dynamics of contemporary societies. The significance of statisticians, policymakers, and researchers intensifies as they play a crucial role in navigating this shifting terrain. The digital age necessitates not only technical expertise but also a commitment to ethical principles, ensuring responsible data use with measures to safeguard privacy and promote transparency.

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DERIVING NUMBERS FROM A CENTRAL BANK'S TEXTUAL RELEASES. THE CASE STUDY OF THE NATIONAL BANK OF UKRAINE TWITTER/X POSTS*

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For this study, we collected 552 Twitter/X posts published by the National Bank of Ukraine on its official profile in English. We collected all tweets published since June 6, 2019. The sample ends in August 2023. 488 posts were published before the invasion and 64 – after the Russian invasion.

The goal of the study is:

• to assess the sentiment of the NBU tweets in the comparative context (before the invasion and during the war – we assume less positiveness after the invasion);

• to assess the subjectivity of the NBU tweets in the comparative context (before the invasion and during the war – we assume less subjectivity after the invasion);

• assess the applicability of ChatGPT as a sentiment/subjectivity analysis tool compared with standard dictionary methods.

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To transform the textual content of the corpus into numbers, we applied three methods: standard dictionary approach, Valence Aware Dictionary and sEntiment Reasoner (VADER), ChatGPT.

We decided to apply two lexicons for dictionnary method: Harvard IV Dictionary (HD) (Stone et al., 1962) and (Loughran and McDonald, 2011) (LM). HD dictionary is a general lexicon, unigram-based, designed to analyse sociological and psychological content. However, we consider the application of this lexicon justified as after the war eruption, we expect more emotional language to be presented by policy-makers. The second lexicon used in this study is LM (Loughran and McDonald, 2011) based on the financial reports published by American listed companies. The LM lexicon consists of 4,150 unigrams. The dictionary avoids standard, emotionally affected words from everyday language.

The second method applied in the study is an approach designed to analyse Twitter/X data – Valence Aware Dictionary and sEntiment Reasoner (Elbagir and Yang, 2019). VADER is a lexicon and rule-based sentiment detection tool attuned explicitly to sentiments expressed in social media, especially microblogs like Facebook and Twitter/X. What distinguishes VADER from the dictionary method is its combination with five generalisable heuristics that embody grammatical and syntactical conventions humans use when expressing or emphasising sentiment intensity. Additionally, we derived the number of positive and negative expressions classified by the embodied lexicon.

The third method applied to asses sentiment applied GPTChat. As AI algorithms and lexicons that feed it are not revealed, we cannot discuss them in detail. We decided to use AI tools to derive sentiments due to their growing popularity and applicability for research. Contrary to dictionary methods and VADER, AI tools can learn with the evolution of language. The prompts were: "Asses the sentiment of text on a scale from -1 to 1" and "Count positive and negative words". The first prompt returned a general sentiment index, and the second one returned numbers we transformed into polarity and subjectivity indices.

The sentiment – tone of the post – was derived directly from VADER algorithm (Vader compound index) and returned by ChatGPT (first prompt). We also calculated the following polarity index based on the dictionary methods and the number of positive and negative words derived from VADER and returned by ChatGPT (second prompt). The natural language processing techniques interpret sentiments, including polarity as the positive, negative, or neutral tone expressed in a text. It determines whether a text expresses a positive or negative sentiment towards a particular entity or topic. The polarity index is presented by the Equation 1:

$$Polarity_{i,t} = \frac{PositiveWords_i - NegativeWords_i}{PositiveWords_i + NegativeWords_i} \qquad (1)$$

where $Polarity_i$ is the sentiment of CB i's post; $PositiveWords_i$ is the number of positive words, and $NegativeWords_i$ is the number of negative words.

Subjectivity refers to how subjective or objective a piece of text is. It determines whether a statement is a fact or an opinion. The more an index diverges from zero, the more opinion-based the text is. The subjectivity coefficient is presented below:

$$Subjectivity_i = \frac{PositiveWords_i + NegativeWords_i}{AllWords_i} \quad (2)$$

where $Subjectivity_i$ is the subjectivity of the post i; and $AllWords_i$ is the number of all words in tweet.

After deriving the sentiments, we compared the sentiments of the NBU posts in the pre-invasion and invasion periods. We searched for the causal inference using Bayesian structural time-series models (Brodersen et al., 2015) – the approach to estimating the causal effect of a designed intervention on a time series. In this case, the Russian aggression was such an intervention. The model works this way: given a response time series (here – sentiments and subjectivity after the invasion) and a set of control time series (sentiments and subjectivity after the invasion), the model predicts the counterfactual behaviour of the time series that would have occurred if the intervention had not happened.

The results of the interventional analysis are summarised as follows:

- No statistically significant change in the polarity indices was reported – the sentiment of posts proxied this way did not change after the invasion.
- The compound sentiment derived from ChatGPT did not change after the invasion.
- The compound sentiment based on VADER algorithm decreased after the invasion – the tone of posts worsened; the result was statistically significant.
- The NBU tweets become less objective according to subjectivity indices based on VADER lexicon and LM, the results are statically significant.
- VADER and the lexicon that feeds the algorithm are the most fragile in capturing the differences in the pre-and during-war period.
- We do not recommend ChatGPT as the tool to detect sentiment as the responses were unstable.

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