.11	0.11	0.06	0.08	0.1	0.14	0.01	0.03
N	1323	1192	1043	943	280	249	479	423	844	769
	B. Abstractness									
Δi_t	-0.301***	-0.266***	-0.259***	-0.286***	-1.093	-0.565	-0.560***	-0.496***	-0.250**	-0.247***
	(0.098)	(0.090)	(0.084)	(0.092)	(0.898)	(1.016)	(0.090)	(0.139)	(0.098)	(0.084)
$g^{2p}_{y_t}$	0.476		0.327		1.219		-0.043		0.731	
	(0.393)		(0.417)		(1.326)		(0.409)		(0.550)	
$g^{2p}_{y_{t-1}}$	0.089		-0.001		0.938		0.053		0.140	
	(0.248)		(0.298)		(0.794)		(0.255)		(0.343)	
RI_t		-0.030		0.001		0.016		0.128		-0.121
		(0.178)		(0.146)		(0.479)		(0.146)		(0.251)
RI_{t-1}		0.351		-0.092		1.479*		-0.056		0.577
		(0.290)		(0.112)		(0.864)		(0.089)		(0.433)
π_t	0.047	0.048	0.037	0.041	0.195	0.139	-0.029	-0.064	0.059	0.094
	(0.044)	(0.055)	(0.048)	(0.073)	(0.156)	(0.108)	(0.058)	(0.060)	(0.049)	(0.066)
π_{t-1}	0.087	0.127*	0.063	0.101**	0.249	0.250*	0.111*	0.221**	0.093	0.097
	(0.054)	(0.067)	(0.044)	(0.048)	(0.186)	(0.146)	(0.058)	(0.086)	(0.066)	(0.076)
u_t	0.083	0.102*	0.095	0.143**	-0.081	-0.024	0.073	0.077	0.057	0.084
	(0.064)	(0.060)	(0.074)	(0.061)	(0.247)	(0.202)	(0.140)	(0.106)	(0.064)	(0.059)
u_{t-1}	0.086	0.074	0.084	0.049	-0.041	-0.046	0.056	0.070	0.112	0.094
	(0.076)	(0.061)	(0.103)	(0.072)	(0.131)	(0.130)	(0.112)	(0.080)	(0.093)	(0.075)
R^2	0.1	0.12	0.11	0.14	0.09	0.15	0.04	0.05	0.12	0.15
N	1332	1200	1043	943	289	257	479	423	853	777

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Table 4: **Fixed effect models for all and sub-groups of countries (part 2)**

	All		Geography				Language			
			Western		Eastern		English speaking		Non-English speaking	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
					C. Informativeness					
Δi_t	0.092	0.093	0.079	0.083	0.194*	0.073	0.103**	0.039	0.017	0.042
	(0.078)	(0.065)	(0.079)	(0.065)	(0.107)	(0.045)	(0.040)	(0.070)	(0.042)	(0.043)
$g^{2p}_{y_t}$	0.273**		0.286*		0.407**		0.431		0.224	
	(0.123)		(0.149)		(0.189)		(0.272)		(0.151)	
$g^{2p}_{y_{t-1}}$	0.135		0.145		0.241**		0.146		0.098	
	(0.102)		(0.128)		(0.096)		(0.323)		(0.132)	
RI_t		−0.062		−0.007		−0.146***		0.153		−0.149*
		(0.087)		(0.112)		(0.049)		(0.166)		(0.082)
RI_{t-1}		−0.032		−0.090		0.127		−0.210***		−0.060
		(0.070)		(0.083)		(0.092)		(0.047)		(0.099)
π_t	−0.015	0.036	−0.008	0.044	−0.027	0.003	0.081**	0.113*	0.003	0.037
	(0.031)	(0.035)	(0.032)	(0.039)	(0.044)	(0.030)	(0.040)	(0.068)	(0.027)	(0.040)
π_{t-1}	−0.001	−0.110**	0.003	−0.112**	−0.021	−0.085**	0.039**	−0.047	0.008	−0.069**
	(0.012)	(0.045)	(0.012)	(0.055)	(0.030)	(0.035)	(0.018)	(0.048)	(0.014)	(0.032)
u_t	0.003	0.049	−0.023	0.044	−0.034*	−0.013	0.152**	0.208**	−0.042	−0.001
	(0.052)	(0.047)	(0.064)	(0.058)	(0.018)	(0.008)	(0.062)	(0.102)	(0.039)	(0.017)
u_{t-1}	0.057**	0.024	0.089***	0.029	−0.031***	−0.021***	0.215***	0.158***	0.046	0.017
	(0.026)	(0.015)	(0.032)	(0.023)	(0.006)	(0.008)	(0.058)	(0.026)	(0.045)	(0.031)
R^2	0.05	0.09	0.04	0.08	0.17	0.21	0.41	0.42	0.01	0.04
N	1332	1200	1043	943	289	257	479	423	853	777
					D. Disunity					
Δi_t	0.031	0.079	0.048	0.111	−0.195	−0.329	0.052	0.049	−0.018	0.012
	(0.082)	(0.085)	(0.082)	(0.089)	(0.456)	(0.445)	(0.076)	(0.091)	(0.097)	(0.085)
$g^{2p}_{y_t}$	0.454**		0.697***		−0.296		0.369		0.484*	
	(0.195)		(0.212)		(0.218)		(0.227)		(0.253)	
$g^{2p}_{y_{t-1}}$	−0.023		0.128		−0.144		−0.146		−0.012	
	(0.150)		(0.154)		(0.292)		(0.232)		(0.206)	
RI_t		0.156		0.072		0.316		0.126		0.192
		(0.163)		(0.174)		(0.349)		(0.089)		(0.252)
RI_{t-1}		0.147		0.186		−0.236		0.029		0.135
		(0.169)		(0.172)		(0.280)		(0.026)		(0.234)
π_t	0.058	0.066	0.051*	0.063	0.149	0.150	0.002	−0.036	0.098**	0.124**
	(0.037)	(0.047)	(0.030)	(0.045)	(0.105)	(0.122)	(0.053)	(0.056)	(0.044)	(0.057)
π_{t-1}	−0.039	−0.063	−0.062**	−0.115**	0.152*	0.184*	−0.026	−0.024	−0.040	−0.061
	(0.030)	(0.053)	(0.030)	(0.053)	(0.089)	(0.107)	(0.029)	(0.050)	(0.036)	(0.066)
u_t	−0.037	−0.009	−0.054	0.004	0.020	−0.011	0.110***	0.113***	−0.103*	−0.073
	(0.048)	(0.047)	(0.067)	(0.063)	(0.039)	(0.045)	(0.030)	(0.025)	(0.056)	(0.055)
u_{t-1}	0.088**	0.069**	0.123**	0.073*	−0.029	−0.026	0.088***	0.076**	0.116*	0.095*
	(0.038)	(0.028)	(0.048)	(0.039)	(0.038)	(0.047)	(0.030)	(0.032)	(0.064)	(0.053)
R^2	0.02	0.03	0.04	0.05	0.17	0.19	0.24	0.24	0.02	0.03
N	1323	1192	1043	943	280	249	479	423	844	769

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Additional signals emerge from economic condition variables in Model 1. Both Western and Eastern countries—mirroring the full sample—show that higher unemployment rates are associated with increased reading difficulty in central bank statements, significant at the 5% (and at the 10% level for the full sample). A similar pattern is observed for English-speaking countries (significant at 5%), but not for their non-English counterparts.

A minor but noteworthy pattern appears in Model 2, where an increase in the current period unemployment rate is also linked to higher readability scores for Western, Eastern and English-speaking countries, albeit with mostly weaker statistical significance.

Next, we turn to the three newly introduced complexity metrics, beginning with **abstractness**. Across the full sample and all country subgroups, the only consistently significant correlation is observed with the change in the policy rate. An exception arises in Eastern countries, where the correlation is statistically insignificant but retains the same direction of association—potentially due to a smaller sample size in that subgroup. Specifically, when monetary expansion is pursued (i.e., a decrease in the policy rate), abstractness tends to increase. This suggests that central banks may adopt more abstract language when loosening policy, possibly to preserve flexibility or to frame complex policy mechanisms in broader conceptual terms.

Regarding the magnitude of these correlations, English-speaking countries exhibit a notably stronger positive association with abstractness—more than twice that of non-English-speaking countries, as well as the overall and Western groups—for the same increase in the policy rate. This divergence underscores the idea that different dimensions of linguistic complexity (e.g., abstractness versus readability) respond to macroeconomic variables in distinct ways. Rather than overlapping, these metrics appear to capture complementary signals, enriching the interpretive power of the framework.

Another noteworthy pattern emerges with respect to lagged inflation. In Model 2, higher inflation in the previous quarter shows predictive power—at the 5% and 10% significance levels—for increased abstractness, though this effect does not hold for non-English-speaking countries.

Turning to **informativeness**, the results reveal that only the quantile recession indicators yield significantly positive coefficients across the full sample and geographic subgroups (Eastern and Western countries alike). Additionally, lagged quantile recession indicators show positive significance for Eastern countries, suggesting that extremely low GDP growth—both contemporaneous and lagged—is associated with more information being conveyed in central bank statements. However, this effect is not observed in linguistic subgroups, where no statistically significant relationship is observed.

A further pattern emerges for Eastern and English-speaking countries: larger and positive changes in the policy rate are associated with increased informativeness, though these effects are only significant at the 5% and 10% levels. This suggests that more substantial policy shifts to combat inflation may prompt central banks to provide richer explanations.

In contrast, economic conditions appear to dominate the predictive power for informativeness. A consistent pattern across most specifications indicates that higher inflation in the previous period is associated with lower informativeness, typically significant at the 5% level. Conversely, higher unemployment rates—particularly in the previous period—are linked to greater informativeness, with significance levels reaching 1% in many cases. Notable exceptions include non-English-speaking countries, where unemployment shows no significant effect, and Eastern countries, where the relationship is inverted.

Eastern countries also present a set of conflicting signals. While extremely low growth (via quantile indicators) increases informativeness, the 3D recession indicator—which incorporates depth, duration, and diffusion—shows a negative relationship at the 1% level. A similar pattern is observed for non-English-speaking countries, albeit at the 10% level. These findings suggest that while isolated recessions may prompt more detailed communication, broader and more systemic downturns may lead to greater restraint or opacity in messaging among Eastern countries.

Finally, we examine Disunity, where the behavioral patterns broadly mirror those observed for readability. Specifically, disunity increases significantly during periods of extremely low real GDP growth, while no clear effects are detected during conventional recession episodes. An exception is found in English-speaking countries, which follow the same directional pattern but without statistical significance, possibly due to sample size.

A consistent finding across most specifications is that higher unemployment in the previous period is associated with increased disunity, suggesting that economic distress prompts more fragmented or less cohesive messaging. This relationship holds across all samples except Eastern countries, where no significant effect is observed. For English-speaking countries, this pattern extends to the current unemployment rate, reinforcing the idea that labor market deterioration drives less unified communication. Additional noteworthy observations include: (i) lower inflation in the previous quarter is linked to increased disunity in Western countries, and (ii) higher current inflation is associated with increased disunity in non-English-speaking countries.

In conclusion, while each dimension of ambiguity in central bank communication—readability, abstractness, informativeness, and disunity—exhibits distinct behavioral patterns, these measures are ultimately mutually reinforcing rather than conflicting. Taken together, they reveal a consistent phenomenon: during periods of extremely low GDP growth or elevated unemployment in the previous period (as reflected in readability, informativeness, and disunity), or when there is a strong imperative to stimulate the economy (as captured by abstractness), the textual complexity of central bank statements tends to increase significantly. This stands in contrast to more conventional recessionary episodes, where the estimated coefficients are often statistically insignificant.

The most notable exceptions arise in Eastern countries, where the signals are inconsistent and often counterintuitive. In these cases, there is limited empirical evidence that textual ambiguity intensifies during periods of economic distress. Meanwhile, non-English-speaking countries exhibit the least predictive responsiveness to the examined variables. Although they generally follow the broader directional patterns, the statistical significance of these relationships is weaker. This may reflect either greater linguistic uniformity or institutional divergence in communication practices.

To extend our findings, we conduct robustness checks by redefining extreme economic events using alternative percentiles of real GDP growth—specifically the 5th and 10th percentiles. The corresponding results are presented in Tables 13 and 14 in the Appendix. Overall, the core conclusions remain consistent, though some shifts in statistical significance are observed. In particular, abstractness now exhibits stronger predictive power under these alternative thresholds, reinforcing the earlier insight: during periods of economic stimulus or crisis, central bank communication tends to become more abstract, reflecting a move away from concrete language. For informativeness, the 5th percentile threshold often yields statistically insignificant results, whereas the 10th percentile produces outcomes closely aligned with those obtained using the 2nd percentile. This suggests that the informativeness metric is responsive to the severity of economic downturns [5].

Taken together, these robustness checks confirm that our overarching conclusions are not driven by the choice of quantile cutoffs. The observed relationships between economic stress and linguistic complexity—particularly in terms of abstractness and informativeness—remain empirically robust across alternative specifications.

We further extend the robustness analysis by incorporating policy inertia—defined as the absence of change in the policy rate—into the regression framework (see Appendix Tables 15 and 14). The rationale is that when policy remains unchanged, it likely reflects stable or similar economic conditions relative to the previous period. This similarity may reduce the need for elaborate justification, resulting in less informative and more compact language.

Consistent with earlier findings, readability, informativeness, and disunity continue to exhibit significant relationships with extreme low growth, but not with conventional recession indicators. These results reinforce the idea that linguistic complexity intensifies during periods of acute economic stress.

However, the behavior of abstractness diverges notably under this specification. All previously observed statistical significance disappears, and instead, abstractness shows positive correlations with the current period's unemployment rate and previous period's inflation. This shift suggests that abstract language may still be employed in response to specific economic pressures, even when policy remains unchanged.

While these differences in coefficient behavior are noteworthy, they do not contradict the broader conclusion: central bank statement textual ambiguity tends to increase during times of crisis. That said, the use of policy inertia introduces a distinct interpretive challenge. Unlike policy rate changes, which convey both direction and magnitude, policy inertia merely signals the absence of movement. This lack of granularity may contribute to its reduced predictive power, as it obscures the underlying motivations and economic context behind the decision to maintain the status quo.

[5] When incorporating a wider range of quantiles from the 10th to the 50th percentile, we observe a general pattern in which the significance level gradually diminishes as the quantile increases. This suggests that the observed behavior is specific to cases where the growth rate is significantly lower than average

6.1.2 Individual countries

This section explores whether the behavioral patterns identified in the aggregate and subgroup analyses are consistently reflected at the individual country level. To this end, regression estimates for each country are presented in Tables 5 and 6. This disaggregated approach allows for a more granular assessment of how linguistic complexity in central bank communication responds to macroeconomic conditions and policy decisions within distinct national contexts.

Table 5: **Fixed effect models for individual countries (part 1)**

	Fed	ECB	JP	AU	CA	CL	CO	HU	IS	KR	NZ	NO	PE	PH	PL	TH
								A. Readability								
Δi_t	0.40	1.07	−3.29	−0.98***	0.01	0.28*	−1.09*	0.20	−0.22*	0.21	0.11	−0.91***	−0.29	1.34**	0.60	0.63
	(0.60)	(0.80)	(1.97)	(0.34)	(0.43)	(0.17)	(0.56)	(0.17)	(0.12)	(0.92)	(0.31)	(0.31)	(0.29)	(0.63)	(0.58)	(1.39)
$g^{2p}_{y_t}$	1.39	1.07**	1.15*	1.15*	−0.28	−0.53	−4.76	0.82	3.91***	−1.16	2.11***	0.06	1.78**	1.18	2.92***	1.59*
	(0.90)	(0.48)	(0.65)	(0.60)	(1.38)	(0.43)	(3.20)	(0.83)	(1.39)	(1.08)	(0.54)	(0.34)	(0.83)	(3.42)	(1.05)	(0.91)
$g^{2p}_{y_{t-1}}$	−0.30	0.02	0.33	0.29	−2.44	0.52	−1.17	0.42	−0.63	−1.56*	2.85***	0.48***	1.98*	0.98	0.81	−1.00**
	(1.02)	(0.82)	(0.67)	(0.27)	(1.49)	(0.52)	(0.98)	(0.26)	(0.50)	(0.88)	(0.41)	(0.18)	(1.09)	(2.36)	(0.95)	(0.46)
π_t	−0.18	−0.36	−0.29	0.03	−0.19	0.11	0.37	−0.03	−0.15	−0.54*	0.38	0.00	0.37*	−0.06	0.15	0.10
	(0.20)	(0.27)	(0.34)	(0.11)	(0.21)	(0.15)	(0.42)	(0.11)	(0.14)	(0.31)	(0.27)	(0.12)	(0.21)	(0.23)	(0.19)	(0.11)
π_{t-1}	−0.29*	−0.25	0.19	0.17*	0.38**	−0.30**	−0.08	−0.00	−0.15	0.10	−0.01	−0.06	0.08	−0.04	−0.10	−0.39***
	(0.15)	(0.25)	(0.33)	(0.09)	(0.18)	(0.12)	(0.37)	(0.08)	(0.12)	(0.31)	(0.21)	(0.09)	(0.14)	(0.19)	(0.15)	(0.12)
u_t	−0.04	0.73	2.62*	−0.58	0.14	0.62***	0.68	−0.38	1.48**	−0.95	−0.03	−0.52*	−0.28**	0.06	1.19***	1.15
	(0.15)	(0.98)	(1.55)	(0.40)	(0.21)	(0.18)	(0.40)	(0.62)	(0.67)	(0.92)	(0.54)	(0.29)	(0.13)	(0.31)	(0.41)	(0.76)
u_{t-1}	0.30	−0.71	−2.27	0.59	0.78***	−0.26	−0.23	0.55	−0.67	0.02	0.23	0.41	0.14	0.01	−1.07**	0.51
	(0.21)	(0.96)	(1.38)	(0.44)	(0.23)	(0.20)	(0.34)	(0.63)	(0.63)	(0.65)	(0.53)	(0.29)	(0.16)	(0.27)	(0.42)	(0.78)
N	99	99	55	84	98	98	37	88	62	99	99	99	85	79	95	47
R^2_{adj}	0.181	0.37	0.18	0.055	0.211	0.244	0.127	0.081	0.662	0.047	0.134	0.128	0.322	0.019	0.101	0.278
								B. Abstractness								
Δi_t	−0.95**	0.26	−17.94**	−0.23	−0.22	0.03	0.01	−0.16	−0.04	0.16	−0.54*	−0.49	−0.52	−0.18	0.43	−3.44***
	(0.44)	(0.41)	(7.26)	(0.32)	(0.45)	(0.18)	(0.17)	(0.12)	(0.16)	(0.37)	(0.32)	(0.31)	(0.34)	(0.28)	(0.28)	(1.03)
$g^{2p}_{y_t}$	−1.32	0.28	3.53	−1.85***	1.14*	−1.18	−3.79*	1.16*	−0.35	−0.87	0.31	2.79***	−1.17**	1.45	0.90	1.29
	(0.88)	(0.30)	(2.43)	(0.53)	(0.69)	(0.78)	(1.97)	(0.62)	(1.08)	(0.82)	(0.59)	(0.51)	(0.56)	(1.80)	(0.62)	(1.15)
$g^{2p}_{y_{t-1}}$	−0.08	−2.26***	3.27	−0.82	−0.65	−0.45	−3.45***	0.13	0.77*	0.06	0.90	0.60	−1.50***	−0.95	0.97***	0.34
	(0.49)	(0.44)	(2.44)	(0.57)	(0.81)	(0.41)	(0.68)	(0.30)	(0.39)	(0.41)	(0.70)	(0.75)	(0.53)	(1.02)	(0.36)	(0.50)
π_t	0.01	−0.04	−0.60	−0.17	0.06	0.13	−0.32**	0.03	−0.38	−0.01	−0.28	0.23	−0.03	−0.14	−0.12	0.21
	(0.14)	(0.11)	(0.90)	(0.14)	(0.19)	(0.17)	(0.12)	(0.03)	(0.25)	(0.22)	(0.18)	(0.16)	(0.24)	(0.11)	(0.09)	(0.19)
π_{t-1}	0.28**	−0.16	0.45	−0.28*	0.23	−0.19	0.15	−0.01	0.45**	0.38**	0.32**	0.29	0.08	0.17**	0.16*	−0.11
	(0.14)	(0.12)	(0.80)	(0.15)	(0.20)	(0.13)	(0.13)	(0.04)	(0.21)	(0.18)	(0.16)	(0.18)	(0.20)	(0.07)	(0.09)	(0.20)
u_t	0.18	1.96***	−4.17	1.16***	−0.03	0.13	0.28	0.54	−0.03	−0.05	−0.41	0.09	0.20**	0.06	1.01***	0.45
	(0.12)	(0.46)	(5.06)	(0.41)	(0.13)	(0.23)	(0.23)	(0.61)	(0.78)	(0.67)	(0.38)	(0.51)	(0.08)	(0.15)	(0.28)	(1.02)
u_{t-1}	−0.06	−1.98***	3.24	−1.42***	0.50***	−0.29	0.00	−0.13	0.07	0.77	0.28	0.74**	−0.22**	0.11	−1.00***	0.68
	(0.13)	(0.46)	(5.03)	(0.39)	(0.14)	(0.27)	(0.21)	(0.64)	(0.70)	(0.69)	(0.42)	(0.35)	(0.10)	(0.13)	(0.27)	(0.91)
N	99	99	64	84	98	98	37	88	62	99	99	99	85	79	95	47
R^2_{adj}	0.042	0.175	0.025	0.199	0.071	−0.003	0.254	0.588	0.114	0.108	−0.016	0.226	0.036	0.076	0.153	0.197

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Table 6: **Fixed effect models for individual countries (part 2)**

	Fed	ECB	JP	AU	CA	CL	CO	HU	IS	KR	NZ	NO	PE	PH	PL	TH
								C. Informativeness								
Δi_t	0.10	0.58***	−2.19	0.10	0.02	−0.02	0.11	−0.05	−0.07**	0.21	−0.05	0.43	0.13	−0.01	0.16*	0.34
	(0.08)	(0.21)	(1.35)	(0.08)	(0.09)	(0.08)	(0.14)	(0.10)	(0.03)	(0.24)	(0.08)	(0.26)	(0.08)	(0.04)	(0.09)	(0.42)
$g^{2p}_{y_t}$	0.40*	0.43***	0.53*	0.59***	0.40	1.21**	1.13**	1.15**	−0.13*	0.13	0.12	−0.46	−0.10	0.43	0.30	0.59**
	(0.21)	(0.14)	(0.27)	(0.12)	(0.34)	(0.49)	(0.43)	(0.53)	(0.07)	(0.19)	(0.12)	(0.47)	(0.13)	(0.26)	(0.31)	(0.26)
$g^{2p}_{y_{t-1}}$	−0.11	−0.15	0.35	0.39**	0.39*	0.97***	0.78**	0.42	0.08	0.12	0.27**	−0.75*	−0.14	0.10	0.14	0.08
	(0.23)	(0.51)	(0.29)	(0.19)	(0.20)	(0.18)	(0.29)	(0.26)	(0.08)	(0.19)	(0.13)	(0.44)	(0.16)	(0.21)	(0.28)	(0.17)
π_t	0.01	0.16	−0.04	0.01	0.05	0.07	−0.08	−0.02	−0.05**	−0.16*	0.06	−0.19	−0.05	0.01	0.02	−0.01
	(0.04)	(0.10)	(0.14)	(0.04)	(0.05)	(0.05)	(0.09)	(0.04)	(0.02)	(0.08)	(0.05)	(0.12)	(0.06)	(0.02)	(0.04)	(0.04)
π_{t-1}	−0.06**	−0.27**	−0.01	−0.04	−0.01	−0.01	0.01	0.04	0.03	−0.02	−0.00	−0.11	0.03	0.00	0.02	−0.00
	(0.03)	(0.13)	(0.14)	(0.04)	(0.04)	(0.04)	(0.07)	(0.04)	(0.03)	(0.08)	(0.04)	(0.11)	(0.06)	(0.01)	(0.03)	(0.05)
u_t	−0.04	1.40***	−0.66	−0.17	−0.01	−0.14	−0.20***	−1.18***	0.10	−0.47**	−0.09	−0.25	0.01	−0.02	−0.27	0.14
	(0.03)	(0.52)	(0.63)	(0.12)	(0.06)	(0.14)	(0.06)	(0.36)	(0.10)	(0.18)	(0.09)	(0.38)	(0.03)	(0.02)	(0.18)	(0.22)
u_{t-1}	0.08*	−1.51***	0.37	0.05	0.01	0.17	0.01	0.91**	−0.07	−0.12	0.24	0.43	−0.02	0.00	0.32*	0.50**
	(0.04)	(0.54)	(0.61)	(0.13)	(0.05)	(0.17)	(0.05)	(0.35)	(0.09)	(0.13)	(0.16)	(0.33)	(0.02)	(0.02)	(0.18)	(0.19)
N	99	99	64	84	98	98	37	88	62	99	99	99	85	79	95	47
R^2_{adj}	0.081	0.146	0.106	0.106	0.037	0.135	0.449	0.409	0.199	0.282	0.076	0.124	−0.004	−0.001	0.307	0.283
								D. Disunity								
Δi_t	0.09	0.64*	1.76	−0.05	−0.23	0.19*	−0.40**	0.03	−0.14*	0.14	0.10	−0.02	0.26	0.88**	0.69**	−0.07
	(0.32)	(0.36)	(1.40)	(0.14)	(0.29)	(0.10)	(0.18)	(0.11)	(0.07)	(0.38)	(0.15)	(0.40)	(0.27)	(0.36)	(0.32)	(0.82)
$g^{2p}_{y_t}$	1.20**	0.56***	−0.61	0.03	−0.10	0.03	−0.09	0.53	1.43***	0.31	0.49	0.02	1.34	−0.95	0.86	−0.86
	(0.56)	(0.17)	(0.55)	(0.15)	(0.58)	(0.49)	(1.48)	(0.36)	(0.19)	(0.37)	(0.31)	(0.46)	(1.11)	(1.81)	(0.54)	(0.54)
$g^{2p}_{y_{t-1}}$	0.53	−0.02	−1.18*	−0.48***	−1.03***	−0.41	−0.40	0.09	0.02	−0.01	−0.52	−0.26	1.01	1.58	0.14	−0.01
	(0.34)	(0.47)	(0.60)	(0.14)	(0.32)	(0.64)	(0.40)	(0.16)	(0.68)	(0.39)	(0.40)	(0.26)	(1.15)	(1.10)	(0.33)	(0.32)
π_t	0.01	−0.14	0.15	0.12**	−0.16	0.12	0.41**	−0.02	0.05	−0.13	0.12	0.03	−0.07	−0.09	−0.01	0.11
	(0.11)	(0.14)	(0.27)	(0.06)	(0.12)	(0.09)	(0.16)	(0.05)	(0.10)	(0.15)	(0.10)	(0.13)	(0.14)	(0.13)	(0.09)	(0.07)
π_{t-1}	−0.19**	−0.09	−0.20	0.01	0.10	−0.21***	−0.26*	0.02	−0.17*	−0.03	−0.09	−0.09	−0.03	0.10	0.01	−0.10
	(0.09)	(0.13)	(0.23)	(0.06)	(0.09)	(0.08)	(0.13)	(0.04)	(0.09)	(0.15)	(0.10)	(0.09)	(0.15)	(0.08)	(0.07)	(0.09)
u_t	−0.04	0.45	1.71	0.01	−0.01	0.31**	0.05	−0.65**	0.74***	−0.05	0.33	−0.29	−0.16	0.18	−0.20	0.13
	(0.07)	(0.55)	(1.28)	(0.15)	(0.11)	(0.13)	(0.19)	(0.26)	(0.18)	(0.35)	(0.21)	(0.33)	(0.19)	(0.16)	(0.32)	(0.53)
u_{t-1}	0.05	−0.38	−2.10*	0.21	0.12	0.03	0.12	0.74***	−0.62***	−0.59**	−0.34	0.48**	0.17	−0.12	0.17	−0.42
	(0.07)	(0.55)	(1.24)	(0.13)	(0.13)	(0.12)	(0.16)	(0.26)	(0.18)	(0.26)	(0.23)	(0.24)	(0.14)	(0.12)	(0.32)	(0.60)
N	99	99	55	84	98	98	37	88	62	99	99	99	85	79	95	47
R^2_{adj}	0.054	0.373	0.066	0.078	0.012	0.27	0.225	0.08	0.467	0.041	−0.029	−0.021	0.008	0.054	0.244	−0.055

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Starting with readability, the results reveal notable heterogeneity across central banks. The Federal Reserve (Fed) does not exhibit the aggregate-level patterns; all coefficients are statistically insignificant, with the sole exception of lagged inflation, which reaches significance at the 10% level. This limited responsiveness is similarly observed in Canada, where only lagged unemployment shows significance, and Hungary, where no significant relationships are detected.

In contrast, both the European Central Bank (ECB) and the Bank of Japan (BoJ) display a clear increase in readability during periods of extremely low GDP growth, consistent with the broader findings. Similar patterns of increased readability complexity during crisis episodes are also evident in Iceland, New Zealand, Australia, Peru, Poland, and Thailand.

A separate group of countries—including Australia, Colombia, Iceland, and Norway—demonstrate a strong association between the need to stimulate the economy (captured by a negative coefficient on Δi, indicating a decrease in the policy rate) and higher readability complexity. Interestingly, Chile and the Philippines exhibit the opposite relationship. Additionally, a subset of countries—Chile, Iceland, Korea, New Zealand, and the Philippines—do not show significant signals for either policy rate changes or extreme recession indicators. However, they may still exhibit correlations with other macroeconomic variables, such as inflation or unemployment, including their lagged values.

Turning to abstractness, only the Fed, BoJ, and Bank of Thailand display patterns consistent with the aggregate analysis—namely, a primary correlation with policy rate changes. A distinct group of countries—including the ECB, Australia, Colombia, and Peru—show stronger predictive power through quantile recession indicators. For Australia and Colombia, the current indicators are significant, while for the ECB, Peru, and Colombia, lagged recession indicators are more influential. These relationships suggest a shift toward concreteness during crisis periods, possibly reflecting a move toward more direct and accessible language. Conversely, Canada, Hungary, Norway, and Poland exhibit an increase in abstractness during such periods, indicating that crisis communication in these contexts may lean toward broader conceptual framing or more generalized messaging.

Regarding informativeness, the majority of countries exhibit increased information provision during periods of economic crisis—whether defined by current or lagged indicators. This suggests that central banks generally respond to heightened economic stress with more detailed and explanatory communication. However, exceptions to this trend include Iceland and Norway, both of which demonstrate lower informativeness in response to lagged recession indicators. These deviations may reflect institutional preferences for brevity or strategically ambiguous messaging during downturns. The remaining countries show limited or no statistically significant signals, indicating that informativeness may be more sensitive to institutional norms or contextual factors in certain settings

Turning to disunity, several central banks—most notably the Federal Reserve, the ECB, and Iceland—exhibit increased disunity during crisis periods. This likely reflects the need to address multiple facets of economic distress, resulting in more fragmented or multi-themed messaging. In contrast, Australia and Canada show decreased disunity in response to lagged recession indicators, suggesting a preference for more cohesive and streamlined communication during prior economic contractions. With respect to policy rate changes, the ECB, the Philippines, and Poland display increased disunity following economic stimulation (i.e., rate cuts), possibly due to the need to justify unconventional measures or address diverse stakeholder concerns. Conversely, Colombia and Iceland demonstrate greater unity under similar conditions. For the remaining countries, correlations with unemployment and inflation—including their lagged values—are more prevalent, though no consistent pattern emerges. This variability underscores the complexity of linking macroeconomic indicators to linguistic structure, and suggests that institutional, cultural, or political factors may mediate how central banks communicate under stress.

The comprehensive analysis across aggregate, subgroup, and individual country levels reveals a nuanced yet coherent picture of how central bank communication complexity responds to evolving economic conditions. While specific textual dimensions—readability, abstractness, informativeness, and disunity—and country-specific contexts introduce meaningful heterogeneity, several overarching patterns emerge. First, periods of extreme economic crisis, particularly severe contractions in real GDP growth, consistently trigger an increase in communication complexity. This heightened textual ambiguity - manifested through different aspects - suggests a deliberate or inherent shift in central bank messaging during times of acute economic stress. Second, the influence of monetary policy actions on linguistic complexity varies across contexts. While general findings underscore the relevance of policy rate changes for certain complexity dimensions (specifically abstractness), individual country analyses reveal that these relationships are not universal. The direction and magnitude of effects differ across economies, highlighting the influence of institutional heterogeneity. Finally, robustness checks—including alternative definitions of extreme events and the use of policy inertia—confirm the stability of core conclusions. Although some metrics (e.g., abstractness) exhibit sensitivity to specification choices, the broader narrative remains intact: central bank communication becomes more complex along multiple linguistic dimensions during times of crisis. Country-level analysis further reveals speaker-specific fixed effects. Central bank communication is not monolithic; it is shaped by national context, institutional design, and individual leadership. This heterogeneity underscores the importance of tailoring textual analysis to both macroeconomic conditions and the communicative style of each central bank.

6.1.3 Flip side of the story - inflation and CPI

Moving beyond the context of economic recessions, we now investigate whether similar behavioral patterns in central bank communication complexity emerge during periods of economic overheating, specifically those marked by extremely high inflation. The regression results for these scenarios are presented in Tables 17 and 18 in the Appendix 8.5.

In addition, we examine the role of the Consumer Price Index (CPI) level—reported in Appendix 8.5 Tables 19 and 20—as a complementary indicator. Unlike inflation, which captures the rate of change, the CPI level serves as a more normalized benchmark, akin to the policy rate, and may offer a different lens through which to interpret central bank behavior.

The rationale for including the price level stems from recent empirical observations. As highlighted by Forbes et al. (2025), the post-pandemic period exhibited a surprisingly low "loss ratio," wherein inflation was successfully reduced with minimal impact on output. This outcome deviates from conventional expectations rooted in the Phillips Curve framework. However, this anomaly may be better understood by considering the elevated price level that preceded monetary tightening. In such a context, the effectiveness of policy interventions may appear more plausible, as the inflationary surge was built upon an already high price base. Consequently, examining whether central bank communication complexity responds differently to inflation rates versus absolute price levels provides valuable insight into the strategic framing and justification of policy decisions. This distinction may reveal whether central banks perceive inflation as a transient shock or a structural shift, and whether their messaging adapts accordingly to manage expectations and preserve credibility.

The behavioral patterns observed during episodes of high inflation present a markedly different picture compared to those seen in recessionary contexts. Unlike the consistent surge in textual complexity during severe downturns, extremely high inflation does not produce a uniform increase or decrease across the various ambiguity dimensions. Instead, the most significant signals—particularly for readability—originate from the unemployment rate, especially its lagged values. This finding aligns with earlier results, reinforcing the notion that unemployment retains strong predictive power when conditioned on both inflation and growth dynamics. Notably, unemployment also exhibits significant influence over abstractness in this context, a relationship that was absent in the recession analysis.

For readability, regional differences emerge. In Eastern countries, extremely high inflation combined with declining unemployment is associated with lower readability, suggesting more concise or simplified messaging. In Western countries, higher growth rates correlate with lower readability, potentially reflecting more technical or inflation-combating communication during periods of economic strength. Overall, neither inflation nor extreme inflation shows significant predictive power for readability in the aggregate

Turning to abstractness, the results mirror those from the recession analysis in one key respect: when there is a need for economic stimulation, abstractness tends to increase—except in Eastern countries. However, a new pattern emerges: higher inflation and extremely high inflation are also associated with increased abstractness in Eastern countries, indicating a shift toward more conceptual or generalized language during inflationary episodes for these countries.

For informativeness, significant effects are largely confined to English-speaking countries. In these cases, periods of extremely high inflation, coupled with declining growth and rising unemployment, lead to a marked increase in informativeness. This suggests that central banks in these contexts respond to inflationary pressure with more detailed and explanatory communication. Western countries also exhibit increased informativeness, though only in response to extremely high inflation, with other indicators (aside from unemployment) showing limited influence.

Finally, regarding disunity, the data indicate that higher inflation tends to correlate with

Table 7: Average targeted economic agents across countries

Country	Financial Sector	Central Bank	Government	Households	Firms
Australia	0.231	0.219	0.037	0.348	0.164
Canada	0.095	0.489	0.047	0.167	0.202
Chile	0.119	0.528	0.039	0.171	0.143
Colombia	0.157	0.524	0.108	0.093	0.119
ECB	0.240	0.285	0.175	0.133	0.167
Fed	0.054	0.589	0.027	0.287	0.043
Hungary	0.155	0.431	0.125	0.141	0.147
Iceland	0.122	0.590	0.066	0.159	0.063
Indonesia	0.468	0.227	0.090	0.034	0.180
Japan	0.334	0.475	0.031	0.032	0.128
Korea	0.298	0.183	0.052	0.170	0.297
NewZealand	0.110	0.390	0.069	0.180	0.252
Norway	0.148	0.561	0.033	0.179	0.079
Peru	0.336	0.520	0.029	0.051	0.064
Philippines	0.149	0.725	0.045	0.035	0.046
Poland	0.117	0.269	0.100	0.232	0.281
Thailand	0.224	0.329	0.131	0.055	0.262

greater disunity in central bank statements—except in Eastern and English-speaking countries, where the directional signs are similar but lack statistical significance. In Western countries, lower growth is associated with increased disunity, consistent with the broader theme that economic stress prompts more fragmented or multifaceted messaging.

Robustness check using price level instead, revealing similar patterns, with main conclusions staying the same. To conclude, the analysis of central bank communication during periods of high inflation reveals a distinct behavioral pattern compared to recessionary contexts. Unlike the consistent rise in complexity seen during downturns, extremely high inflation does not uniformly affect textual ambiguity metrics. Instead, unemployment—especially lagged values—emerges as a key predictor across readability and abstractness. Abstractness tends to increase both when economic stimulation is needed and during inflationary pressure, while informativeness rises notably in English-speaking countries under inflation-driven stress. Disunity generally escalates with inflation, though regional variations persist. Overall, these findings suggest that while central banks respond to inflation with nuanced shifts in communication, the patterns are less uniform and more context-dependent than those observed during recessions.

6.2 Supplement Findings

6.2.1 Economic agents targeting

Table 7 reports the average proportion of central bank statements directed toward each economic agent. This descriptive analysis seeks to evaluate whether concerns about the general public's (households') reliance on central bank communications are empirically grounded. Since the proportions are constructed to sum to one for each document, the average magnitudes presented in the table are directly comparable across agents, offering a data-driven perspective on the relative communicative emphasis placed on different audiences.

Table 8: Correlation between the ambiguity measurement and the targeted economic agents

	Financial Sector	**Central Bank**	**Government**	**Households**	**Firms**
Readability	0.207	-0.109	0.261	-0.287	0.109
Abstractness	-0.269	-0.091	0.529	0.132	0.104
Informativeness	0.458	-0.53	0.663	-0.116	0.176
Disunity	-0.133	-0.338	0.558	0.117	0.394

The data reveal that households receive a meaningful share of attention in central bank communications—typically ranging from 5% to 30%—which is substantial when compared to the dominant focus on the central bank itself. This proportion becomes even more notable when combined with the attention directed toward firms, reinforcing the relevance of public-facing messaging. These findings lend empirical support to concerns about the accessibility and clarity of central bank statements for the general public.

Moreover, Table 8 offers descriptive correlations between ambiguity metrics and the targeted economic agents, suggesting that if linguistic complexity is systematically associated with household-directed messaging, it may have important implications for how effectively central banks engage with and guide public expectations

Intriguingly, when solely examining the correlation with households, the relationship with communication complexity is generally not high. For instance, the correlation with readability is negative at almost -0.3, suggesting that when central banks are concerned about households, the language used tends to be less complex or more accessible. This stands in stark contrast to communications directed at government, where complexity is consistently associated with a higher level across all ambiguity aspects. Firms also experience a similar trend, but primarily for disunity (as other correlations are close to zero), which might not be detrimental given the diverse industries encompassed by "firms." Communications targeting the central bank itself exhibit less complexity and a more concentrated topic discussion, which aligns with expectations for internal or self-referential discourse. Finally, for the financial sector, the signals are mixed: an increase in complexity is observed in readability and informativeness, but also a lower level of abstractness. It is important to note, however, that these correlations with the financial sector are generally not strong.

The analysis of central bank communication targeting reveals that households represent a notable, although not dominant, segment of central bank concern, particularly when considering the collective attention given to households and firms. This descriptive evidence suggests that apprehension regarding the accessibility of central bank communications for the general public is empirically well-founded. Interestingly, when households are the primary focus, the communication tends to be less complex, as indicated by a negative correlation with readability, in clear contrast to messaging directed at government, which are generally associated with higher complexity. The mixed signals for the financial sector and the more concentrated, less complex communication directed at the central bank itself further underscore the tailored nature of central bank messaging. This highlights that central banks do, to varying degrees, adjust their communication styles

Table 9: Correlation between the ambiguity measurement and the sentimental variables

	Net Hawk	Pos (Fin)	Neg (Fin)	Pos (Agent)	Neg (Agent)
Readability	0.411	0.298	-0.367	0.492	-0.492
Abstractness	0.539	0.474	0.243	-0.075	0.075
Informativeness	0.5	0.396	-0.073	0.386	-0.386
Disunity	0.677	0.606	0.128	0.163	-0.163

in response to their perceived audience, with a discernible effort towards clearer language when addressing the broader public.

6.2.2 Other textual characteristics

Regarding other prominent sentiment variables frequently employed in the literature, we investigate whether they exhibit particular patterns of interest. To this end, we examine the correlation between our textual ambiguity measurements and the levels of net hawkishness, as well as positive/negative tones (considering both standard measurements and those accounting for economic agents). The results can be seen in Table 9.

The most striking aspect of the results is the relatively strong positive correlation between hawkish/positive tones and more complex statements. This relationship is evident through comparatively higher positive correlations with readability, abstractness, informativeness, and disunity—ranging approximately from 0.3 to 0.7. These findings suggest that central banks, which generally adopt a more hawkish tone or convey a more positive sentiment, tend to produce statements that are more difficult to read, more diverse in vocabulary, more disunified, and more abstract.

This may seem surprising, as previous results indicate heightened linguistic complexity during periods of extremely low growth. There is also some evidence of increased complexity during episodes of extremely high inflation, though this pattern is less consistent. However, these correlations should be interpreted as reflecting average tendencies rather than marginal responses. Specifically, they suggest that if a central bank is characterized by a more hawkish/positive tone over the long run, its language tends to be more textually complex. During times of low growth, regardless of a central bank's baseline complexity—whether in readability or abstractness—its communication can intensify beyond the existing average.

Conversely, the signals associated with negative tones are considerably more mixed, although they generally trend in the opposite direction of positive tones. This ambiguity may be partly attributed to the presence of neutral tones, which are not explicitly accounted for in this analysis. The divergence between hawkish and positive/negative sentiment suggests that central banks may differ in their long-run communication strategies depending on whether they prefer to express confidence and tightening or caution and loosening—potentially reflecting their underlying preferences in managing market expectations. In our sample, central banks that prioritize fighting inflation over stimulating growth, or that consistently adopt a more optimistic tone, tend to employ a more complex across all textual dimensions communication strategy overall.

6.2.3 Topic evolutions

The analysis of topic evolution in central bank statements provides crucial insights into the shifting focus of central bank communications over time. The identified topics and their most relevant keywords are detailed in Figure 4 in Appendix 8.5.

Given the sheer number of topics and the considerable overlap in keyword meanings, we have grouped and renamed them for clearer interpretation:

- **Central Bank-Specific Language:** Intriguingly, the three major central banks in our sample appear to be "recognized" and grouped into distinct topics based on their unique communication styles: The ECB Language (Topic 5), The FED Language (Topic 8), and The Japanese Language (Topic 7). This distinction is not attributable to the length of their statements, as other central banks (e.g., Indonesia) have significantly longer documents, and the Latent Dirichlet Allocation (LDA) method employed is inherently robust to document length variations. Upon closer inspection, we observe that the ECB topic is primarily concerned with growth and development, while the Fed topic centers more on inflation, interest rates, and policy targets. Japan, on the other hand, exhibits a unique set of keywords that strongly indicate a focus on guidelines, specific policies, and asset purchases, reflecting its distinctive monetary policy approach.

- **Macroeconomic Themes:** The next main categories of topics identified are broadly divided into Growth and Inflation. The "Growth" theme encompasses topics 12, 13, and 14, highlighting their shared focus on economic expansion. For "Inflation," a larger cluster comprising topics 3, 4, 6, 9, 11, and 15 consistently emphasizes price stability concerns.

- **Operational and Financial Context:** Other notable topics include Central Bank Operations (Topic 1), which likely covers technical aspects of monetary policy implementation, and Finance (Topic 2), a more loosely defined category that touches upon broader financial market dynamics.

- Pandemic: This particular topic arises due to the recent event of the Pandemic that swept the world. This topic only particularly active during the pandemic period between the end of 2019 and 2022.

This grouping allows for a more structured understanding of the thematic evolution and emphasis within central bank communications across different economies.

Table 10 illustrates the average proportion of statements dedicated to each topic for every country. This purely descriptive analysis helps ascertain the relative emphasis central banks place on various themes.

Intriguingly, the data reveals two distinct groups of countries whose communications predominantly revolve around either economic growth or inflation. Excluding the three major central banks (the Federal Reserve, which leans towards inflation; the ECB, which emphasizes growth; and Japan,

Table 10: Average topic proportion for each country

Country	Inflation	Growth	FedLang	JapanLang	ECBLang	Pandemic	CBOper	Finance
Armenia	0.9520	0.0105	0.0012	0.0014	0.0056	0.0128	0.0132	0.0034
Australia	0.1925	0.7217	0.0014	0.0010	0.0113	0.0573	0.0140	0.0008
Canada	0.2156	0.7192	0.0040	0.0017	0.0111	0.0387	0.0086	0.0012
Chile	0.9000	0.0398	0.0024	0.0084	0.0066	0.0272	0.0096	0.0061
Colombia	0.9049	0.0299	0.0024	0.0005	0.0077	0.0341	0.0188	0.0015
ECB	0.1316	0.0066	0.0005	0.0002	0.7908	0.0279	0.0059	0.0366
Fed	0.1848	0.0194	0.7621	0.0008	0.0042	0.0150	0.0097	0.0040
Hungary	0.8918	0.0356	0.0008	0.0009	0.0264	0.0265	0.0158	0.0022
Iceland	0.6442	0.0391	0.2060	0.0007	0.0209	0.0277	0.0508	0.0105
Indonesia	0.2022	0.7591	0.0004	0.0008	0.0107	0.0077	0.0093	0.0098
Japan	0.0313	0.0324	0.0018	0.8292	0.0098	0.0126	0.0800	0.0029
Korea	0.5491	0.1122	0.0024	0.0358	0.0040	0.0115	0.0122	0.2727
NewZealand	0.3461	0.3799	0.0034	0.0021	0.0127	0.2506	0.0028	0.0024
Norway	0.2954	0.5589	0.0015	0.0011	0.0042	0.0123	0.0098	0.1169
Peru	0.7768	0.0054	0.0021	0.0007	0.0016	0.0211	0.1909	0.0014
Philippines	0.5458	0.0496	0.0023	0.3127	0.0239	0.0356	0.0253	0.0048
Poland	0.8553	0.0082	0.0007	0.0007	0.0055	0.0449	0.0836	0.0010
Thailand	0.1243	0.8128	0.0032	0.0023	0.0086	0.0384	0.0033	0.0071

which presents a unique, mixed thematic focus), we observe countries primarily concentrated on inflation (e.g., Armenia, Chile, Colombia, Hungary, Peru, and Poland) and those primarily focused on growth (e.g., Australia, Canada, Indonesia, and Thailand). Some countries exhibit particularly interesting mixes: Iceland, for instance, primarily focuses on inflation but also dedicates a notable 0.2 percent of its topic proportion to language similar to the Fed's (which is inflation-leaning). The Philippines shows more than 50% thematic alignment with inflation but also a substantial 30% overlap with Japan's thematic profile. Other countries, such as Korea, New Zealand, and Norway, maintain a relatively balanced thematic focus between growth and inflation.

To extend this analysis, a graph illustrating the evolution of growth versus inflation topics, averaged across all countries (excluding the three major central banks) for a given period, reveals further insights.

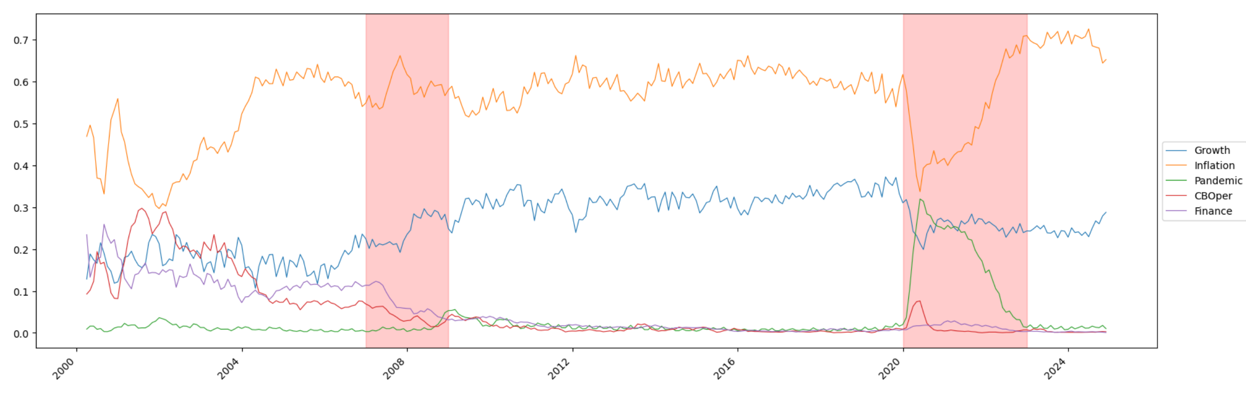

Figure 1: Topic evolution over time, excluding the Fed, ECB and Japan

The topic of inflation has predominantly remained the main focus over time, as expected, given the central bank's core mandate of maintaining price stability. However, the topic of growth has been steadily on the rise since 2000. This finding aligns with previous literature, such as Luangaram and Wongwachara (2017), which also observed growth becoming an increasingly important theme within central bank statements globally. Nonetheless, this trend was notably interrupted by the COVID-19 pandemic in late 2019, as the "pandemic topic" temporarily gained prominence. Despite the pandemic's direct impact waning after 2022, the inflation topic subsequently took an even higher priority, surging beyond its pre-pandemic levels. This post-pandemic surge in inflation-related communication suggests a deep and potentially lasting impact of the crisis on central bank communication strategies. However, a slight inverted trend observed near the end of 2024 for both topics hints at the possibility of a gradual reversion to pre-pandemic communication priorities. It is also worth noting that for the ECB, its own specific language during the pandemic significantly decreased in prominence, giving way to the inflation topic, mirroring the shift seen in other countries. In contrast, the United States (Fed) and Japan maintained a dominance of their own distinctive topics before, during, and after the pandemic, unlike the ECB, further highlighting cross-country variations in communication strategies during crises.

Connecting these findings to complexity measures, we focus on the two main topics—growth and inflation—and find limited correlation with various aspects of linguistic complexity. For the growth topic, only readability shows a notable correlation, at –0.23, suggesting that statements involving growth tend to be easier to understand. In contrast, the inflation topic exhibits a relatively strong positive correlation of 0.38 with abstractness and a negative correlation of –0.20 with informativeness, indicating that communications about inflation are generally more abstract and less detailed. This pattern aligns to some extent with the hawkishness results, as greater preferences for fighting inflation appear to be associated with more abstract linguistic framing.

7 Conclusions, Limitations and Future Directions

This study uncovers consistent patterns in the linguistic complexity of central bank communications, particularly during periods of economic distress. Across most samples and subsamples, central bank statements become harder to read, more informative, and exhibit greater disunity during episodes of extremely low growth—a trend not mirrored by conventional recession indicators or periods of extremely high inflation. Abstractness, meanwhile, tends to increase when there is a need for economic stimulation, conditional on broader macroeconomic conditions. The unemployment rate emerges as a robust predictor of textual ambiguity, with higher rates generally associated with more complex language. However, these patterns do not hold uniformly: Eastern countries display a distinct set of behaviors, marked by mixed and often contradictory signals. At the individual country level, substantial variation further underscores the importance of controlling for individual speaker characteristics and institutional context.

Beyond macroeconomic triggers, the analysis reveals that central banks devote a substantial share of attention to the general public—including households and firms—underscoring the importance of audience-targeted communication. Moreover, central banks characterized by more hawkish or optimistic tones tend to exhibit greater linguistic complexity in their statements on average, possibly reflecting the abstract nature of communication associated with inflation-fighting strategies. This pattern is further supported by the inflation topic, which shows a positive correlation with abstractness, albeit with moderate strength.

Several limitations remain. First, the dataset—based on Luangaram and Wongwachara (2017)—could be expanded to include additional central banks, such as those in South Africa and other Asian economies, to improve coverage and generalizability. Second, the analytical framework is methodologically straightforward; future research would benefit from non-linear models or more sophisticated structures capable of disentangling the dual forces of anchoring and flexibility in central bank messaging. Finally, while this study offers descriptive insights into the relationship between target audience and linguistic complexity, further work—potentially involving regression-based approaches and theoretical development—is needed to explore these dynamics more rigorously.

Taken together, this study not only deepens our understanding of how central banks adjust their communication strategies in response to economic conditions, but also introduces a novel and more intricate framework for measuring textual complexity. By moving beyond traditional readability metrics and incorporating dimensions such as abstractness, informativeness, and disunity, the paper offers a more statistically grounded and multidimensional approach to analyzing central bank statements. This methodological advancement opens the door for future research to explore the strategic use of language in monetary policy with greater precision, and invites further inquiry into how complexity interacts with audience targeting, sentiment, and institutional context. As central banks continue to navigate increasingly volatile economic landscapes, the clarity, tone, and structure of their messaging will remain central to effective policy transmission—and this paper provides a foundation for understanding that complexity with greater nuance and empirical depth.

8 Appendix

8.1 Examples of How Linguistic Complexity Can Signal Anchoring-Flexibility Trade-off

The two examples are referred to as

- (1) "The Committee will set the rate at 0.25 percent until inflation reaches 2 percent and unemployment falls below 5 percent. We expect these conditions to be met by mid-2026."
- (2) "The Committee anticipates that maintaining the current policy rate may be appropriate as long as inflation trends toward 2 percent and labor market indicators improve. These conditions could potentially be met by mid-2026, although considerable uncertainty remains"

Intuitively, example (1) is much clearer than example (2), offering significantly less room for interpretive flexibility.

In terms of linguistic complexity measurements, we report the following metrics (for readability, and because many of them function similarly, we randomly select three for demonstration purposes without compromising interpretations):

1. For example (1):
   - Readability: Flesch-Kincaid Grade Level = 8.37; Coleman-Liau Index = 10.74; LIX = 45.53
   - Abstractness: 3.17
   - Informativeness: 0.64
   - Disunity: 0.32
2. For example (2):
   - Readability: Flesch-Kincaid Grade Level = 13.63; Coleman-Liau Index = 18.51; LIX = 61.74.
   - Abstractness: 3.41
   - Informativeness: 0.77
   - Disunity: 0.42

The readability differences are straightforward. To allow for more flexible expectations, additional content is introduced to express this layer of freedom, which increases the average sentence length and the likelihood of longer words (e.g., appropriate, potentially).

Regarding abstractness, modal words such as may and potentially introduce abstract elements that express flexibility while reducing clarity. Moreover, the avoidance of specific thresholds—such as replacing the unemployment rate with the more vague phrase labor market indicators—further decreases concreteness, thereby increasing overall abstractness.

In terms of informativeness, the effort to avoid rigid commitments and express expectations in a more nuanced way requires additional information and more diverse language. This is reflected in phrases like "although considerable uncertainty remains", along with the use of modal verbs and adverbs that help dilute the assertiveness. However, in the same example, the phrase "although considerable uncertainty remains" adds informational content about the economic outlook, even as it introduces hedging language—demonstrating how this feature of complexity can simultaneously dilute commitment and enrich interpretation.

Finally, although less visible, sentence transitions become less coherent. The flexible goals expressed in the first sentence of example (2) result in a longer and less direct formulation, making the referent "these conditions" in the second sentence less immediately clear. Additionally, modal verbs and uncertainty-related expressions tend to be less semantically linked to concrete economic terms, which often reduces the overall coherence between sentences.

In general, these metrics should be viewed as statistical tools. They are not always definitive (e.g., higher abstractness does not imply greater complexity in every instance), but they tend to hold true on average. Similarly, higher textual complexity typically signals an intention to preserve flexibility or strategic ambiguity in central bank communication but not always.

8.2 Detailed Differences Between Types of "Recession Indicators"

First, Figure 2 illustrates the differences among four types of 3D recession indicators for the United States. Notably, the NBER indicator applies a more stringent threshold for defining recessions, identifying fewer periods compared to the OECD-based measures.

Figure 2: Four types of recession indicators for the United States

Second, to highlight the differences between the quantile recession indicators and the 3D recession indicators, at the aggregate level across all countries, Figure 3 presents a bar graph comparing their respective counts

According to the graph, one of the most puzzling observations arises during the post-pandemic phase, which—based on conventional expectations—should have marked the onset of an expansionary cycle rather than a recession. Yet, the 10th percentile indicates relatively low growth in 2024, albeit only for a few countries. Meanwhile, the 25th percentile appears overly inclusive and may fail to adequately capture deep recessions. This anomaly is observed in aggregate across multiple countries, not merely within the jurisdictions of the Federal Reserve (FED) or the European Central Bank (ECB), which might otherwise have explained the deviation.

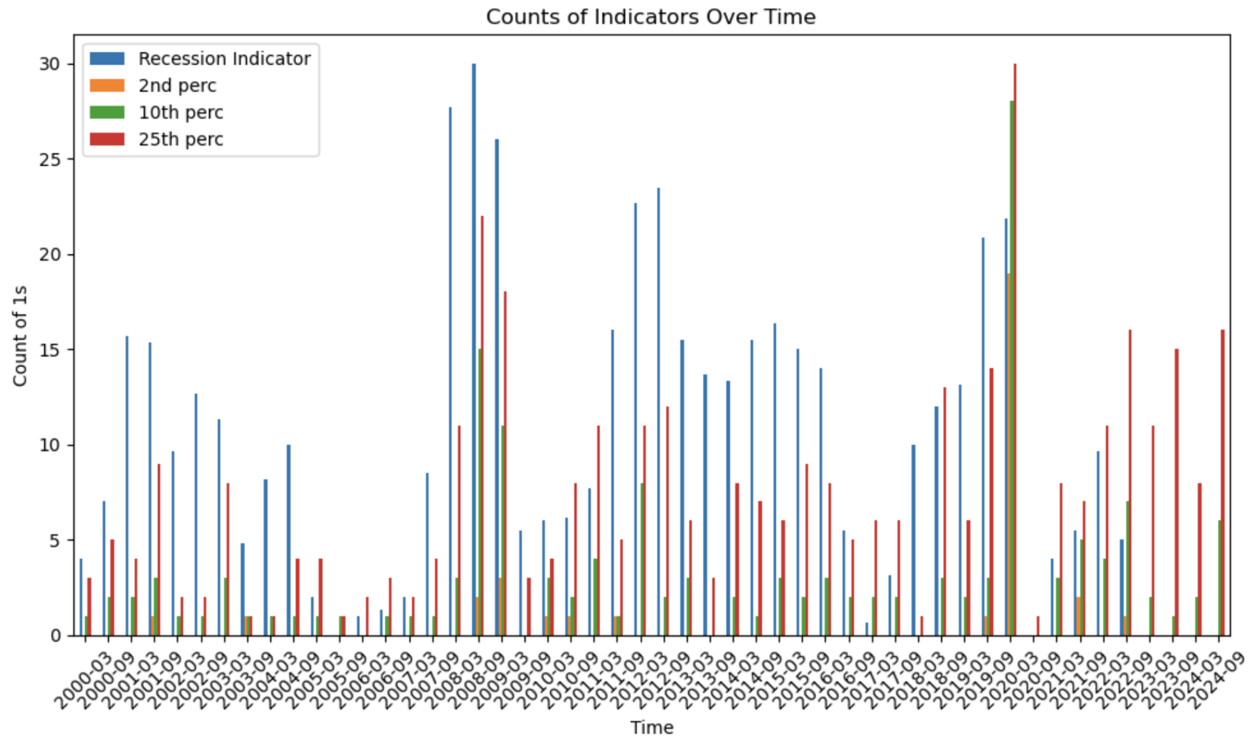

Figure 3: Total counts of 1s - recessions - across all countries

When examining countries individually, the quantile-based recession indicator tends to be a stricter measure than the 3D approach, which incorporates depth, diffusion, and duration. Notably, most exceptions to this pattern emerge during the post-pandemic period, echoing trends seen in the aggregate data. Instances where the quantile indicator—particularly at the 5th/10th percentile rather than the more extreme 2nd percentile—fails to align with the three major recessions are relatively frequent and span across all countries. Moreover, quantile-based recession signals can appear even when the 3D framework does not register a downturn. In essence, the quantile-based and 3D-based approaches capture distinct dimensions of economic contractions. Neither is a subset of the other; each reveals unique recessionary signals that may be overlooked by the alternative method.

More on Conventional Recession Indicators:
The National Bureau of Economic Research (NBER) defines a recession as a significant decline in economic activity that is both widespread across the economy and sustained for more than a few months. According to the NBER committee, a recession must exhibit three key characteristics—**depth**, **diffusion**, and **duration**—each of which must be present to some degree. However, exceptionally severe conditions in one dimension can partially offset weaker signals in the others. A notable example cited in their Q&A illustrates this principle: "A notable example is the February 2020 peak in economic activity. Despite the brief duration of the subsequent downturn, the committee determined that the magnitude and breadth of the decline were sufficient to classify it as a recession. The trough was later identified as occurring in April 2020, just two months after

the peak."

In contrast, an expansion is defined as any period during which the economy is not in recession. Expansion is considered the economy's default state, and recessions are typically short-lived. Nonetheless, the time required for economic activity to return to its previous peak can be substantially longer, reflecting the uneven pace of recovery.

More on OECD Recession Criteria:

The OECD's recession methodology has historically mirrored that of the NBER, albeit with somewhat looser criteria. This distinction becomes evident when comparing the OECD's recession indicators for the United States with those of the NBER, which tend to apply more stringent thresholds.

According to archived definitions, the OECD identifies recession periods using a framework based on **Composite Leading Indicators** (CLIs) and **reference turning points**. These indicators track economic activity across multiple sectors to detect peaks and troughs in the business cycle. A recession is defined as the interval between a peak and the subsequent trough, with turning points determined on a monthly basis—though exact dates within the month are not specified. For practical applications, recession periods are often visualized as spanning from the 15th of the peak month to the 15th of the trough month in daily data representations.

This methodology aligns with classical business cycle analysis, emphasizing broad-based economic contractions rather than focusing solely on GDP declines. The OECD's approach underscores the importance of diffusion, depth, and duration—consistent with international standards—while allowing for expert judgment in identifying economic turning points.

Thus, we infer that the primary differences between conventional recession indicators and quantile-based GDP growth measures lie in their treatment of diffusion and duration. Quantile indicators of real GDP growth capture only the depth of economic contractions, whereas conventional frameworks—such as those employed by institutions like the OECD—implicitly incorporate diffusion (the extent to which the downturn spans across sectors) and duration (the length of the downturn). While diffusion is inherently difficult to observe directly, duration is more readily measurable.

If significant discrepancies emerge between the results of these two recession indicators, it suggests that recessions of similar depth can convey markedly different signals depending on their persistence and sectoral reach. These differences influence not only how economic conditions are interpreted but also the diversity and nuance of language required to communicate them effectively.

There are several intuitions regarding the informativeness during recession:

- **Extended duration** may imply that the economic environment remains largely unchanged over time, leading to repetitive policy communications (e.g., "The situation continues; therefore, the policy stance remains unchanged"). Such repetition can diminish the novelty and informational value of each statement.

- **Broad diffusion** across industries may prompt the use of more generalized language in policy discourse, thereby reducing sector-specific insights and limiting linguistic diversity.

However, this interpretation warrants caution. If a recession affects a wide range of industries, aggregate real GDP growth would typically be extremely low—consistent with signals from extreme quantile indicators. Yet, it remains plausible that even amid widespread stagnation, certain sectors may perform relatively well. This mirrors phenomena such as the resilience of inferior goods during downturns or shifts in consumer preferences that benefit specific industries.

Accordingly, I propose treating these as two distinct categories of recession indicators: **quantile recession indicators** and **3D recession indicators**, with "3D" referring to depth, diffusion, and duration. Within the context of this analysis, duration emerges as a particularly salient differentiator. It is reasonable to assume that monetary policy councils face considerable challenges in forecasting the duration of a recession with confidence at the time of decision-making—if such foresight were possible, policy interventions would likely be more immediate and targeted.

Furthermore, the accurate identification of 3D recession indicators often depends on multiple rounds of data revision, which are typically unavailable to policymakers in real time. Despite these limitations, 3D indicators offer a more comprehensive and expert-validated framework, making them especially valuable for retrospective analysis and historical interpretation.

8.3 Detailed Descriptions of Readability Measurements

- **Gunning-Fog** is a readability index originally developed for English writing, but works for any language. The index estimates the years of formal education needed to understand the text on a first reading. A Gunning-Fog index of 12 requires the reading level of a U.S. high school senior (around 18 years old). The formula for calculating the index is:

  $$Gradelevel = 0.4 \times (ASL + PHW)$$

  Where ASL is the average sentence length (total words / total sentences), and PHW is the percentage of hard words (words with three or more syllables).

- **SMOG** or Simple Measure of Gobbledygook, is a readability formula that estimates the years of education required to understand a piece of writing. It primarily focuses on the complexity of words, using the number of polysyllabic words in the text. The formula is:

  $$SMOGIndex = 1.043\sqrt{30(hard\_words/n\_sentences))} + 3.1291$$

- **Flesch reading ease** is a readability score that indicates how easy a text is to read. Higher scores indicate easier reading, while lower scores indicate more difficult reading. The score is calculated using the following formula:

  $$FleschReadingEase = 206.835 - (1.015ASL) - (84.6ASW)$$

  Where ASL is the average sentence length and ASW is the average number of syllables per word.

- **Flesch-Kincaid grade** is a readability metric that estimates the grade level needed to comprehend a text. It is based on the average sentence length and average number of syllables per word. The formula is:

$$Flesch - KincaidGrade = 0.39(ASL) + 11.8(ASW) - 15.59$$

- **Automated readability index** is a readability test that calculates an approximate U.S. grade level needed to understand a text. It is based on the average number of characters per word and the average sentence length. The formula is:

$$ARI = 4.71(n\_chars/n\_words) + 0.5(n\_words/n\_sentences) - 21.43$$

- **Coleman-Liau index** is a readability test that estimates the U.S. grade level needed to understand a text. It is based on the average number of letters per 100 words and the average number of sentences per 100 words. The original formula is:

$$CLI = 0.0588L - 0.296S - 15.8$$

  Where L is the average number of characters per 100 words and S is the average number of sentences per 100 words. In our implementation we average over the entire text instead of just 100 words.

- **Lix** is a readability measure that calculates a readability score based on the average sentence length and the percentage of long words (more than six characters) in the text. The formula is:

$$Lix = (n\_words/n\_sentences) + (n\_long\_words * 100)/n\_words$$

- **Rix** is a readability measure that estimates the difficulty of a text based on the proportion of long words (more than six characters) in the text. The formula is:

$$Rix = (n\_long\_words/n\_sentences)$$

8.4 Topic Modeling

8.4.1 Detailed Text Preprocessing

- **Tokenization**: The text is segmented into individual words and converted to lowercase. Special characters such as commas and periods are retained to avoid misprocessing contractions (e.g., preserving “don’t” rather than converting it to “dont”).

- **Lemmatization**: Tokens are reduced to their base or dictionary form. For example, "changed" becomes "change", and "was" becomes "be".
- **Inclusion of n-grams**: Phrases ranging from bigrams to four-grams (2–4 word sequences) are incorporated. To ensure relevance, only phrases that appear at least 50 times across the corpus and rank within the top 25 percent of the log-likelihood ratio of appearance are retained.
- **Stop word and punctuation removal**: Common stop words and punctuation marks are removed to reduce noise and improve topic extraction.

8.4.2 LDA Process

- Initialization: Each word in every document is randomly assigned to one of K predefined topics. This initial assignment serves as a starting point for the iterative refinement. For this study, K = 15 is selected—a reasonable number given the number of countries in the dataset and the potential for later aggregation into broader thematic categories.
- Iterative Refinement (Gibbs Sampling Loop): For each word in each document, the algorithm performs the following steps:
  - Temporarily removes the current topic assignment for the word.
  - Calculates the probability of assigning the word to each of the K topics, based on two key factors: (i) the likelihood of the word appearing in a given topic (based on its frequency across all documents), and (ii) the likelihood of the topic appearing in the current document (based on how many words in the document are assigned to that topic).
- Reassignment: The word is then re-assigned to a topic based on the calculated probabilities. This step incorporates Dirichlet priors—α for the document-topic distribution and β for the topic-word distribution—which serve as smoothing parameters. In this study, both priors are set to $1/K$, promoting balanced topic representation.
- Convergence: The process repeats for a fixed number of iterations or until topic assignments stabilize. Over time, words that frequently co-occur tend to cluster within the same topics, and documents with similar thematic content exhibit higher probabilities for those shared topics.

It is important to note that the initial topic modeling results can be relatively difficult to interpret. Common terms such as increase and decrease, as well as quantity indicators like millions and billions, tend to appear frequently across documents but offer limited insight into the thematic content of a topic. These high-frequency, low-specificity terms are therefore excluded during the final stages of text preprocessing to enhance interpretability.

Table 11: Central bank statements availability

Country	Central Bank Name	Date Available	Number of Statements
Armenia	Central Bank of Armenia	2009-2024	144
Australia	Reserve Bank of Australia	2000-2024	207
Canada	Bank of Canada	2000-2024	198
Chile	Banco Central de Chile	2000-2024	266
Colombia	Banco de la República	2015-2024	87
European Union	European Central Bank	2000-2024	256
Hungary	Magyar Nemzeti Bank	2002-2024	273
Iceland	Central Bank of Iceland	2009-2024	123
Indonesia	Bank Indonesia	2005-2024	214
Japan	Bank of Japan	2000-2024	318
South Korea	Bank of Korea	2000-2024	270
New Zealand	Reserve Bank of New Zealand	2000-2024	100
Norway	Norges Bank	2000-2024	199
Peru	Banco Central de Reserva del Perú	2001-2024	288
Philippines	Bangko Sentral ng Pilipinas	2001-2024	217
Poland	Narodowy Bank Polski	2001-2024	273
Thailand	Bank of Thailand	2002-2024	177
United States	Federal Reserve System	2000-2024	199

8.5 Tables and Graphs

Table 12: Quality check for Central Bank statements

Country	$Passed$	n_{stopw}	$m_{wlength}$	n_{words}	symbol/w	$p_{ellipsis}$	$p_{bulletpoints}$	$m_{dupstat}$
Armenia	0.99	135.46	4.75	353.31	0.00	0.00	0.00	0.01
Australia	1.00	259.30	4.68	626.06	0.00	0.00	0.00	0.00
Canada	1.00	184.52	4.67	471.03	0.00	0.00	0.00	0.01
Chile	1.00	135.72	4.79	361.98	0.00	0.00	0.00	0.00
Colombia	0.79	178.24	4.58	479.05	0.00	0.00	0.00	0.04
ECB	0.57	605.31	4.82	1568.06	0.00	0.00	0.00	0.08
Fed	0.93	153.32	4.87	461.94	0.00	0.00	0.00	0.02
Hungary	0.82	343.55	4.78	941.93	0.00	0.00	0.01	0.03
Iceland	0.98	157.71	4.58	414.77	0.00	0.00	0.00	0.01
Indonesia	0.86	497.07	4.88	1639.27	0.00	0.00	0.00	0.03
Japan	0.75	167.47	4.55	450.07	0.00	0.00	0.00	0.04
Korea	0.98	154.40	4.87	410.36	0.00	0.00	0.00	0.01
NewZealand	0.99	156.53	4.83	404.98	0.00	0.00	0.00	0.00
Norway	0.84	194.68	4.59	513.88	0.00	0.00	0.01	0.03
Peru	0.94	158.18	4.64	449.63	0.00	0.00	0.00	0.03
Philippines	1.00	129.95	4.90	384.57	0.00	0.00	0.00	0.00
Poland	0.85	290.67	4.61	794.50	0.00	0.00	0.00	0.03
Thailand	0.92	154.80	5.01	427.93	0.00	0.00	0.00	0.02

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Table 13: **Fixed effect models for 5 and 10 bottom percentile (part 1)**

	All		Geography				Language			
			Western		Eastern		English speaking		Non-English speaking	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
					A. Readability					
Δi_t	−0.011	−0.014	−0.021	−0.028	0.669*	0.631	0.241	0.180	−0.099	−0.103
	(0.099)	(0.107)	(0.110)	(0.118)	(0.377)	(0.403)	(0.170)	(0.190)	(0.113)	(0.125)
$g^{5p}_{y_t}$	0.624***		0.742***		0.371		0.780**		0.656**	
	(0.210)		(0.239)		(0.462)		(0.330)		(0.301)	
$g^{5p}_{y_{t-1}}$	0.662***		0.646***		0.647		0.680		0.595**	
	(0.160)		(0.180)		(0.495)		(0.462)		(0.248)	
$g^{10p}_{y_t}$		0.350**		0.376**		0.150		0.314		0.432**
		(0.139)		(0.147)		(0.275)		(0.225)		(0.214)
$g^{10p}_{y_{t-1}}$		0.287**		0.139		0.604		0.102		0.315
		(0.144)		(0.117)		(0.517)		(0.158)		(0.231)
π_t	0.004	−0.000	0.075	0.072	−0.013	−0.006	−0.011	−0.047	0.033	0.034
	(0.062)	(0.065)	(0.071)	(0.079)	(0.136)	(0.147)	(0.156)	(0.151)	(0.061)	(0.066)
π_{t-1}	−0.057	−0.055	−0.070	−0.068	0.109	0.106	−0.065	−0.034	−0.054	−0.057
	(0.046)	(0.047)	(0.048)	(0.047)	(0.204)	(0.210)	(0.113)	(0.108)	(0.052)	(0.056)
u_t	−0.020	−0.000	0.072	0.117	0.123***	0.137***	0.019	0.110	−0.025	−0.023
	(0.069)	(0.075)	(0.063)	(0.077)	(0.045)	(0.041)	(0.103)	(0.111)	(0.078)	(0.083)
u_{t-1}	0.108	0.089	0.190*	0.146	0.039	0.028	0.354**	0.265**	0.056	0.054
	(0.080)	(0.080)	(0.105)	(0.108)	(0.027)	(0.037)	(0.163)	(0.118)	(0.093)	(0.094)
R^2	0.02	0.02	0.11	0.1	0.06	0.06	0.1	0.09	0.01	0.01
N	1323	1323	1043	1043	280	280	479	479	844	844
					B. Abstractness					
Δi_t	−0.298***	−0.289***	−0.259***	−0.255***	−1.119	−1.147	−0.574***	−0.579***	−0.256***	−0.254**
	(0.095)	(0.094)	(0.082)	(0.081)	(0.911)	(0.960)	(0.111)	(0.121)	(0.093)	(0.099)
$g^{5p}_{y_t}$	0.236		0.167		0.596		−0.232		0.417	
	(0.210)		(0.221)		(0.723)		(0.426)		(0.263)	
$g^{5p}_{y_{t-1}}$	0.234		0.098		1.033*		0.106		0.296	
	(0.157)		(0.164)		(0.594)		(0.164)		(0.257)	
$g^{10p}_{y_t}$		0.288**		0.194		0.765**		−0.176		0.477**
		(0.146)		(0.157)		(0.352)		(0.238)		(0.193)
$g^{10p}_{y_{t-1}}$		0.217		0.055		1.072***		0.092		0.263
		(0.154)		(0.147)		(0.339)		(0.163)		(0.241)
π_t	0.045	0.042	0.035	0.032	0.197	0.231	−0.032	−0.029	0.053	0.050
	(0.044)	(0.047)	(0.049)	(0.051)	(0.143)	(0.153)	(0.060)	(0.053)	(0.049)	(0.054)
π_{t-1}	0.088	0.088*	0.064	0.065	0.247	0.222	0.117**	0.115*	0.097	0.096
	(0.054)	(0.054)	(0.044)	(0.045)	(0.179)	(0.172)	(0.052)	(0.059)	(0.067)	(0.066)
u_t	0.095	0.084	0.102	0.096	−0.042	−0.042	0.084	0.079	0.083	0.069
	(0.060)	(0.060)	(0.068)	(0.063)	(0.223)	(0.214)	(0.140)	(0.134)	(0.053)	(0.059)
u_{t-1}	0.073	0.084	0.076	0.082	−0.076	−0.072	0.044	0.049	0.086	0.100
	(0.068)	(0.067)	(0.088)	(0.083)	(0.134)	(0.139)	(0.121)	(0.093)	(0.078)	(0.080)
R^2	0.1	0.1	0.11	0.11	0.09	0.11	0.04	0.04	0.12	0.13
N	1332	1332	1043	1043	289	289	479	479	853	853

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Table 14: **Fixed effect models for 5 and 10 bottom percentile (part 2)**

	All		Geography				Language			
			Western		Eastern		English speaking		Non-English speaking	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
					C. Informativeness					
Δi_t	0.090	0.093	0.076	0.078	0.175^{*}	0.165	0.132^{*}	0.115^{**}	0.012	0.015
	(0.081)	(0.081)	(0.082)	(0.082)	(0.103)	(0.114)	(0.076)	(0.053)	(0.043)	(0.043)
$g_{y_t}^{5p}$	0.097		0.076		0.203^{*}		0.362		0.029	
	(0.103)		(0.126)		(0.114)		(0.252)		(0.107)	
$g_{y_{t-1}}^{5p}$	0.058		0.038		0.168^{***}		−0.030		−0.001	
	(0.088)		(0.111)		(0.052)		(0.260)		(0.098)	
$g_{y_t}^{10p}$		0.088^{*}		0.057		0.176^{***}		0.167^{***}		0.057
		(0.048)		(0.059)		(0.057)		(0.054)		(0.048)
$g_{y_{t-1}}^{10p}$		0.079^{*}		0.042		0.192^{***}		-0.098^{**}		0.076
		(0.042)		(0.049)		(0.063)		(0.050)		(0.049)
π_t	−0.015	−0.016	−0.008	−0.010	−0.029	−0.023	0.082^{*}	0.072^{**}	0.003	0.001
	(0.031)	(0.031)	(0.033)	(0.033)	(0.041)	(0.038)	(0.047)	(0.035)	(0.027)	(0.026)
π_{t-1}	−0.001	−0.000	0.002	0.003	−0.020	−0.024	0.032^{**}	0.042^{**}	0.008	0.009
	(0.013)	(0.013)	(0.012)	(0.012)	(0.028)	(0.028)	(0.015)	(0.017)	(0.014)	(0.015)
u_t	0.014	0.012	−0.006	−0.007	-0.024^{**}	-0.021^{**}	0.152^{***}	0.178^{**}	−0.029	−0.031
	(0.046)	(0.047)	(0.054)	(0.056)	(0.012)	(0.010)	(0.040)	(0.076)	(0.032)	(0.034)
u_{t-1}	0.047^{*}	0.049^{**}	0.072^{**}	0.073^{***}	-0.039^{***}	-0.041^{***}	0.216^{***}	0.190^{***}	0.033	0.036
	(0.025)	(0.024)	(0.028)	(0.027)	(0.004)	(0.005)	(0.077)	(0.043)	(0.042)	(0.042)
R^2	0.04	0.04	0.04	0.04	0.17	0.18	0.41	0.41	0.0	0.0
N	1332	1332	1043	1043	289	289	479	479	853	853
					D. Cohesion					
Δi_t	0.029	0.021	0.048	0.042	−0.199	−0.170	0.066	0.050	−0.028	−0.033
	(0.082)	(0.083)	(0.083)	(0.085)	(0.450)	(0.447)	(0.094)	(0.094)	(0.096)	(0.097)
$g_{y_t}^{5p}$	0.211		0.371^{**}		−0.280		0.119		0.243	
	(0.134)		(0.147)		(0.181)		(0.116)		(0.183)	
$g_{y_{t-1}}^{5p}$	0.033		0.151		−0.173		0.092		−0.113	
	(0.109)		(0.107)		(0.130)		(0.132)		(0.146)	
$g_{y_t}^{10p}$		0.067		0.176^{**}		−0.178		0.162		0.010
		(0.111)		(0.087)		(0.283)		(0.100)		(0.163)
$g_{y_{t-1}}^{10p}$		−0.106		−0.055		−0.051		-0.174^{**}		−0.182
		(0.077)		(0.062)		(0.170)		(0.083)		(0.112)
π_t	0.056	0.056	0.050^{*}	0.049	0.148	0.147	0.004	−0.004	0.099^{**}	0.100^{**}
	(0.037)	(0.037)	(0.029)	(0.031)	(0.101)	(0.094)	(0.052)	(0.054)	(0.045)	(0.045)
π_{t-1}	−0.038	−0.037	-0.063^{**}	-0.062^{**}	0.153	0.155	−0.028	−0.021	−0.041	−0.041
	(0.030)	(0.031)	(0.030)	(0.031)	(0.094)	(0.098)	(0.031)	(0.031)	(0.037)	(0.037)
u_t	−0.021	−0.006	−0.035	−0.010	0.018	0.016	0.124^{***}	0.143^{***}	−0.086	−0.070
	(0.048)	(0.047)	(0.066)	(0.063)	(0.042)	(0.042)	(0.023)	(0.040)	(0.054)	(0.053)
u_{t-1}	0.071^{*}	0.057^{*}	0.104^{**}	0.079^{*}	−0.027	−0.027	0.073^{**}	0.057^{**}	0.100	0.084
	(0.040)	(0.033)	(0.051)	(0.045)	(0.037)	(0.034)	(0.030)	(0.024)	(0.064)	(0.057)
R^2	0.02	0.02	0.04	0.03	0.17	0.17	0.23	0.24	0.02	0.02
N	1323	1323	1043	1043	280	280	479	479	844	844

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Table 15: **Fixed effect models for policy inertia (part 1)**

	All		Geography				Language			
			Western		Eastern		English speaking		Non-English speaking	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	A. Readability									
$\Delta i_t = 0$	0.060	0.111	0.136	0.106	−0.377	−0.273	0.183	0.169	−0.138	−0.023
	(0.234)	(0.253)	(0.224)	(0.202)	(0.279)	(0.298)	(0.312)	(0.275)	(0.251)	(0.320)
$g^{2p}_{y_t}$	1.305***		1.534***		0.480		1.136**		1.309**	
	(0.390)		(0.446)		(1.051)		(0.514)		(0.589)	
$g^{2p}_{y_{t-1}}$	0.611**		0.703**		0.054		0.748		0.471	
	(0.299)		(0.356)		(0.893)		(0.811)		(0.314)	
RI_t		−0.032		−0.338		0.205		−0.588		0.228
		(0.320)		(0.354)		(0.327)		(0.585)		(0.354)
RI_{t-1}		0.234		−0.162		0.311		−0.788		0.574**
		(0.275)		(0.344)		(0.201)		(0.531)		(0.230)
π_t	−0.002	−0.053	0.080	0.015	0.018	−0.009	−0.027	−0.274	0.006	0.003
	(0.064)	(0.081)	(0.067)	(0.111)	(0.137)	(0.093)	(0.167)	(0.183)	(0.064)	(0.083)
π_{t-1}	−0.060	−0.006	−0.064	0.010	0.059	0.070	−0.012	0.250***	−0.049	−0.034
	(0.047)	(0.073)	(0.056)	(0.073)	(0.185)	(0.147)	(0.091)	(0.089)	(0.049)	(0.084)
u_t	−0.046	0.046	0.043	0.228*	0.084	0.110	0.064	0.322**	−0.066	−0.007
	(0.069)	(0.097)	(0.071)	(0.118)	(0.088)	(0.076)	(0.114)	(0.158)	(0.074)	(0.088)
u_{t-1}	0.131*	0.041	0.218**	0.029	0.093	0.070	0.308*	0.077	0.094	0.049
	(0.078)	(0.089)	(0.103)	(0.144)	(0.069)	(0.061)	(0.173)	(0.218)	(0.095)	(0.086)
R^2	0.02	0.01	0.11	0.11	0.05	0.05	0.1	0.14	0.01	0.02
N	1365	1234	1052	952	313	282	479	423	886	811
	B. Abstractness									
$\Delta i_t = 0$	0.262	0.311	−0.106	−0.188	1.454**	1.563*	−0.213	−0.290	0.465	0.597
	(0.315)	(0.385)	(0.158)	(0.161)	(0.715)	(0.841)	(0.256)	(0.273)	(0.408)	(0.510)
$g^{2p}_{y_t}$	0.763		0.379		3.071		0.072		1.212	
	(0.524)		(0.423)		(1.962)		(0.429)		(0.759)	
$g^{2p}_{y_{t-1}}$	0.274		0.051		2.662***		0.050		0.404	
	(0.291)		(0.295)		(1.013)		(0.254)		(0.406)	
RI_t		0.080		0.006		0.309***		0.164		0.061
		(0.138)		(0.157)		(0.114)		(0.149)		(0.181)
RI_{t-1}		0.389		−0.046		1.447**		0.012		0.625
		(0.294)		(0.118)		(0.712)		(0.083)		(0.423)
π_t	0.005	0.003	−0.041	−0.057	0.244***	0.177*	−0.075	−0.098**	0.033	0.053
	(0.064)	(0.069)	(0.057)	(0.077)	(0.086)	(0.099)	(0.050)	(0.045)	(0.078)	(0.089)
π_{t-1}	0.197**	0.275**	0.124**	0.172***	0.576**	0.623**	0.094*	0.214***	0.208**	0.272*
	(0.093)	(0.128)	(0.058)	(0.058)	(0.257)	(0.286)	(0.057)	(0.082)	(0.105)	(0.140)
u_t	0.123**	0.146**	0.119*	0.163***	−0.133	−0.049	0.128	0.113	0.071	0.115*
	(0.059)	(0.058)	(0.068)	(0.063)	(0.249)	(0.194)	(0.139)	(0.104)	(0.064)	(0.062)
u_{t-1}	0.076	0.060	0.064	0.034	−0.173	−0.203	0.001	0.041	0.129	0.093
	(0.078)	(0.059)	(0.098)	(0.070)	(0.173)	(0.191)	(0.092)	(0.061)	(0.102)	(0.077)
R^2	0.11	0.14	0.11	0.13	0.24	0.29	0.03	0.04	0.15	0.18
N	1376	1244	1052	952	324	292	479	423	897	821

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Table 16: **Fixed effect models for policy inertia (part 2)**

	All		Geography				Language			
			Western		Eastern		English speaking		Non-English speaking	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
					C. Informativeness					
$\Delta i_t = 0$	0.169*	0.139	0.162	0.139	0.194*	0.153	−0.072	−0.071	0.145	0.083
	(0.087)	(0.104)	(0.103)	(0.121)	(0.115)	(0.135)	(0.107)	(0.113)	(0.090)	(0.113)
g^{2p}_{yt}	0.300**		0.289*		0.484		0.430		0.282	
	(0.133)		(0.150)		(0.301)		(0.286)		(0.179)	
g^{2p}_{yt-1}	0.119		0.116		0.281*		0.158		0.099	
	(0.092)		(0.112)		(0.146)		(0.337)		(0.137)	
RI_t		−0.040		0.007		−0.088***		0.150		−0.119
		(0.085)		(0.113)		(0.019)		(0.156)		(0.078)
RI_{t-1}		−0.027		−0.103		0.169		−0.223***		−0.037
		(0.085)		(0.093)		(0.118)		(0.059)		(0.123)
π_t	0.012	0.064	0.017	0.072	−0.005	0.012	0.097**	0.121*	0.013	0.054
	(0.019)	(0.039)	(0.019)	(0.045)	(0.035)	(0.019)	(0.040)	(0.065)	(0.019)	(0.041)
π_{t-1}	−0.009	−0.112**	−0.011	−0.124**	0.001	−0.052*	0.028	−0.057	0.010	−0.066**
	(0.019)	(0.050)	(0.021)	(0.062)	(0.020)	(0.029)	(0.027)	(0.046)	(0.014)	(0.034)
u_t	−0.004	0.040	−0.023	0.039	−0.061**	−0.030	0.131**	0.198*	−0.045	−0.010
	(0.045)	(0.044)	(0.057)	(0.056)	(0.027)	(0.019)	(0.061)	(0.107)	(0.037)	(0.020)
u_{t-1}	0.063**	0.030*	0.087***	0.031	−0.029***	−0.028***	0.239***	0.170***	0.051	0.024
	(0.027)	(0.016)	(0.033)	(0.024)	(0.008)	(0.009)	(0.062)	(0.037)	(0.046)	(0.035)
R^2	0.05	0.08	0.05	0.08	0.19	0.17	0.41	0.42	0.02	0.03
N	1376	1244	1052	952	324	292	479	423	897	821
					D. Cohesion					
$\Delta i_t = 0$	−0.140	−0.135	0.016	0.018	−0.698	−0.732	−0.172***	−0.155***	−0.239	−0.228
	(0.163)	(0.180)	(0.097)	(0.097)	(0.475)	(0.531)	(0.041)	(0.046)	(0.257)	(0.284)
g^{2p}_{yt}	0.422*		0.704***		−0.730*		0.392*		0.401	
	(0.221)		(0.207)		(0.424)		(0.227)		(0.331)	
g^{2p}_{yt-1}	−0.018		0.128		−0.400		−0.126		0.000	
	(0.145)		(0.138)		(0.347)		(0.249)		(0.208)	
RI_t		0.085		0.100		−0.074		0.123		0.076
		(0.188)		(0.201)		(0.345)		(0.091)		(0.277)
RI_{t-1}		0.084		0.123		−0.217		0.008		0.065
		(0.148)		(0.133)		(0.158)		(0.033)		(0.206)
π_t	0.063**	0.088**	0.072**	0.108**	0.072	0.091	0.019	−0.021	0.082**	0.120**
	(0.031)	(0.043)	(0.033)	(0.052)	(0.050)	(0.068)	(0.052)	(0.050)	(0.035)	(0.050)
π_{t-1}	−0.056*	−0.100*	−0.078**	−0.149**	0.084	0.094*	−0.049*	−0.045	−0.045	−0.088
	(0.033)	(0.056)	(0.037)	(0.062)	(0.072)	(0.056)	(0.025)	(0.042)	(0.039)	(0.069)
u_t	−0.043	−0.012	−0.062	−0.009	0.089	0.045	0.086***	0.096***	−0.098	−0.066
	(0.048)	(0.048)	(0.066)	(0.062)	(0.055)	(0.042)	(0.026)	(0.024)	(0.060)	(0.052)
u_{t-1}	0.093**	0.070***	0.129**	0.081**	−0.017	−0.004	0.116***	0.098**	0.110*	0.086*
	(0.041)	(0.026)	(0.052)	(0.040)	(0.052)	(0.053)	(0.039)	(0.041)	(0.065)	(0.047)
R^2	0.02	0.02	0.04	0.04	0.13	0.13	0.24	0.25	0.02	0.02
N	1365	1234	1052	952	313	282	479	423	886	811

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Table 17: **Fixed effect models for extreme inflation values (part 1)**

	All		Geography				Language			
			Western		Eastern		English speaking		Non-English speaking	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
					A. Readability					
Δi_t	-0.080	-0.063	0.017	-0.054	0.688	0.539	0.025	0.102	-0.133	-0.165
	(0.124)	(0.116)	(0.123)	(0.129)	(0.447)	(0.495)	(0.058)	(0.178)	(0.146)	(0.131)
π_t^{2p}	-0.094		0.132		-0.936^{**}		-0.181		0.093	
	(0.398)		(0.492)		(0.417)		(0.811)		(0.408)	
π_{t-1}^{2p}	-0.281		-0.162		-0.142		0.103		-0.286	
	(0.292)		(0.320)		(0.709)		(0.373)		(0.327)	
π_t		0.020		0.100		-0.045		-0.025		0.059
		(0.068)		(0.080)		(0.120)		(0.144)		(0.066)
π_{t-1}		-0.068		-0.092^{*}		0.129		-0.051		-0.072
		(0.049)		(0.047)		(0.217)		(0.108)		(0.055)
g_{y_t}	-0.030	-0.033	-0.088^{***}	-0.088^{***}	0.044	0.050	-0.081	-0.090	-0.014	-0.015
	(0.042)	(0.044)	(0.025)	(0.030)	(0.039)	(0.034)	(0.051)	(0.064)	(0.040)	(0.042)
$g_{y_{t-1}}$	-0.014	-0.015	-0.059^{**}	-0.059^{**}	0.020	0.016	-0.053	-0.057	0.003	0.003
	(0.038)	(0.040)	(0.024)	(0.028)	(0.051)	(0.034)	(0.040)	(0.048)	(0.038)	(0.040)
u_t	-0.008	0.002	0.012	0.021	0.156^{**}	0.144^{***}	0.043	0.034	-0.010	-0.006
	(0.093)	(0.091)	(0.101)	(0.099)	(0.072)	(0.044)	(0.121)	(0.167)	(0.104)	(0.101)
u_{t-1}	0.097	0.090	0.262^{**}	0.252^{*}	0.037	0.019	0.355^{***}	0.341^{***}	0.040	0.038
	(0.085)	(0.086)	(0.129)	(0.130)	(0.040)	(0.038)	(0.096)	(0.112)	(0.086)	(0.090)
R^2	0.01	0.02	0.11	0.11	0.06	0.06	0.1	0.1	0.0	0.0
N	1313	1313	1034	1034	279	279	475	475	838	838
					B. Abstractness					
Δi_t	-0.197^{*}	-0.347^{***}	-0.159^{*}	-0.277^{***}	-0.790	-1.368	-0.431^{***}	-0.577^{***}	-0.129	-0.307^{**}
	(0.109)	(0.129)	(0.096)	(0.104)	(0.713)	(1.002)	(0.096)	(0.118)	(0.115)	(0.135)
π_t^{2p}	0.169		-0.081		1.008^{**}		-0.152		0.393	
	(0.275)		(0.310)		(0.417)		(0.258)		(0.354)	
π_{t-1}^{2p}	-0.069		-0.095		-0.063		-0.271		0.159	
	(0.329)		(0.378)		(0.424)		(0.473)		(0.419)	
π_t		0.052		0.041		0.174^{*}		-0.027		0.070
		(0.042)		(0.048)		(0.103)		(0.054)		(0.048)
π_{t-1}		0.086		0.059		0.254		0.112^{*}		0.086
		(0.056)		(0.044)		(0.203)		(0.065)		(0.065)
g_{y_t}	-0.003	0.006	-0.012	-0.003	0.045	0.028	0.006	0.022	-0.003	0.008
	(0.019)	(0.021)	(0.016)	(0.019)	(0.076)	(0.056)	(0.028)	(0.031)	(0.018)	(0.021)
$g_{y_{t-1}}$	0.023	0.028	0.009	0.016	0.098	0.057^{*}	-0.034^{**}	-0.022	0.032	0.040
	(0.023)	(0.024)	(0.019)	(0.022)	(0.071)	(0.034)	(0.017)	(0.022)	(0.028)	(0.029)
u_t	0.153^{***}	0.133^{***}	0.141^{***}	0.126^{***}	0.038	-0.041	0.089	0.085	0.160^{***}	0.128^{***}
	(0.059)	(0.051)	(0.047)	(0.045)	(0.221)	(0.198)	(0.099)	(0.094)	(0.061)	(0.046)
u_{t-1}	0.021	0.035	0.031	0.052	-0.003	-0.077	0.010	0.045	0.026	0.039
	(0.053)	(0.051)	(0.075)	(0.072)	(0.151)	(0.157)	(0.093)	(0.098)	(0.063)	(0.056)
R^2	0.07	0.1	0.09	0.11	0.01	0.09	0.04	0.04	0.09	0.12
N	1322	1322	1034	1034	288	288	475	475	847	847

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Table 18: **Fixed effect models for extreme inflation values (part 2)**

	All		Geography				Language			
			Western		Eastern		English speaking		Non-English speaking	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
					C. Informativeness					
Δi_t	0.078	0.113	0.067	0.093	0.116	0.185	0.166***	0.137***	0.025	0.018
	(0.060)	(0.101)	(0.063)	(0.105)	(0.118)	(0.113)	(0.060)	(0.052)	(0.030)	(0.065)
π_t^{2p}	0.108		0.171**		−0.010		0.341**		0.134	
	(0.083)		(0.084)		(0.132)		(0.135)		(0.115)	
π_{t-1}^{2p}	0.168*		0.185*		0.136		0.402**		0.185*	
	(0.087)		(0.102)		(0.102)		(0.162)		(0.108)	
π_t		−0.013		−0.006		−0.027		0.078**		0.004
		(0.032)		(0.034)		(0.040)		(0.038)		(0.031)
π_{t-1}		−0.005		−0.002		−0.019		0.033**		0.006
		(0.015)		(0.015)		(0.028)		(0.015)		(0.015)
g_{y_t}	−0.029	−0.031	−0.028	−0.029	−0.031*	−0.030*	−0.071**	−0.065**	−0.010	−0.010
	(0.018)	(0.020)	(0.021)	(0.024)	(0.018)	(0.017)	(0.031)	(0.033)	(0.006)	(0.007)
$g_{y_{t-1}}$	−0.024	−0.026	−0.022	−0.024	−0.032*	−0.028*	−0.026	−0.025	−0.009	−0.009
	(0.015)	(0.016)	(0.018)	(0.020)	(0.019)	(0.016)	(0.016)	(0.017)	(0.005)	(0.006)
u_t	−0.020	−0.018	−0.051	−0.050	−0.037***	−0.028**	0.074	0.104	−0.038	−0.041
	(0.036)	(0.039)	(0.032)	(0.035)	(0.011)	(0.014)	(0.068)	(0.074)	(0.032)	(0.036)
u_{t-1}	0.082**	0.080**	0.121***	0.118***	−0.039***	−0.030***	0.258***	0.257***	0.045	0.046
	(0.042)	(0.040)	(0.045)	(0.040)	(0.005)	(0.009)	(0.062)	(0.061)	(0.044)	(0.046)
R^2	0.05	0.05	0.05	0.05	0.16	0.19	0.4	0.41	0.01	0.01
N	1322	1322	1034	1034	288	288	475	475	847	847
					D. Disunity					
Δi_t	0.083	−0.002	0.091	0.045	0.264	−0.254	−0.047	0.015	0.080	−0.066
	(0.083)	(0.093)	(0.082)	(0.090)	(0.435)	(0.496)	(0.074)	(0.101)	(0.097)	(0.108)
π_t^{2p}	−0.259		−0.127		−0.690*		0.030		−0.300	
	(0.177)		(0.184)		(0.357)		(0.134)		(0.225)	
π_{t-1}^{2p}	−0.268		−0.303		−0.048		0.245		−0.370*	
	(0.163)		(0.186)		(0.337)		(0.187)		(0.204)	
π_t		0.067*		0.062**		0.135		0.012		0.106**
		(0.037)		(0.029)		(0.091)		(0.045)		(0.045)
π_{t-1}		−0.045		−0.076**		0.158*		−0.034		−0.045
		(0.032)		(0.031)		(0.093)		(0.025)		(0.038)
g_{y_t}	−0.019	−0.017	−0.052***	−0.053***	0.070	0.066	−0.018	−0.024	−0.009	−0.004
	(0.024)	(0.026)	(0.014)	(0.015)	(0.075)	(0.060)	(0.021)	(0.027)	(0.025)	(0.026)
$g_{y_{t-1}}$	−0.009	−0.006	−0.043**	−0.043**	0.088	0.067	0.003	−0.001	−0.001	0.005
	(0.029)	(0.030)	(0.020)	(0.020)	(0.079)	(0.052)	(0.020)	(0.023)	(0.031)	(0.032)
u_t	−0.023	−0.022	−0.096	−0.087	0.081	0.026	0.114***	0.118**	−0.062	−0.073
	(0.070)	(0.066)	(0.066)	(0.068)	(0.056)	(0.026)	(0.033)	(0.050)	(0.080)	(0.074)
u_{t-1}	0.075*	0.074*	0.170***	0.161***	0.010	−0.043	0.091**	0.078*	0.083	0.086
	(0.045)	(0.044)	(0.049)	(0.051)	(0.041)	(0.056)	(0.043)	(0.045)	(0.059)	(0.063)
R^2	0.02	0.02	0.04	0.05	0.06	0.19	0.24	0.24	0.01	0.02
N	1313	1313	1034	1034	279	279	475	475	838	838

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Table 19: **Fixed effect models for extreme price level (part 1)**

	All		Geography				Language			
			Western		Eastern		English speaking		Non-English speaking	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
					A. Readability					
Δi_t	−0.108	0.004	0.014	0.008	0.597	0.302	−0.020	0.110	−0.137	−0.091
	(0.127)	(0.116)	(0.120)	(0.133)	(0.382)	(0.549)	(0.249)	(0.081)	(0.141)	(0.121)
CPI_t^{2p}	−0.549		−0.149		−0.791		−0.824		−0.334	
	(0.453)		(0.471)		(0.754)		(0.859)		(0.476)	
CPI_{t-1}^{2p}	−0.320		−0.153		−0.252		−0.131		−0.164	
	(0.246)		(0.277)		(0.812)		(0.481)		(0.339)	
CPI_t		−0.090		0.047		0.052		−0.140		−0.012
		(0.139)		(0.166)		(0.172)		(0.263)		(0.120)
CPI_{t-1}		0.085		−0.054		−0.029		0.137		0.004
		(0.137)		(0.164)		(0.164)		(0.262)		(0.118)
g_{y_t}	−0.030	−0.031	−0.088***	−0.089***	0.049	0.051**	−0.086*	−0.081*	−0.014	−0.016
	(0.042)	(0.044)	(0.025)	(0.027)	(0.038)	(0.025)	(0.046)	(0.044)	(0.041)	(0.042)
$g_{y_{t-1}}$	−0.014	−0.016	−0.059**	−0.060**	0.023	0.033	−0.056	−0.055*	0.003	0.001
	(0.038)	(0.040)	(0.024)	(0.026)	(0.052)	(0.051)	(0.038)	(0.028)	(0.039)	(0.040)
u_t	−0.013	−0.009	0.010	0.008	0.151**	0.139***	0.032	0.016	−0.012	−0.010
	(0.095)	(0.096)	(0.102)	(0.103)	(0.075)	(0.051)	(0.143)	(0.169)	(0.104)	(0.103)
u_{t-1}	0.101	0.097	0.263**	0.258*	0.037	0.052	0.360***	0.366***	0.042	0.038
	(0.085)	(0.089)	(0.129)	(0.133)	(0.038)	(0.042)	(0.106)	(0.110)	(0.084)	(0.090)
R^2	0.01	0.02	0.11	0.11	0.05	0.08	0.1	0.1	0.0	0.01
N	1313	1310	1034	1032	279	278	475	473	838	837
					B. Abstractness					
Δi_t	−0.197*	−0.328**	−0.169*	−0.255**	−0.766	−1.471	−0.551***	−0.308***	−0.113	−0.286*
	(0.112)	(0.131)	(0.100)	(0.106)	(0.767)	(1.016)	(0.103)	(0.088)	(0.118)	(0.148)
CPI_t^{2p}	0.069		0.094		−0.106		−1.051***		0.612*	
	(0.328)		(0.378)		(0.640)		(0.185)		(0.338)	
CPI_{t-1}^{2p}	−0.671		−0.335		−1.788		−0.565*		−0.779	
	(0.574)		(0.260)		(2.484)		(0.342)		(1.091)	
CPI_t		0.129		0.090		0.542**		−0.055		0.125
		(0.102)		(0.069)		(0.263)		(0.106)		(0.119)
CPI_{t-1}		−0.122		−0.086		−0.512**		0.034		−0.110
		(0.101)		(0.067)		(0.249)		(0.113)		(0.116)
g_{y_t}	−0.003	−0.001	−0.012	−0.009	0.040	0.007	0.001	−0.020	−0.004	0.003
	(0.018)	(0.018)	(0.016)	(0.017)	(0.073)	(0.053)	(0.025)	(0.028)	(0.017)	(0.018)
$g_{y_{t-1}}$	0.022	0.026	0.010	0.012	0.094	0.100*	−0.038*	−0.060***	0.030	0.038
	(0.023)	(0.024)	(0.019)	(0.020)	(0.068)	(0.059)	(0.020)	(0.021)	(0.027)	(0.029)
u_t	0.151**	0.154***	0.141***	0.147***	0.025	−0.028	0.064	0.036	0.161***	0.155***
	(0.059)	(0.058)	(0.049)	(0.048)	(0.228)	(0.211)	(0.100)	(0.094)	(0.061)	(0.056)
u_{t-1}	0.022	0.022	0.031	0.030	0.005	0.021	0.025	0.024	0.025	0.033
	(0.052)	(0.051)	(0.074)	(0.072)	(0.146)	(0.145)	(0.090)	(0.087)	(0.061)	(0.054)
R^2	0.07	0.08	0.09	0.09	0.02	0.06	0.05	0.07	0.09	0.12
N	1322	1319	1034	1032	288	287	475	473	847	846

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

Table 20: **Fixed effect models for extreme price level (part 2)**

	All		Geography				Language			
			Western		Eastern		English speaking		Non-English speaking	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
					C. Informativeness					
Δi_t	0.095	0.096	0.089	0.083	0.111	0.067	0.297**	0.113**	0.033	−0.004
	(0.063)	(0.101)	(0.067)	(0.106)	(0.128)	(0.056)	(0.126)	(0.057)	(0.029)	(0.057)
CPI_t^{2p}	0.214		0.245		0.004		0.500*		0.166	
	(0.134)		(0.154)		(0.147)		(0.289)		(0.166)	
CPI_{t-1}^{2p}	0.187		0.227		0.070		0.216		0.247	
	(0.182)		(0.177)		(0.525)		(0.236)		(0.235)	
CPI_t		−0.039		−0.025		−0.049		0.108		0.017
		(0.063)		(0.065)		(0.041)		(0.066)		(0.047)
CPI_{t-1}		0.044		0.029		0.058		−0.095		−0.012
		(0.060)		(0.062)		(0.047)		(0.065)		(0.045)
g_{y_t}	−0.029	−0.028	−0.028	−0.027	−0.032*	−0.026**	−0.072**	−0.060**	−0.010	−0.009
	(0.018)	(0.018)	(0.021)	(0.022)	(0.018)	(0.011)	(0.032)	(0.028)	(0.006)	(0.006)
$g_{y_{t-1}}$	−0.025*	−0.023	−0.023	−0.022	−0.032*	−0.028**	−0.028*	−0.015	−0.009*	−0.007
	(0.015)	(0.015)	(0.018)	(0.019)	(0.019)	(0.013)	(0.016)	(0.018)	(0.005)	(0.005)
u_t	−0.017	−0.017	−0.047	−0.047	−0.037***	−0.036***	0.089	0.122	−0.036	−0.039
	(0.036)	(0.036)	(0.032)	(0.029)	(0.014)	(0.010)	(0.073)	(0.075)	(0.031)	(0.031)
u_{t-1}	0.081**	0.084**	0.118***	0.121***	−0.038***	−0.032***	0.243***	0.235***	0.044	0.047
	(0.041)	(0.041)	(0.044)	(0.045)	(0.004)	(0.010)	(0.054)	(0.050)	(0.043)	(0.046)
R^2	0.05	0.06	0.05	0.06	0.16	0.23	0.4	0.43	0.01	0.03
N	1322	1319	1034	1032	288	287	475	473	847	846
					D. Cohesion					
Δi_t	0.058	0.003	0.071	0.049	0.220	−0.376	−0.016	0.026	0.068	−0.072
	(0.086)	(0.096)	(0.084)	(0.097)	(0.390)	(0.566)	(0.112)	(0.102)	(0.100)	(0.117)
CPI_t^{2p}	−0.255		−0.186		−0.359		−0.345		−0.160	
	(0.272)		(0.304)		(0.218)		(0.277)		(0.374)	
CPI_{t-1}^{2p}	0.141		0.093		0.411		0.110		0.207	
	(0.256)		(0.230)		(0.763)		(0.235)		(0.405)	
CPI_t		0.102		0.070		0.501*		0.019		0.179*
		(0.075)		(0.056)		(0.271)		(0.069)		(0.094)
CPI_{t-1}		−0.107		−0.078		−0.483*		−0.023		−0.184*
		(0.076)		(0.058)		(0.264)		(0.073)		(0.096)
g_{y_t}	−0.017	−0.019	−0.051***	−0.053***	0.073	0.039	−0.021	−0.027*	−0.008	−0.007
	(0.024)	(0.024)	(0.014)	(0.013)	(0.073)	(0.049)	(0.021)	(0.015)	(0.025)	(0.024)
$g_{y_{t-1}}$	−0.007	−0.008	−0.041**	−0.043**	0.090	0.092	0.001	−0.004	0.001	0.003
	(0.029)	(0.030)	(0.020)	(0.020)	(0.079)	(0.070)	(0.020)	(0.018)	(0.031)	(0.032)
u_t	−0.024	−0.026	−0.098	−0.100	0.082	0.024	0.114***	0.112***	−0.061	−0.073
	(0.070)	(0.070)	(0.067)	(0.068)	(0.054)	(0.036)	(0.039)	(0.041)	(0.081)	(0.079)
u_{t-1}	0.077*	0.074*	0.172***	0.168***	0.009	0.023	0.087*	0.086*	0.083	0.085
	(0.046)	(0.045)	(0.049)	(0.049)	(0.042)	(0.042)	(0.047)	(0.051)	(0.058)	(0.060)
R^2	0.02	0.02	0.04	0.06	0.06	0.16	0.24	0.24	0.01	0.02
N	1313	1310	1034	1032	279	278	475	473	838	837

Note: The superscripts *, ** and *** respectively denote significance at the 10%, 5% and 1% levels. Coefficient estimates are reported with standard deviation within parentheses.

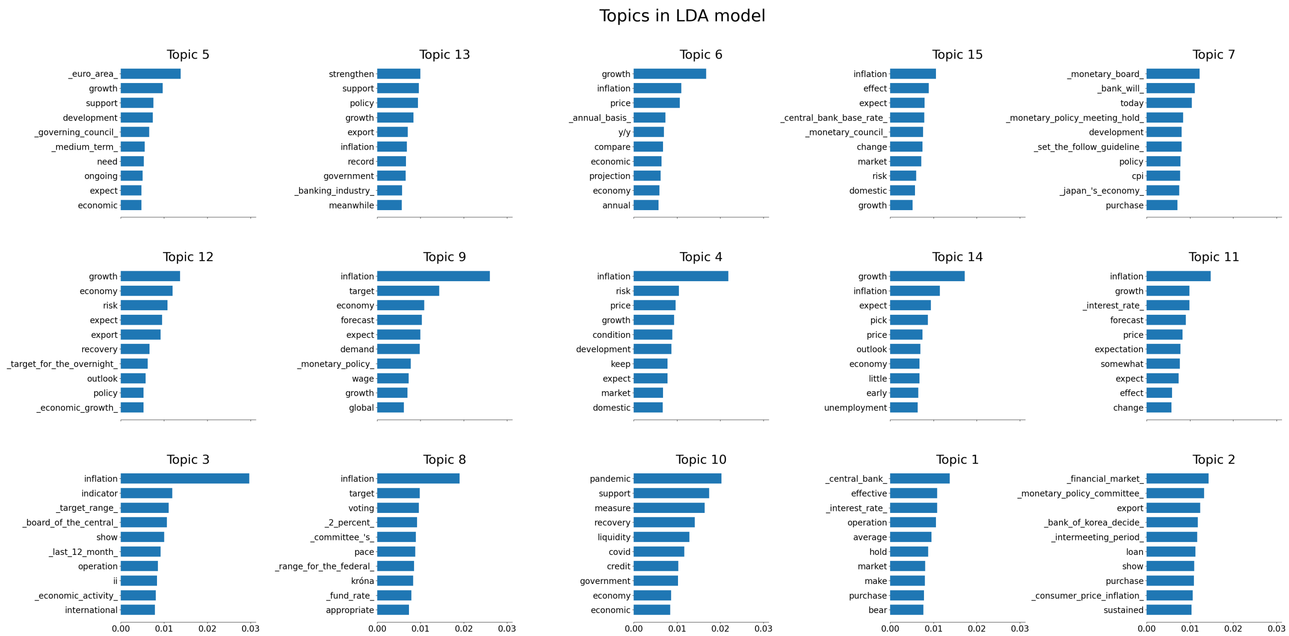

Figure 4: Topics and their keywords

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