“Central bank communication complexity during wartime and inflation expectation alignment”

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CENTRAL BANK COMMUNICATION COMPLEXITY DURING WARTIME AND INFLATION EXPECTATION ALIGNMENT

Abstract

This study examines the post-decision announcements of the National Bank of Ukraine (NBU) during the pre-war and wartime periods from 2018 to 2025, focusing on changes in communication complexity and their subsequent impact on the anchoring of household inflation expectations. Based on various readability measures, we document a significant increase in the linguistic complexity of NBU communications during the war. For example, the Flesch-Kincaid Grade Level index indicates that the number of years of schooling required to understand NBU announcements increased by approximately one additional year. Despite these changes, we find no statistically significant effect on the gap between household inflation expectations and the NBU's inflation forecast. At the same time, the expectations gap narrowed substantially during the war period, likely due to the convergence of households and NBU predictions under shock conditions. Moreover, the gap continued to narrow as inflation pressures eased. Our econometric analysis relies on dynamic specifications with robust inference to account for persistence, serial correlation, and structural breaks associated with the full-scale invasion. The findings contribute to the literature on central bank communication by providing rare wartime evidence from a small open economy, highlighting the limits of textual complexity as a policy tool for shaping household expectations.

Keywords monetary policy, central bank communication, inflation expectations, wartime macroeconomics, textual analysis

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INTRODUCTION

Central bank communication plays a crucial role in the modern world of numerous information flows. This study analyzes the readability and transparency of the National Bank of Ukraine (NBU) post-decision communications during the full-scale war. The analysis helps to quantify how complex, clear, and consistent these texts are and whether these textual characteristics are associated with households' inflation-expectation alignment with the NBU. We use the data for the period 2018–2025, which represents regular Monetary Policy Committee meetings of the NBU and monthly household surveys of inflation expectations. While central bank announcements have a significant impact on financial market players, there is much less evidence of their effect on the general public, especially during such crisis episodes as a full-scale war.

When forming their predictions and views, individuals may exhibit different behavioral biases ranging from emotional reactions to cognitive limitations. Overconfidence may be especially severe when individuals form contrarian forecasts under adverse and highly uncertain conditions. Conservatism, status quo bias, and anchoring and adjust-

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ment may contribute to slow expectations updating and pronounced persistence. Finally, framing the information, including the way NBU reports present assessments, risks, and forward-looking guidance, may significantly impact individual predictions and analysis. In contrast, professional analysts from the NBU may be much more efficient in terms of managing individual biases, applying more structured forecasting methods, and having access to much larger volumes of information. Their forecast can be treated as a benchmark anchor against which households' expectation alignment can be assessed. In this paper, expectation anchoring is operationalized as the absolute gap between household inflation expectations and the corresponding NBU inflation forecast, with smaller gaps indicating tighter alignment.

With the formal adoption of an inflation-targeting regime in 2015, the NBU made significant reforms aimed at increasing its transparency. Using the data from the central bank website, Shapoval (2021) calculated a set of metrics assessing the general design and quality of the communication policy as of 2021. Such indices as Dincer-Eichengreen (DE) aggregated measure over political, economic, procedural, policy, and operational transparency received very high scores, indicating substantial progress in this direction (Dincer & Eichengreen, 2014). Despite high institutional transparency, de facto results heavily depend on the content and accessibility of specific outputs, including reports, releases, policy announcements, and posts on social media. This leaves open the scientific problem of whether readability, linguistic complexity, and the tone of NBU post-decision communication are associated with household inflation-expectation alignment, especially during the wartime period.

1. LITERATURE REVIEW

Multiple papers analyzed the impact of communication strategies on real economic variables. Early contributions focus primarily on financial-market outcomes rather than households' expectations. Anufriieva and Shapoval (2019) confirmed a statistically significant correlation between the exchange rate and reported macroeconomic indicators in the press releases, briefings, quarterly publications, and other media channels. Successful expectation management can significantly decrease uncertainty. Yukhymenko and Sorochan (2023) showed that an increase in the number of messages on NBU's website by 1% can lead to a decrease in exchange rate volatility of up to 1.2% over the next 10 days, especially if the news is related to monetary policy. Finally, Gao et al. (2023) assessed the impact of fixed and floating messages on the black-market premium. When the Russian Federation started the full-scale invasion, NBU fixed the official exchange rate to anchor the expectations and reduce the panic. However, this policy created disequilibrium in the market that resulted in a divergence between the quotes proposed by authorized banking and non-banking institutions and black-market dealers. Applying an advanced AI model (ChatGPT), the authors have classified NBU announcements into those focused on fixed or floating regimes and calculated the respective sentiment index. Messages containing fixed-related information increased the premium, and this effect was asymmetrically impacting more sell-side than buy-side quotes.

Overall, this strand of literature demonstrates that central bank communication materially affects market behavior, particularly during crisis periods, but remains largely focused on prices and volatility rather than the expectation alignment of households. A separate and more recent literature examines how central bank communication evolved during wartime conditions.

When focusing on the evolution of communication strategy during the war, Szyszko et al. (2025) conducted a comprehensive analysis of NBU official post-decision announcements and respective posts on X (formerly Twitter) before and after Russia's full-scale invasion. Having applied non-parametric testing techniques, they found a statistically significant difference in sentiment and subjectivity of reports. Notably, key indices such as HD or BN, and VADER detected an increase in sentiment and polarity (more adjectives and adverbs expressing evaluation, fewer neutral tokens). The authors explained it by a low comparison base (very negative tone during the COVID-19 pandemic) and a very short period of GDP decline at the beginning of the invasion. Overall, the subjectivity of reports has also increased. Based on the constructed war dictionary, war language frequency increased from 1% to 3%, reflecting pervasive wartime impact on all aspects of economic life, including monetary policy communication. Such saturation is expected under the current conditions. Similar results were obtained for the less formal communication on the X platform. One of the key conclusions is that the NBU did not adopt propagandistic language by making their reports more negative to obtain additional financial resources from international organizations, governments, and central banks. While the paper provides one of the first systematic assessments of the impact of war on NBU language, it did not examine in depth such important aspects as communication complexity or readability. It only notes that official reports became longer by more than one-third when measured in the number of words. This gap is particularly important given that longer texts do not necessarily imply higher complexity or lower accessibility for non-professional audiences.

Another strand of the literature directly examines how central bank communication affects household inflation expectations. Coibion et al. (2022), using a survey of more than 20,000 U.S. respondents from the Nielsen Homescan panel, tested multiple hypotheses. In particular, they found that information about past inflation rate, reading the Federal Open Market Committee (FOMC) statement, value of Federal Reserve inflation target, and news articles – all have a statistically and economically significant impact on households' expectations. These effects are relatively persistent in the short run and gradually fade over time, highlighting the importance of consistent, continuous communication. Interestingly, providing respondents with the original FOMC announcement or even a much simpler news article from "USA Today" has a much smaller effect on expectations than, for example, information about the FOMC inflation forecast. Among three key inflation indicators: past inflation level, future forecast, and target level, all three have a similar significant effect; however, providing forecasted value has a more persistent impact on households. Therefore, we use NBU forecasts as an anchor in this study.

Evidence on the role of textual complexity and tone for household expectations remains mixed, especially in wartime contexts. Erokhin and Klachkova (2024) tested the impact of readability and tone on the inflation expectations for the Russian economy. Even though the Russian Federation has been in active war as an aggressor since February 2022, no explicit tests were conducted to assess wartime changes in communication complexity. Authors found that neither readability nor tone has a statistically significant effect on household expectations, while tone has a small but significant effect on market expectations.

Carotta et al. (2023) analyzed micro-level firm inflation expectations in Uruguay and found that the tone of reports has a statistically significant effect on them. Moreover, lower readability amplifies the effect of negative tone. These results were robust to different model specifications.

In summary, the existing literature provides strong evidence that central bank communication affects markets and expectations but leaves several important questions unanswered. Numerous studies analyze how the complexity of central bank communications influences inflation expectations and the degree of inflation anchoring. However, to the best of our knowledge, this paper is among the first to examine how a large-scale war alters the readability of central bank announcements and how these changes subsequently affect inflation anchoring.

The purpose of the study is to test the presence of a causal effect between the readability of NBU reports and household expectations. Namely, two hypotheses will be examined:

H1: *Full-scale war statistically significantly increased the complexity of NBU communication*

H2: *Changes in readability have a statistically significant effect on households' alignment with the NBU's inflation outlook.*

2. METHOD

First, key variables are defined: inflation expectations, readability, and sentiment indices. Next, we collect, curate, and standardize the data to make them suitable for quantitative and regression analysis.

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There are several ways to test inflation anchoring effectiveness.

Mora Barrenechea et al. (2018) regressed expected inflation against Central Bank of Bolivia projections and targets, past inflation, and control variables. The authors found that short-term expectations heavily depend on the regulator's forecasts, and medium-term expectations are statistically significantly related to announced inflation targets rather than past inflation or short-term expectations.

Households form their expectations 12 months ahead, which is a fixed-horizon forecast. At the same time, the NBU provides in their inflation reports forecasts for the end of the current year and several next years (fixed-event projections). Dovern and Fritsche (2008) have shown that the weighted moving-average transformation of fixed-event forecasts into fixed-horizon forecasts works the best in terms of minimizing the difference between the true prediction dispersion among forecasters and the one calculated based on the proposed method. In addition, as Dovern et al. (2012) argue, potential measurement errors that may be present in this case affect only the dependent variable and should not lead to inconsistent results unless they are correlated with regressors (in contrast to the situation when the errors affect expectations used as explanatory variables). The authors derived fixed-horizon forecasts based on quarterly data frequency, while Mora Barrenechea et al. (2018) used an identical approach with monthly data. To increase the precision and improve alignment with survey timing, we apply a daily weighted moving-average transformation, defined as follows:

$$\pi_t^{e,\,NBU} = \frac{S_{t+1} - D_t}{D_{t+1} - D_t}\pi_{t|t}^{e,\,NBU} + \frac{D_{t+1} - S_{t+1}}{D_{t+1} - D_t}\pi_{t|t+1}^{e,\,NBU}, \tag{1}$$

where $\pi_t^{e,\,NBU}$ is NBU 12-month-ahead expectations, $\pi_{t|t}^{e,\,NBU}$ and $\pi_{t|t+1}^{e,\,NBU}$ are NBU forecasts for the end of the current t and the next $(t + 1)$ years published on the date D_t, D_{t+1} is the one-year-ahead date from publication, and S_{t+1} is the start of the next year.

To characterize communication complexity, we employ a multidimensional set of textual indicators. First, the number of characters, words, and sentences, and their length describe the volume and structure of the text. Second, type-token ratio (TTR – number of unique words over total number of words) and Shannon entropy characterize lexical complexity and consistency. Third, linguistic complexity is represented by polysyllable share (number of words with three or more syllables) and average number of syllables per word. Fourth, general readability and transparency are described with such aggregated indices as Automated Readability Index (ARI), Gunning Fog, SMOG, and Flesch-Kincaid Grade Level (FK). For regression analysis, we use one of the most widely applied indicators – the FK score – defined as follows:

$$RS_t = 0.39\frac{W_t}{S_t} + 11.8\frac{Syl_t}{W_t} - 15.6, \tag{2}$$

where RS_t denotes the FK readability score, W_t, S_t, and Syl_t are the total number of words, sentences, and syllables, respectively.

In addition to readability, sentiment may play an important role in the formation of inflation expectations. Kostyra (2025) showed, based on the analysis of Monetary Policy Committee meeting minutes with the VADER analysis tool, that sentiment scores have a statistically significant effect on Polish 10-Year Treasury yields prediction, which is ultimately related to the expected inflation. There are different approaches to assess the sentiment of textual corpora, namely dictionary-based methods that classify words into positive, negative, and neutral, or more complex and tailored approaches like the VADER algorithm – Valence Aware Dictionary and sEntiment Reasoner presented by Hutto and Gilbert (2014). The latter additionally accounts for punctuation, such as exclamation marks, capitalization, and other aspects to capture emotions. VADER is a rule-based approach trained on short social media texts where abbreviations and other specifics are present. When directly applied to much longer monetary policy announcements, the results are often very polar, being either very close to the extreme –1 or +1 scores. Therefore, only the dictionary-based approach is considered using three sentiment lexicons: VADER, LM (Loughran and McDonald, 2024), and BN (Bennani & Neuenkirch, 2017). LM is constructed based on the financial reports corpora presented by publicly traded US companies and is not directly focused on monetary policy announcements. It includes 2,345 negative and 347 positive unigrams. BN dictionary is exclusively based on monetary policy jargon and was constructed based on 1,618 speeches of the members of the European Central Bank Governing Council (members and presidents of the 11 largest national central banks). There are 26 hawkish and 32 dovish patterns (see Appendix A for more details).

Rutkowska and Szyszko (2024) compared different dictionaries for the analysis of the sentiment of monetary policy reports and speeches. While they did not identify a single dominant dictionary, several key principles were proposed. First, testing the model using multiple dictionaries is essential. Second, it is suggested that the dictionary must be suitable for the research objective, particularly with respect to the target audience. Finally, sentiment dictionaries usually do not contradict each other and produce similar results. Given our target audience is households and their expectations, and we analyze the readability of NBU announcements and speeches, we use the BN dictionary as a baseline and VADER for a robustness check. The standard dictionary-based formula for sentiment calculation is:

$$SI_t = \frac{Pos_t - Neg_t}{W_t} \tag{3}$$

where SI_t, is the sentiment index, Pos_t, Neg_t, and W_t are the number of positive, negative, and total words in the text, and in the case of the BN dictionary, we will have the difference in hawkish and dovish tokens (they cannot necessarily be treated as positive and negative words, respectively).

The Monetary Policy Committee and the NBU Board hold eight meetings per year on monetary policy issues. Following each meeting, NBU governors or their deputies deliver a speech at a press briefing, and a corresponding announcement is disseminated describing the changes in the key policy rate and rationale behind it. We collected 60 speeches and 61 announcements written in English from the beginning of 2018 to October 2025. The July 2018 speech was not available in English translation. Key policy rate decisions were postponed in March and April 2022, so we exclude these observations from the decision-only sample. Even though the April 2022 announcement stated that the key policy rate decision was still postponed, the regulator provided substantially more macroeconomic details about the current situation than in the March 2022 report. Therefore, the former was included in an extended sample for robustness testing. In summary, there are 32 speeches and 33 announcements from pre-full-scale invasion, and 28 of each during the war.

Reports were downloaded from the NBU website with the Monetary Policy Committee meetings schedule. Some hyperlinks were broken and had to be corrected and then automatically extracted using Python scripts. Text appearing after navigation elements (tags, share buttons) was removed. We also removed closing courtesy sentences like "Thank you!", footnotes, additional final hyperlinks to the other pages, etc. At the beginning of the page, date and time metadata were also omitted. We kept headers and lists since they are a natural part of the text, and added full-stops to headers that missed them and semicolons to the list points without punctuation (the last item of the list had a full-stop already present). During document analysis, the Python NLTK library was used to remove stop words, for syllable count, and tokenization of words and sentences.

The typical structure of an announcement consists of a header with a subsequent paragraph that sends a strong signal regarding the decision of the Board of NBU. Next, the rationale behind it is provided, followed by macroeconomic outlooks, potential risks, and future steps. In the end, four technical pieces of information are usually provided: the document approving the decision, expected issue dates of the Monetary Policy Committee meeting minutes, the next macroeconomic forecast, and the next Monetary Policy Committee meeting. Speeches may be less standardized, although they remain highly correlated with announcements.

At each Monetary Policy Committee meeting, NBU announces its decision regarding the key policy rate: whether it will be kept unchanged, increased, or decreased. The rate was relatively high during

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2018–2019, exceeding 17%, and then began to decline sharply in line with the inflation rate, reaching as low as 6% by June 2020. To combat rising prices in 2021, the key policy rate was gradually increased again. On June 2, 2022, NBU raised the rate to a record 25% to tackle the problem of macroeconomic inflationary instability caused by Russia's full-scale aggression. It was kept at this high level for a year, and once inflation decelerated, the interest rate was reduced to below 15%, and it fluctuated around that level, being 15.5% throughout 2025.

To support its decision-making process, NBU produces regular macroeconomic forecasts issued as inflation reports each January, April, July, and October. They contain end-of-period quarterly predictions for the current and future years for nominal, real, fiscal, balance of payments, and monetary indicators. General consumer inflation forecasts are used in this research as an anchor for inflation. In addition, one week before the Monetary Policy Committee meeting, the NBU collects inflation and exchange rate forecasts from leading financial analysts (Yukhymenko, 2022). Households are surveyed each month during the second and third weeks by the external sociological company Info Sapiens. One thousand rotating representative consumers are asked to assess the future inflation and exchange rate levels, and then this information is transformed into 12-month-ahead forecasts. They are asked about future inflation prospects, selecting one of 5% increments, e.g., prices will fall, will lie in the 0-5%, 5-10% interval, and so on (Coibion & Gorodnichenko, 2015).

The State Statistics Service of Ukraine calculates different types of inflation indicators. We use the standard monthly consumer price index (CPI), measuring price increases over the last year.

In order to define properly cause and effect sequence, we need to align correctly all events that are in focus. Household surveys are assumed to start on the 11th of each month and finish in two weeks on the 24th – these are typical dates mentioned on the reports of Info Sapiens research agency over the last few years. If the Committee meeting was conducted before the 11th of a specific month, then its results will affect this month's household survey; if it occurs after the 24th, then on the next month's survey. If the meeting was held between the 11th and 24th, then the weighted average of household expectations is calculated, meaning some households were impacted by the current announcement and some by the past. Monthly inflation levels are published by the State Statistics Service typically before the 10th date of each subsequent month. The date of the NBU quarterly inflation reports is taken as the day of their approval by the NBU Board. We also calculated the number of days since the Committee meeting event or NBU forecast and the end date of the household survey.

Next, we checked the data for unit root presence and stationarity. Based on the Augmented Dickey-Fuller test, the only variables with unit roots are the readability score and interest rate. They contain unit roots, but their first differences are stationary. Taking that into account, the baseline regression model is specified as follows:

$$\begin{aligned} G_t &= \beta_0 + \beta_1 G_{t-1} + \beta_2 \Delta RS_{t-1} \\ &+ \beta_3 SI_{t-1} + \beta_4 W_{t-1} + \beta_5 \pi_{t-1} \\ &+ \beta_6 \Delta r_{t-1} + \beta_7 DS_{t-1} + \beta_8 DN_{t-1} + e_t, \end{aligned} \tag{4}$$

where $G_t = \left|\pi_t^e - \pi_t^{e,\,NBU}\right|$ is the absolute difference between household and NBU 12-month forward-looking expectations, RS_t and SI_t are readability score and sentiment index, respectively, W_t is a war dummy, π_t is the inflation rate over the last year, Δr_t is the change of NBU key policy rate, DS_t and DN_t are the number of days between household or NBU forecasts and the Monetary Policy Committee meeting, respectively. We also consider the introduction of a combined readability and sentiment term instead of standalone readability in one of the specifications.

Central bank transparency is basically a strategic choice made by the regulator, which may influence public expectations and react to them, being an endogenous variable. Luangaram and Wongwachara (2017) found that lower readability expressed as the FK measure is weakly correlated with a higher DE transparency index, which was observed, for example, for the Central Bank of Hungary and the Czech National Bank. Other papers, such as Celler (2024), reported opposite results for selected countries: Moldova, with the lowest DE transparency, has the lowest readability complexity among six Central and Eastern European small open economies. To test for endogeneity, lagged readability and sentiment indices were defined as instruments in a two-stage instrumental variables regression. Based on the Durbin-Wu-Hausman test p-value (0.89 and 0.44), the null hypothesis of exogeneity of readability and sentiment cannot be rejected for the restricted (ordinary least squares – OLS) model but is rejected for the Two-Stage Least Squares Instrumental Variables (IV) model. The latter also has large standard errors for key coefficients, indicating the problem of weak instruments. This is also confirmed by low values of Cragg-Donald F-statistics compared to Stock and Yogo (2005) critical values. Consequently, we focus on the OLS specification as it is both preferred and consistent.

Given the time-series nature of the data and overlapping one-year forecasting horizons, regression is estimated using the Newey-West heteroskedasticity and autocorrelation-consistent (HAC) standard errors. Even though calculated coefficients are correct in terms of inference, residual autoregression remains and is further eliminated by either including additional lagged variables or modeling residuals as AR processes of respective order. As a robustness check, we present multiple model specifications in the next section.

3. RESULTS AND DISCUSSION

We first describe the impact of the war on NBU speeches and announcements in terms of readability and sentiment, and then examine their influence on household inflation anchoring.

The total number of characters and words increased during the war period by more than 20% for speeches and almost 50% for announcements. As can be seen from Figure 1, the longest texts were reported during 2022–2023 and in 2025.

While the number of sentences remains relatively constant for speeches, announcements became longer in this aspect, with 46 vs 62 sentences on average when comparing pre-war and war periods (see Figure 2).

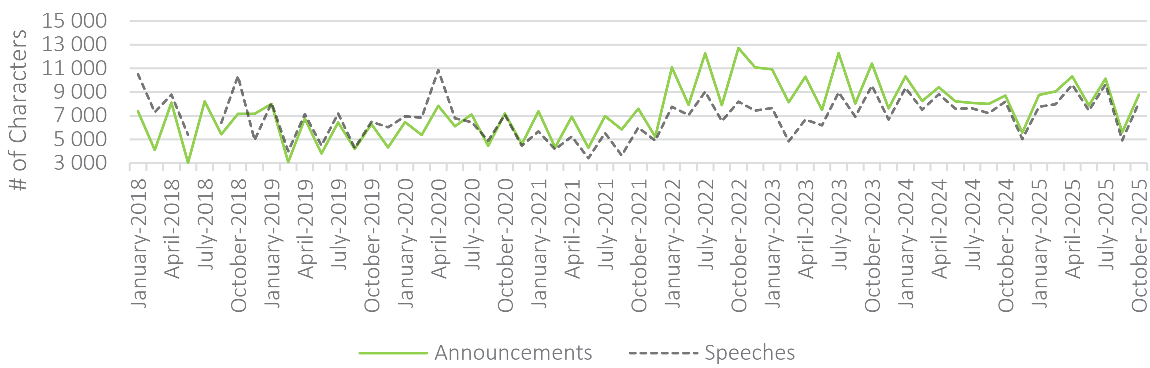

Figure 1. Number of characters per report

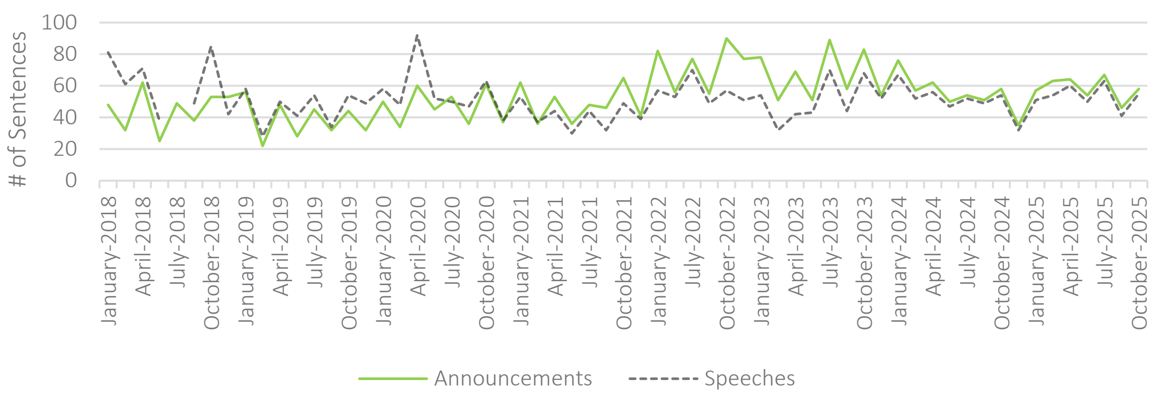

Figure 2. Number of sentences per report

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Table 1. Readability indices

Metric	Period	Governors' speeches				Announcement			
		ARI	Fog	SMOG	FK	ARI	Fog	SMOG	FK
Mean	Pre-war	18.35	16.20	14.66	12.56	19.26	17.00	15.24	13.21
Mean	War	20.34	18.09	16.03	14.31	20.50	18.19	16.11	14.31
Std. dev.	Pre-war	0.88	0.77	0.55	0.68	0.93	0.67	0.47	0.69
Std. dev.	War	0.90	0.91	0.66	0.74	0.71	0.75	0.54	0.62

Average sentence length increased, especially for governors' speeches, from 19.4 to 22.4, and the standard deviation of this measure declined, indicating lower variability during the war. TTR and entropy indicators were stable. At the same time, linguistic complexity increased significantly.

As can be seen from Table 1, all aggregated indices increased when comparing the pre-full-scale invasion period with the wartime period. Based on the FK indicator, the years of education necessary to understand the report have risen to more than 14 years, basically from upper secondary/early undergraduate level to undergraduate level complexity. In other words, more than one additional year of schooling is required to understand reports. Volatility of the indicators moved in different directions: it more often increased for governors' speeches, while it was stable or declined for announcements.

Pre-war and wartime mean values of all readability score indices are statistically different for governors' speeches and NBU announcements (based on the parametric Welch F-test that assumes unequal variances). In addition, the nonparametric Mann-Whitney U test rejects the null hypothesis that pre-war and war samples originate from the same distributions.

Readability FK score was lower before the full-scale invasion, increased significantly after February 24, 2022, the start of the full-scale war, and reached its maximum during 2022–2023 (Figure 3).

When comparing the calculated readability scores with the results for the other central banks, we can see that pre-war numbers were closer to the group of countries with less complex reports, but moved after the start of the war to the middle group. For example, they are similar to those of Narodowy Bank Polski, but still less complex than those of the Federal Reserve or the European Central Bank reports (Szczerba et al., 2024).

To see the micro-level linguistic differences of the changes, we compared one of the simplest NBU Monetary Policy Committee pre-war announcements from 15/04/2021 with the most complex announcements from 25/04/2024. The latter typically contains longer sentences, multi-clause subordinate constructions, and a higher level of lexical abstraction, examples of which are given in Table 2.

In terms of sentiment analysis, VADER and BN-based indices increased, while the LM-based index did not change statistically significantly (Table 3). VADER changes are statistically significant, while BN increase is significant for speeches and marginally significant for announcements. These conclusions are partially consistent with those of Szyszko et al. (2025), who found that BN and LM indices have risen while VADER-based

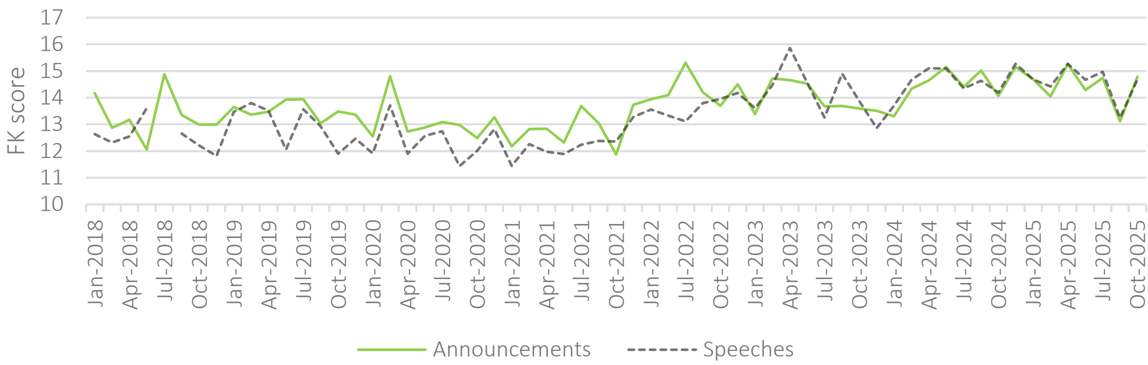

Figure 3. FK score

Table 2. Readability comparison: examples

Dimension	Pre-war example	Post-war example	Comment
Opening policy rationale	*"This step is aimed at gradually slowing down inflation in H2 2021 and returning it to the 5% target already in H1 2022."*	*"Considering a decline in actual and expected price pressures and lower risks to inflows of international financial support, the NBU continues the easing cycle of its interest rate policy."*	Post-war sentence has an introductory participial clause and contains abstract nouns like easing cycle.
Inflation dynamics	*"In March, consumer inflation accelerated to 8.5% yoy, while core inflation reached 5.9%."*	*"Actual consumer inflation slowed to 3.2% yoy in March and was below the NBU's forecast published in the January 2024 Inflation Report. … Core inflation also slowed (to 4.2% yoy) but was rather close to the NBU's forecast"*	The pre-war message is more numeric and factual, while the post-war message contains additional phrases.
Risk description	*"The key risk to the macroeconomic forecast is the imposition of stricter quarantine measures in Ukraine and globally, and the slow pace of the vaccination campaign domestically."*	*"The course of the full-scale war continues to be the key risk to inflation dynamics and economic development."*	Although shorter, the wartime risk anchors subsequent long enumerations, increasing average sentence length overall.
Operational details	*"The decision to increase the key policy rate, to 7.5%, was approved by an NBU Board Decision on the key policy rate No. 142, dated 15 April 2021."*	*"The key policy rate cut was approved by the NBU Board Resolution No. 133 On Key Policy Rate, and rates on refinancing loans by NBU Board Resolution No. 134 On Setting Rates on Standing Facilities of the National Bank of Ukraine."*	Wartime announcements expand technical detail, increasing syllables per sentence.

Table 3. Sentiment indices

Metric	Period	Governors' speeches			Announcement		
		VADER	LM	BN	VADER	LM	BN
Mean	Pre-war	0.016	–0.014	0.024	0.013	–0.017	0.023
Mean	War	0.035	–0.018	0.031	0.035	–0.019	0.028
Std. dev.	Pre-war	0.012	0.013	0.013	0.013	0.014	0.016
Std. dev.	War	0.019	0.012	0.011	0.019	0.012	0.010

results were inconclusive. The discrepancy can be explained by the shorter sample that consists of 36 post-decision announcements for the end of 2019 – beginning of 2024, and potentially a different version of the LM dictionary.

BN sentiment index reached its lowest values during the early COVID-19 pandemic, the spring of 2020, and in July 2025. Its highest values were observed at the beginning of 2018 and 2025. Hawkish 2025 peak may be caused by accelerating inflation at that time.

We estimated the baseline regression model as specified in equation (4) with the coefficients provided in column 2 of Table 4 – model M1. However, based on a serial correlation test, residual correlation remains, especially at lags 6 and 8. After adding the corresponding lagged dependent variables, IV regression and OLS regression with HAC standard errors were estimated (models M2 and M3, respectively). As stated in the Methodology section, IV regression was rejected based on the Durbin-Wu-Hausman test and the weak instru-

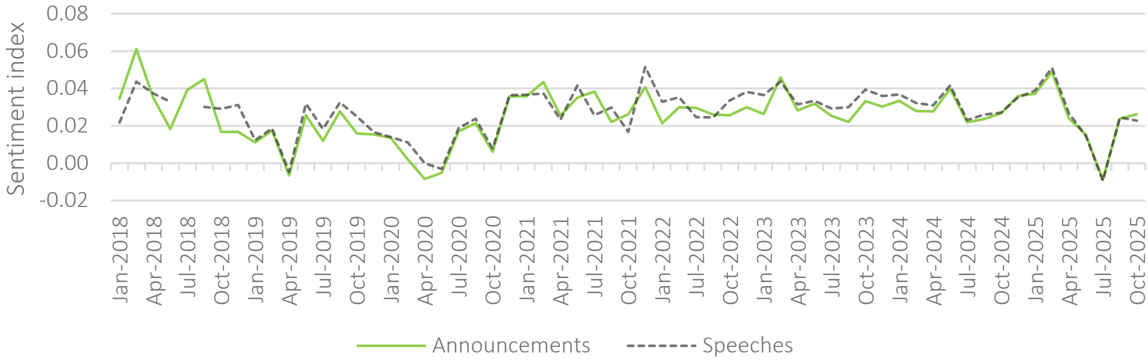

Figure 4. Sentiment index

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Table 4. Estimation results: baseline models

Variable	OLS + HAC	IV regression	OLS + HAC	OLS + AR	OLS + HAC interaction
Model	**M1**	**M2**	**M3**	**M4**	**M5**
C	0.033	0.064	0.881	–0.585	0.026
Gap_{t-1}	0.355**	0.290***	0.291***		0.279***
Gap_{t-6}		–0.346	–0.342		–0.337*
Gap_{t-8}		0.184	0.214*		0.170
ΔRS	–0.136	–0.179	–0.191	–0.090	–2.506
SI	2.542	–0.402	–31.665	28.743**	–0.445
War	–1.618**	–1.975***	–1.717***	–2.941***	–2.010***
Inflation	0.238***	0.329***	0.329***	0.416***	0.334***
ΔR	0.080	–0.223	–0.033	–0.191	–0.245**
$Days_{Survey}$	0.006	0.008	0.010*	0.008	0.009**
$Days_{NBU}$	0.003	0.001	–0.003	0.002	0.002
AR(1)				0.206*	
AR(4)				–0.168	
AR(6)				–0.420***	
AR(8)				–0.402***	

Note: *** denotes significant coefficients at 99% confidence level, ** – at 95%, and * – at 90% confidence level. "OLS + HAC interaction" model instead of ΔRS has an interaction term SI*ΔRS.

ments test. The latter regression specification (OLS + HAC – M3) has no serial correlation (marginally absent), is homoskedastic, and has normally distributed residuals – see Table B1 in Appendix B for more details. If autoregressive terms are introduced instead of lagged dependent variables (specification M4 in Table 4), serial correlation is completely removed. However, given that we report HAC-robust inference results, we consider OLS model M3 as a key one. Introduction of the readability-sentiment interaction term (model M5 in Table 4) does not change the results significantly.

Despite different model specifications, there is a strong tendency for them to align in terms of coefficient significance and even their values. As we can see from Table 4, readability and announcement sentiment are not statistically significant, meaning households do not pay much attention to the report structure and complexity. On the contrary, during the wartime period, households and NBU expectations became more aligned – the gap dropped by 1.7%, which is a significant value from an economic perspective. It can be caused by the simultaneous convergence of expectations to the focal point when both parties spiked their inflation projections due to the shock, rather than simple better inflation anchoring. We can also see that higher inflation is associated with a higher expectations gap. Namely, if inflation increases by 1%, the expectations gap increases by 0.3%. Inflation complicates forecasting due to a more volatile environment and increased disagreement between households and NBU predictions. Based on the lagged dependent variables, around one-third of the last expectations gap is carried over into the current period, which can be explained by sticky information, partial updating, and behavioral anchoring. The later the household survey is conducted after the Monetary Policy Committee meeting date, the larger the gap tends to be, although this result is not robust across specifications.

We conducted additional robustness checks using an extended sample that included April's 2022 observation. In contrast to the March announcements, this datapoint is much more informative because it includes substantially more macroeconomic analysis and explanation. The results are provided in Table 5, and they are in line with the baseline regressions described previously. In addition, using the decision-only sample, we estimated a model with sentiment represented by the VADER dictionary instead of the BN dictionary (model M4 in Table 5). We can see that war and inflation effects are statistically significant, consistent with the baseline estimates. The interest rate also becomes significant in this specification, implying that 1% increase leads to a 0.2% reduction in the gap.

Different regression model specifications provide generally consistent results: war and inflation have

Table 5. Estimation results: robustness checks

Variable	OLS + HAC	IV regression	OLS + HAC	OLS + HAC (VADER)
Model	**M1**	**M2**	**M3**	**M4**
C	–0.024	0.073	0.359	0.064
Gap_{t-1}	0.366**	0.399**	0.321***	0.286***
Gap_{t-6}			–0.149*	–0.346**
Gap_{t-8}				0.190
ΔRS	–0.134	–0.655	–0.125	–0.181
SI	3.370	3.619	–2.598	–2.407
War	–1.680**	–1.541**	–1.776***	–1.913***
Inflation	0.237***	0.216***	0.273***	0.330***
ΔR	0.045	0.200	0.007	–0.221**
$Days_{Survey}$	0.004	0.000	0.009	0.008
$Days_{NBU}$	0.005	0.006	0.004	0.001

Note: *** denotes significant coefficients at 99% confidence level, ** – at 95%, and * – at 90% confidence level.

a significant effect on the household-NBU forecasting gap, while readability and sentiment of NBU announcements are not significant.

The research does not reject the original hypothesis *H1,* confirming that NBU reports became more complex during the wartime period. While it does not have any impact on the household inflation expectations gap (so hypothesis *H2* was rejected), NBU could still consider reducing language complexity to make the content of announcements and reports more accessible to the general public. While such steps are already being taken to some extent, e.g., using such popular social networks as Facebook or X, a two-layer communication strategy can be implemented by leaving current reports for professional market players and providing additional short and simple texts focused on households.

CONCLUSION

The purpose of this study is to assess whether the readability of NBU communication affects the alignment of household inflation expectations with official forecasts during wartime. The paper contributes to the literature by providing new evidence on central bank communication and expectation formation in a small open economy during wartime conditions.

The results indicate that NBU speeches and post-decision announcements became more complex during the war, but they did not have a statistically significant impact on the expectations gap. The expectations gap narrowed when inflation decreased, which may reflect lower uncertainty and forecasting difficulty in a volatile environment. This tendency persisted over time, given that one-third of the current gap is explained by its lagged value.

These findings imply that simplifying the linguistic structure of central bank communications alone is unlikely to improve expectations anchoring among households. Instead, expectation formation appears to be primarily driven by macroeconomic conditions and persistent behavioral factors such as information stickiness, behavioral anchoring, and adjustment biases. However, using simpler messages may still make them more accessible to the general public. The insights may also be relevant for other emerging economies experiencing wartime conditions or significant macroeconomic instability as geopolitical tensions and the frequency of armed conflicts increase globally.

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AUTHOR CONTRIBUTIONS

Conceptualization: Roman Semko.
Data curation: Roman Semko.
Formal analysis: Roman Semko.
Funding acquisition: Roman Semko.
Investigation: Roman Semko.
Methodology: Roman Semko.
Project administration: Roman Semko.
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Software: Roman Semko.
Supervision: Roman Semko.
Validation: Roman Semko.
Visualization: Roman Semko.
Writing – original draft: Roman Semko.
Writing – reviewing & editing: Roman Semko.

GENERATIVE AI STATEMENT

A generative AI tool (ChatGPT) was used to improve grammar, clarity, and readability of the manuscript and abstract. The author reviewed and edited all outputs and takes full responsibility for the content.

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APPENDIX A. BN hawkish and dovish unigrams

Table A1. BN hawkish and dovish unigrams

Hawkish				Dovish			
#	Pattern	#	Pattern	#	Pattern	#	Pattern
1	accelerat*	14	positive	1	collaps*	17	downward*
2	better	15	rais*	2	contraction	18	fall*
3	boom*	16	ris*	3	dampen*	19	fragil*
4	emerg*	17	stabili*	4	decelerat*	20	low*
5	expansion	18	stable	5	declin*	21	negative
6	fast*	19	strengthen*	6	decreas*	22	poor
7	favo(u)rabl*	20	strong*	7	delay*	23	recession*
8	firm*	21	subdued	8	depression	24	slow*
9	great*	22	unsustainable	9	destabili*	25	sluggish
10	high*	23	upside	10	deteriorat*	26	small*
11	improv*	24	upswing	11	difficul*	27	struggling
12	increas*	25	upturn	12	diminish*	28	sustainable
13	larger	26	upward*	13	disappear*	29	unfavo(u)rabl*
				14	downside	30	unstable
				15	downswing	31	weak*
				16	downturn	32	worse

APPENDIX B. Post-estimation diagnostics

Based on the post-estimation diagnostics, the regression results meet the criteria of no serial correlation, homoskedasticity, and normally distributed residuals. Specifically, as can be seen from Table B1, the baseline regression models meet key diagnostics requirements.

Table B1. Diagnostics results

Test Name	Null hypothesis	Statistics	Decision-only sample (M3 Table 4)	Extended sample (M3 Table 5)
Breusch-Godfrey serial correlation LM test	No serial correlation	F-statistic	0.080	0.407
Heteroskedasticity test: Breusch-Pagan-Godfrey	Homoskedasticity	F-statistic	0.129	0.096
Normality test	Residuals are normally distributed	Jarque-Bera-statistics	0.979	0.822

As can be seen from the correlograms on Figures B1 and B2, and from the p-values of the Ljung-Box Q-statistics, autocorrelation and partial correlation are not statistically significant.

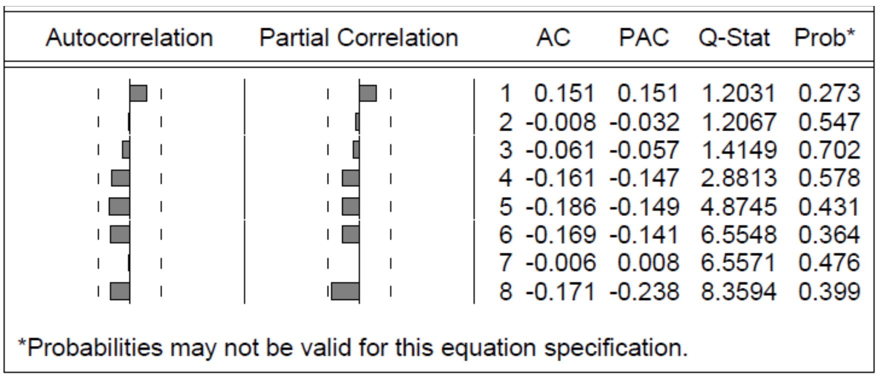

Figure B1. Correlogram for regression M3 from Table 4

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.169	0.169	1.6498	0.199
		2	0.033	0.004	1.7133	0.425
		3	-0.056	-0.064	1.9011	0.593
		4	-0.137	-0.121	3.0518	0.549
		5	-0.097	-0.054	3.6376	0.603
		6	-0.225	-0.208	6.8694	0.333
		7	-0.105	-0.056	7.5908	0.370
		8	0.020	0.028	7.6172	0.472

*Probabilities may not be valid for this equation specification.

Figure B2. Correlogram for regression M3 from Table 5

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