WORDS MATTER: DOES NBU COMMUNICATION AFFECT EXCHANGE RATE?

by

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A thesis submitted in partial fulfillment of
the requirements for the degree of

MA in Economic Analysis.

Kyiv School of Economics

2022

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Kyiv School of Economics

Abstract

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In this thesis, I study the impact of NBU's communication on the UAH/USD exchange rates. Data consists of the NBU's posts from its official website and Twitter page. I extract their sentiment (using statistical sentiment analysis) and topic (using transformer-based machine learning model called BERTopic), and run a regression analysis using an EGARCH model.

The main finding is that most of the topics do not have any effect on the exchange rate. The sentiment appeared to be significant in some model specifications, but its estimate implies that positive tweets only increase exchange rate volatility.

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ACKNOWLEDGMENTS

I would like to express my deepest gratitude to the Armed Forces of Ukraine, National Police, State Border Guard Service of Ukraine, volunteers, doctors, IT Army, and everyone serving our country and defending Ukraine from invaders. I thank all our foreign partners who support and help us in these difficult times.

I would also like to thank my thesis advisor Professor Sergii Kiiashko, who guided and supported me during this research. Without your help and advice, this thesis would not be possible.

Finally, I am grateful to all the research workshop professors who shared their expertise and many helpful suggestions. Your feedback made this thesis much better and more organized.

LIST OF ABBREVIATIONS

AI. Artificial Intelligence.

CB. Central Bank

CPI. Consumer Price Index.

DBSCAN. Density-Based Spatial Clustering of Applications with Noise.

ECB. European Central Bank.

EGARCH. Exponential Generalized Auto Regressive Conditional Heteroskedasticity.

ER. Exchange Rate.

HDBSCAN. Hierarchical Density-Based Spatial Clustering of Applications with Noise.

LDA. Latent Dirichlet Allocation.

ML. Machine Learning.

NBU. National Bank of Ukraine

NLP. Natural Language Processing.

OLS. Ordinary Least Squares.

OW. Official Website.

TF-IDF. Term Frequency – Inverse Document Frequency.

UMAP. Uniform Manifold Approximation and Projection.

Chapter 1

INTRODUCTION

The National Bank of Ukraine (NBU) is one of the key policymakers in Ukraine, which conducts inflation-targeting monetary policy and regulates the banking sector. The NBU sets the key policy rate, smooths the exchange rate fluctuations, manages international reserves, and introduces macroprudential policy measures to achieve its goals. However, another important tool to affect the Ukrainian economy is the NBU's communication.

Zholud et al. (2019) have named monetary communication one of the three elements that drive the capacity of the expectations channel. The expectations channel, in turn, is one of the five channels of transmission mechanism, which means it defines how the central bank's monetary policy decisions affect different aspects of the economy. And although communication is not the most crucial element of NBU's strategy, it does play a significant role in the formation of economic agents' expectations.

Bernanke et al. (2004) provided evidence that central bank communications can help to shape public expectations of future policy actions. Similarly, Woodford (2005) argues that open and transparent communication reduces uncertainty and increases the accuracy of central bank policies. Finally, Blinder et al. (2008) state that communication is a powerful tool that has the ability to influence financial markets and improve the predictability of central bank decisions.

All this evidence supports the hypothesis of the importance of the central bank's communication. As a result, many central bankers have recently become interested in the effect it might have on their countries' economies. Many of the most prominent papers devoted to this topic are listed in the next chapter. However, there are very few studies dedicated to Ukraine, and even the existing ones concentrate mainly on the importance of communication rather than on its effects. This thesis aims to fill the gap by analyzing the NBU's written communications so that the Ukrainian central bank can better understand the consequences of its messages.

To study the effect of NBU's communication on the Ukrainian economy, this thesis proposes to explore the relationship between the texts written by NBU's representatives and the fluctuations in the exchange rate. The foreign exchange market is a highly dynamic system, and exchange rates experience certain fluctuations on a daily basis. These fluctuations reflect the changes in people's expectations, and, including other control variables, it is possible to track the effect of NBU's communication on the expectations.

The main focus of this study is put on written communication due to two reasons. First of all, other formats of communication (audio, video) include many additional characteristics that may significantly affect expectations. Among them are the speaker's intonations, pauses, facial expressions, etc. Unfortunately, combining all the relevant variables in one research is impossible. Since there are no such studies yet, it will be more accurate to concentrate on one aspect of communication only. The second reason is that working with the texts opens the possibility for exploring new data sources. In particular, this thesis utilizes Twitter to get NBU's messages.

Twitter is a popular social network used by many organizations and institutions for official communication. NBU also uses Twitter, where it posts news and announcements. Messages from Twitter (also called tweets) differ from traditional news and reports posted on the official website (OW) in a variety of ways: they appear more often (sometimes even multiple times a day), they are shorter, and they are often written in a less formal language. Unlike the official NBU's reports, which are usually neutral in tone, tweets can become much more emotional and carry additional valuable features. For example, emojis, which are often present in tweets, have proved themselves to be extremely helpful for sentiment analysis.

Overall, this thesis utilizes two main characteristics of written communication: tone and topic. Tone (or sentiment) is a numerical feature that represents how positive/negative a message is. Schmeling and Wagner (2019) have shown how a more positive tone is associated with increased asset prices, while a negative tone causes an opposite effect. The same happens with the exchange rate.

The second characteristic is the topic. It is a categorical variable that describes the subject of the message. Most tweets can be divided into categories: inflation, fiscal policy, reforms, etc. Such division allows exploring the relative effect of each topic on exchange rate fluctuations.

To extract these characteristics, natural language processing (NLP) techniques are used. NLP is a field of artificial intelligence, and it provides powerful mechanisms for analyzing texts. Most modern economics studies related to textual analysis apply statistical tools like the TF-IDF approach or LDA. For example, Vo (2019) has successfully applied a lexical approach to measure sentiment and LDA for topic modeling. Although statistical techniques have proved themselves useful, they have a significant drawback – they put aside the meaning of texts and rely solely on the number of occurrences of certain words or phrases. This results in a "blind" analysis when the relationships between different parts of the text stay unnoticed. Machine learning has gone a long way since the introduction of statistical methods, and now it provides a number of comprehensive models taught on billions of texts. They allow us to analyze textual data much more deeply, extract hidden patterns and utilize the power of natural language. This thesis makes use of one such model for topic modeling. It might turn out to be more accurate and faster.

Overall, this thesis differs from previous literature in three ways. First, it fills the gap for the Ukrainian central bank since the existing papers concentrate on other countries. Second, it introduces a new data source – Twitter, which provides more suitable data for sentiment analysis. Apart from just analyzing Twitter data, I also compare it with the news from NBU's official website. Finally, this thesis utilizes the latest state-of-the-art model for natural language processing. The results of this study can be used to correct and improve NBU's messages so that they will not form undesirable expectations. The central bank can adjust its communication in a way it needs to diminish uncertainty and smooth the exchange rate.

The rest of this thesis is organized as follows. Chapter 2 provides the literature review. Chapter 3 explains the methodology used in this study. Chapter 4 covers data extraction, data preprocessing, and data description. Chapter 5 shows estimation results. The last chapter is devoted to conclusions and possible implications.

Chapter 2

LITERATURE REVIEW

The question of the impact of central banks' communication on various macroeconomic indicators has been studied before. However, in most cases, the authors limit themselves by providing guides for effective communication or determining the problems and possible improvements. Among such studies, Sholopak (2021) has tried to systematize the important patterns of forward guidance techniques as the central bank's communication tool in monetary policy. Similarly, De la Rubia (2018) has highlighted the most significant tools and instruments central banks use or should use in their communication.

Many studies only slightly touch on the subject of CB communication and do not apply textual analysis. For example, Dunets (2020) has studied how monetary policy communications affect inflation expectations. However, the author concentrates on the accuracy of bank forecasts and how they differ from economic agents' expectations. No textual characteristics are used in the paper. Lustenberger and Rossi (2020) also do not apply textual analysis. They assess the transparency of CB communication but do that by relying on a set of quite subjective criteria. They also focus on the accuracy of CB forecasts rather than determining the characteristics of CB messages and their effect on the economy. Radovan and Horvath (2010) applied GARCH analysis to communication-related variables (e.g., the number of days when CB representative commented on the price stability, interest rates, etc.) to determine the effect of Czech National Bank communication on exchange rate volatility. However, they focus on whether the central bank talked to the markets rather than on interpreting the content of its communication.

Other papers, on the contrary, may utilize textual analysis but with a different purpose. For instance, Sukhomlyn (2018) has explored how the tone and readability of independent auditor reports affect banks' performance.

The study by Hansen et al. (2019) has a much more related topic. Researchers use inflation reports of the Bank of England to study the long-run effect on interest rates. They show that the news on economic uncertainty can have a significant impact by measuring a set of high-dimensional signals. Many other researchers have studied similar problems. Kohn and Sack (2004), for example, have examined the effect of Federal Reserve communication on the unconditional variance of asset prices, while Ehrmann and Fratzscher (2007) analyzed the effects of interviews and speeches by central bank committee members on interest rates. None of these papers, however, concentrates entirely on exchange rate. Moreover, there are no such papers for Ukraine. This thesis, on the contrary, will concentrate on the tone of NBU communication and examine its impact on the exchange rate.

Some papers use manually assigned characteristics to determine the effect of CB communication. Conrad and Lamla (2010) construct a communication index to track the impact of ECB press conferences on the exchange rate, while Rosa (2011) manually measures Fed's tone and shows communication affects the exchange rate along with Fed's actions.

The idea of more recent papers (including this one) was to automate the extraction of language-related characteristics. Vo (2019) uses machine learning to extract the sentiment and topic of the textual information from the European Central Bank press conferences. The author uses the above-mentioned statistical techniques and finds that more positive sentiment is associated with the appreciation of the euro and decreasing exchange rate volatility. Moreover, the researcher states that the exchange rate responds more to topics of economic growth and central bank liquidity provision.

Hansen and McMahon (2016) also use tools from computational linguistics (field in machine learning) to explore how written communication affects markets and real economic variables. However, the authors did not find a strong effect of any kind of communication on real economic variables. This is one of the few research projects reaching such a conclusion.

Overall, most researchers agree that CB communication affects the economy and plays a significant role in expectations formation. The most relevant studies propose various features to measure this effect (namely, tone and topic). Some papers apply modern statistical tools to extract these features, while others get along with less informative variables that do not take semantics into account.

Despite a large number of existing papers concerning CB communications, there are certain gaps. The primary one is the lack of research on Ukraine. NBU has been quite active in recent years, and there has been quite a lot of textual communication to analyze. A common trait of all papers is also their data sources. Official CB reports and news have always been used for the analysis, despite them being formal and often neutral. The ignorance of modern media platforms (like Twitter) may have resulted in biased outcomes. Finally, there exist lots of powerful language models capable of producing accurate and reliable results relying on all aspects of data: from syntax to semantics. The usage of such models can bring entirely new insights and show previously unseen patterns. This thesis will try to fix all of these issues by utilizing the most relevant data and the most powerful NLP techniques.

Chapter 3

METHODOLOGY

The objective of this work is to test whether NBU's written communication has an impact on the Ukrainian economy. To investigate this relationship, several steps have to be made. First of all, textual features have to be extracted from NBU's messages. This thesis will utilize two textual variables: tone (sentiment) and topic. Then, the regression analysis has to be run on these features alongside several control variables.

3.1. Sentiment Analysis

The sentiment is an attitude or judgment that reflects one's feelings. People form sentiments about everything: books, movies, other people, etc. When talking about texts, sentiment (also known as tone) shows the emotional meaning of communication.

In natural language processing, sentiment is usually divided into three categories: positive, negative, and neutral. However, it can also be represented by a continuous value, most often between -1 and 1, where 1 stands for positive sentiment and -1 for negative. The positive sentiment reflects positive emotions: happiness, joy, etc. Negative sentiment indicates the opposite. A neutral tone is usually present in unemotional, dry, or formal texts. In the context of CB communication, positive sentiment may represent news that is considered good for the economy: GDP increase, inflation decrease, etc. Negative sentiment, in turn, is used for pessimistic messages. Finally, a neutral tone (which is usually prevalent in official posts) simply carries a piece of information without any emotional meaning.

Extracting sentiment is a relatively simple task of natural language processing which is called sentiment analysis. It can be done with both statistical and linguistical methods. And although the linguistical approach has proved itself to be more insightful and powerful, there have been no suitable models developed for Ukrainian languages so far. Training such a model is an expensive and time-consuming process, and it lies beyond the scope of this thesis. Therefore, a statistical approach is used here to extract sentiment.

Statistical sentiment analysis is a machine learning task that relies on words and their occurrences in texts. The more positive words a text has, the more positive its sentiment. The same goes for negative sentiment. There have already been created many lists with positive and negative words, including the lists for the Ukrainian language, that can be used to determine the sentiment of the text. The one I will be using was created by Serhii Kupriienko. It consists of almost 6000 words, and it is regularly updated.

With such a list, it is now possible to calculate the sentiment of a tweet using the formula proposed by Jurafsky and Martin (2008):

$$Sentiment = \frac{1}{n}\sum_{i=1}^{k} m_i * sentiment(word_i), \tag{3.1}$$

where

- $sentiment(word_i)$ – the sentiment of the word *i*. This value is provided with the list of positive/negative words, and it equals 1 for positive words and -1 for negative words.
- m_i – the number of occurrences of the word *i* in the text.
- k – the number of words in the positive/negative list.

- n – the number of words in the text.

Basically, the process of calculating sentiment includes iterating over the whole positive/negative list, finding the words from this list in the text, summing up the product of their sentiment and number of occurrences, and dividing the result by the number of words in the text.

This formula produces a value between -1 and 1, which represents the sentiment of the text. The closer the value to 1, the more positive the sentiment. The closer the value to -1, the more negative the sentiment is. 0 implies neutral sentiment. This value can also be converted to a categorical variable. For example, all sentiments that are below -0.5 can be considered negative, while values above 0.5 – positive. Such an approach, although simple, is not often used in practice since continuous variables are usually more convenient for econometric models. Therefore, this thesis will utilize sentiment in the form of a continuous variable.

Before going further, let us briefly discuss the limitations of the proposed approach. Apart from the fact that it is impossible to account for all the existing phrases that carry emotional meaning, words may actually have different levels of positivity/negativity. For example, the word "great" is definitely more positive than the word "good", while the word "hate" is much more negative than the word "dislike". The list I am using in this thesis includes only two possible sentiment values: -1 and 1. This, unfortunately, does not allow us to divide the words into different levels. Fixing this issue would require a lot of manual work and cross-checking, which is beyond the capabilities of this research.

Another list-related problem is that some positive words may still be used in negative messages and vice versa. For example, the sentence "The inflation has increased by 2%" is obviously negative, even though it contains the word "increased", which is labeled as positive in the list. This issue, however, is mitigated by the fact that NBU communication is mostly neutral (as can be seen in later sections), which compensates for such errors.

Nevertheless, this statistical approach is far from perfect. Ideally, we would use newer methods, but, as was said before, there were no well-performing linguistic models for the Ukrainian language developed yet. When such models appear, it will be very interesting to compare the results with this thesis.

3.2. Topic Analysis

The topic is another important characteristic of the text, which describes the subject discussed. Topics are important because people may react differently to various subjects. For example, inflation-related messages may cause a higher response than news describing ongoing research projects. Apart from that, sentiment may have a different impact depending on the topic of the message. A negative inflation-related post, for example, would definitely be more critical than a neutral message on an unclear topic.

Classifying tweets into topics is another common task in natural language processing. Both supervised, and unsupervised machine learning can be applied here. A supervised approach would produce more accurate results but would also need a lot of manual labeling. Unsupervised methods, on the other hand, perform worse but do not need any manual work. Since the tweets are usually not divided into categories (unless someone does it manually), this thesis will utilize an unsupervised approach (which is called topic modeling) to determine topics for tweets.

One of the most popular algorithms for topic modeling is LDA (Latent Dirichlet Allocation) – a statistical approach that relies solely on words and phrases and their use in texts. But unlike the previous case with sentiment analysis, there are several Ukrainian pretrained linguistic models that can potentially produce more accurate results. This thesis will make use of one such model – BERTopic, developed by Maarten Grootendorst (2022).

BERTopic is a topic modeling method that relies on using a transformer-based language model called BERT, which was created by Devlin et al. (2019). BERT is an extremely sophisticated model capable of producing state-of-the-art results on many different tasks. It was trained on huge quantities of textual data, including Wikipedia, and it has incredible generalization capabilities.

BERTopic uses BERT for building vector representations of texts (also called word embeddings). Being transformer-based implies having an understanding of the surrounding context, which makes BERT perfect for this task. These embeddings now represent the meaning of the full text, considering its context.

As the next step, constructed vectors are reduced in dimensionality by UMAP (for optimization purposes) and clustered into dense groups using HDBSCAN. HDBSCAN (Campello et al. 2013) is a modification of a popular density-based clustering algorithm, DBSCAN (developed by Ester et al. 1996), which transforms it into a hierarchical clustering method.

Each cluster received from the HDBSCAN represents one topic and provides up to 10 most important words for topic identification. Using these words, it is possible to assign a name to each topic (e.g., inflation, monetary policy, etc.). Thus, a new categorical feature is created and can be used for the regression analysis.

One possible limitation of this approach is an inability to control the created clusters. We can set in advance the desired number of clusters, but there is no guarantee that each of them will make sense and will be perfectly separable from the others. Therefore, extensive parameter fine-tuning and post-result checks are required to ensure that all the received clusters are valuable for the analysis.

3.3. Regression analysis

After receiving the text characteristics described above, we can finally use regression analysis to determine the impact they cause on the exchange rate (if any). There is currently no unique way to measure the effect of central bank communication on exchange rates. Related literature uses a wide variety of econometric methods: from simple OLS regressions to more comprehensive models such as GJR or Conditional Mean.

But probably the most popular approach is using different versions of GARCH models. They are very common across central banks (see Fišer and Horváth 2010 for an example), and they work particularly well with high-frequency time-series data (which is used in this thesis). According to McMillan and Speight (2012), no other model has the same performance as GARCH for daily data. Because of these two reasons, this thesis will make use of the GARCH approach.

GARCH (stands for Generalized Auto Regressive Conditional Heteroskedasticity) is a statistical model used to analyze time series data with varying volatility. This method is commonly used when working with financial data: stock prices, market indices, exchange rates, etc. Because the variance of exchange rates is not constant over time (especially in Ukraine), GARCH should be perfect for analyzing it.

More specifically, this thesis will use an Exponential GARCH model (EGARCH) of volatility proposed by Nelson (1991). This version of GARCH is also often encountered in related literature (see Lafarguette and Veyrune 2021 for an example), and it is a relatively small model that still allows for nonlinear relationships. EGARCH has three components:

- Drift:

$$r_t = Intercept + \rho r_{t-1} + \theta X_t + \varepsilon_t, \tag{3.2}$$

  where X is a vector of exogenous regressors.

- Volatility:

$$log\sigma_t^2 = \omega + \beta g(r_{t-1}), \tag{3.3}$$

  where $g(r_t) = \alpha r_t + \gamma(|r_t| - E|r_t|)$

- Distribution of errors:

$$\varepsilon_t = \sigma_t \epsilon_t, \tag{3.4}$$

  where the error term follows Tskew distribution:

$$\epsilon_t \sim TSK(\vartheta, \lambda) \tag{3.5}$$

In the above equations, $Intercept, \rho, \theta, \beta, \alpha, \gamma, \vartheta, \lambda$ are estimated by the model.

To choose the appropriate number and order of lags, I use AIC and BIC criteria (Akaike and Bayesian Information Criteria) as it is a conventional approach used in practice.

The variable of interest in this thesis is the exchange rate. But since GARCH models work with volatilities, I will use log-returns of the exchange rate as the dependent variable. Log-returns (for this and some of the following variables) are calculated using this formula:

$$r_t = \log\left(\frac{e_t}{e_{t-1}}\right), \tag{3.6}$$

where e_t is the level value of the exchange rate in period *t*.

Independent variables include tone (as a continuous value between -1 and 1) and topic (as a categorical variable) of NBU written communication. Apart from these, two control variables are used: the first-differenced Volatility Index (VIX) and log-returns of oil prices.

According to Lafarguette and Veyrune (2021), the latter two variables affect exchange rates in developing countries. Therefore, they can be used to reflect the changes in the economy and control for exogenous factors.

As a result, the drift equation above would have the following form:

$$\log\left(\frac{e_t}{e_{t-1}}\right) = Intercept + \rho \log\left(\frac{e_{t-1}}{e_{t-2}}\right) + \theta_1 tone_t + \theta_2 sentiment_t$$
$$+\ \theta_3(VIX_t - VIX_{t-1}) +\ \theta_4 \log\left(\frac{Oil_t}{Oil_{t-1}}\right) + \varepsilon_t \tag{3.7}$$

Using this equation, we will be able to see whether tone and sentiment have an impact on exchange rate volatility and how strong it is. In case of an existing effect, θ_1 and/or θ_2 would be statistically significant. The statistical insignificance of these estimates would imply the absence of any relationship.

Chapter 4

DATA

This thesis uses three different types of data. The first one is related to NBU communication. Since I compare two data sources of the bank's communication (NBU's official website and its Twitter page), data descriptions for both datasets are provided. It includes two variables: tone and topic. These features describe the textual characteristics of the bank's messages. The second important part of the data is exchange rates. It serves as the dependent variable in this research. Finally, there are two control variables: VIX and oil prices.

4.1. NBU communication

NBU communication data is the most crucial part of this thesis. Unlike most previous studies related to this topic, alongside CB's website, I use an entirely new data source – Twitter, where NBU posts its news and announcements. These messages are much shorter than those on NBU's official webpage and are written in a slightly less formal style. All the texts analyzed in this thesis will be in Ukrainian since English messages appear less often and may sometimes miss essential features (e.g., the wordplays or irony).

Twitter data is available starting from 2014, but there were very few posts in 2014-2015. Therefore, I will use the data from 2016 and up to the end of 2021. There have been 3828 tweets posted in this period. I will use the same time period for the communication on the official website: 3811 news have been written and posted there during this time.

As was said before, two features are extracted from each tweet: sentiment and topic. The sentiment is a continuous variable with a range [-1, 1], where 1 represents the positive sentiment, while -1 represents the negative sentiment (0 stands for neutral tone). Figure 1 shows the distribution of sentiment over the tweets. Although a large portion of tweets is neutral, there are slightly more positive texts than negative.

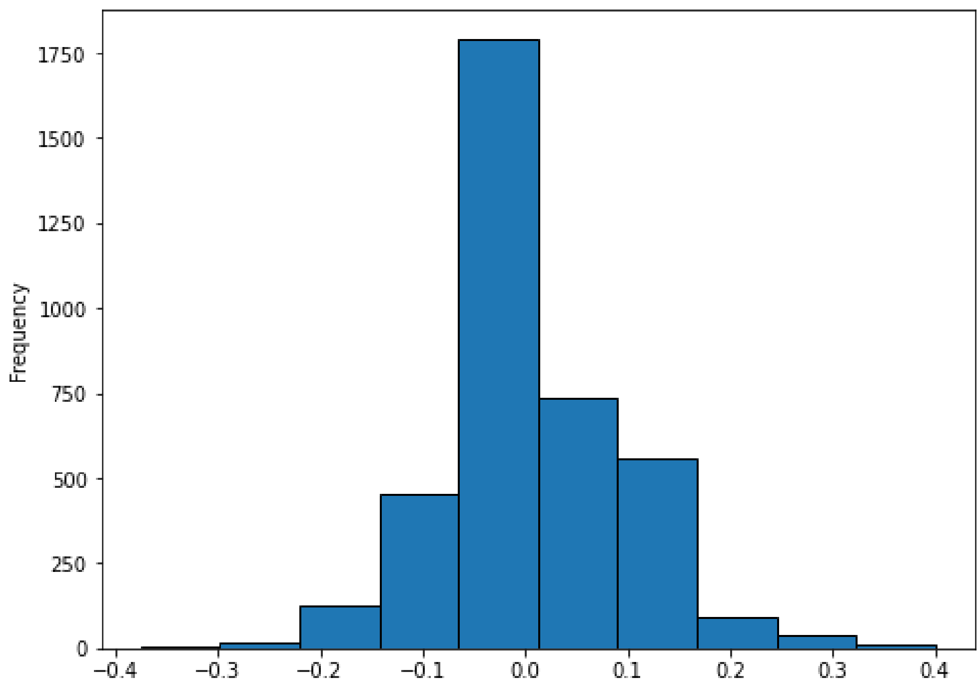

Figure 1. Distribution of sentiment over the tweets.

Figure 2 shows the distribution of sentiment over OW news. The picture is very similar to tweets. This is mainly because many posts are copied partially or entirely between the sources. However, we can clearly see that the frequency of neutral posts is much larger, which confirms the hypothesis that Twitter news is less formal and more emotional.

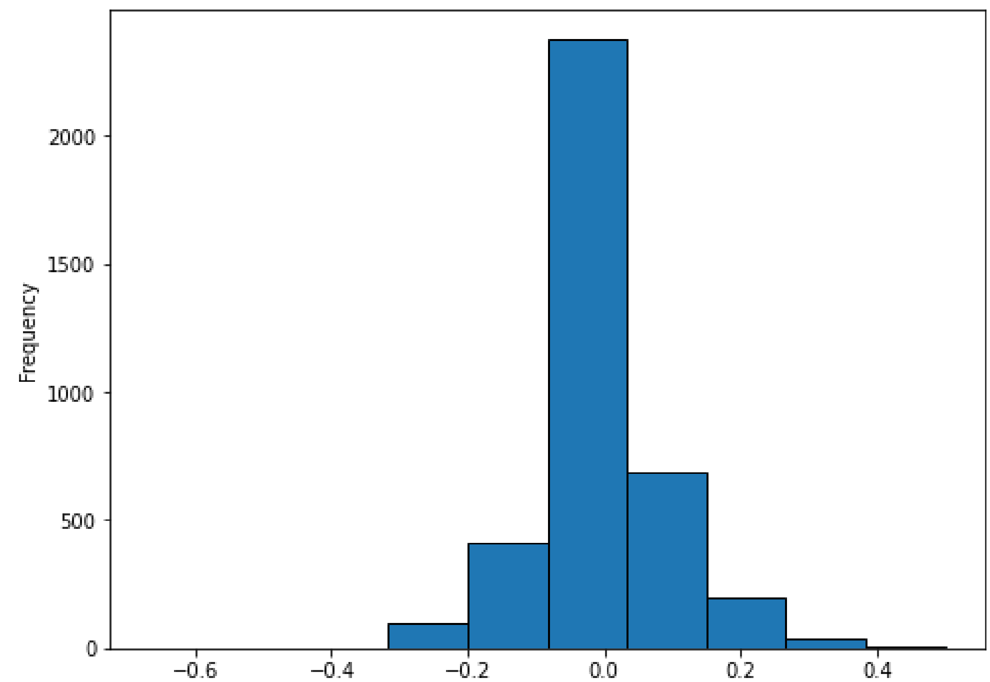

Figure 2. Distribution of sentiment over the news from the official website.

Interestingly enough, there are no tweets with a score of -1 or 1 in both cases, which suggests that NBU communication (even on Twitter) is still very formal (as it probably should be). If we consider all tweets with a score above 0 as positive and with a score below 0 as negative, we will receive 1450 neutral, 1434 positive, and only 944 negative tweets. In comparison, the OW news would be divided into 2200 neutral, 925 positive, and 686 negative posts. These numbers are again in line with the assumption about Twitter's communication style.

Of course, these distributions do not necessarily represent reality due to the limitations of the chosen approach (discussed in the previous section), but it is still not surprising to see such a high number of neutral messages.

Let's look at several examples. Table 1 below provides one positive, one negative, and one neutral post (for each source) with their respective sentiment scores.

Table 1. Examples of tweets with a different sentiment.

Source	Sentiment	Score	Example
Twitter	**Positive**	0.33	Вітаємо авторів монет-переможниць!
Twitter	**Negative**	-0.33	Споживання державного сектору продовжувало зменшуватися – на 9,7% – через складну ситуацію з доходами
Twitter	**Neutral**	0	Уже скоро запрацює новий закон про страхування. ❓ Що зміниться для клієнтів страхових компаній? 👉 Розповідаємо у черговому корисному матеріалі нашого телеграм-каналу:
OW	**Positive**	0.5	Закупівлі Національного банку – конкурентні, відкриті та прозорі
OW	**Negative**	-0.33	ПИТАННЯ ДНЯ: Ставка за кредитом 0% перетворилася у 1 700%. Як цьому запобігти?
OW	**Neutral**	0	Змінено розміри коригуючих коефіцієнтів для застави

Another feature – topic, is a categorical variable. BERTopic provides us with a list of words that describe each subject. Using them, we can manually assign a name to obtained topics. The words are provided in Appendix A, and the assigned topics are shown in Table 2, along with the number of tweets devoted to a topic. As can be seen, there have been extracted 10 categories (including "Other"). Appendix B provides examples of tweets for each of the received topics.

Table 2. Obtained topics and their sizes.

Topic	Name	Name (in Ukrainian)	Number of tweets
0	Other	Інше	2653
1	Crisis	Криза	208
2	Payments	Рахунки та платежі	207
3	Commemorative coins	Пам’ятні монети	176
4	NBU communication	Комунікація НБУ	130
5	Credits	Кредитування	110
6	Inflation	Інфляція	107
7	Security	Безпека	83
8	International reserves	Міжнародні резерви	79
9	About NBU	Про НБУ	75

As for the news from the official NBU website, the situation is easier here since the topics are already provided there by the writers. There is no need to run BERTopic here, and we can receive accurate, human-labeled categories. Appendix C provides the lists of existing topics and their sizes. As can be seen, there are 26 topics, many of which are very small. Such topics would not be very helpful in the regression analysis. Therefore, I have decided to merge low-represented topics into one – "Other". I have set the threshold to 75 posts (minimum number of messages that must be present in a topic), which allowed me to decrease the total number of topics to 11 (including "Other"). Figure 3 shows the distribution of resulting topics, and Figure 4 depicts the evolution of some of the largest topics (apart from "Other") over time. Appendix D provides examples of posts for each topic.

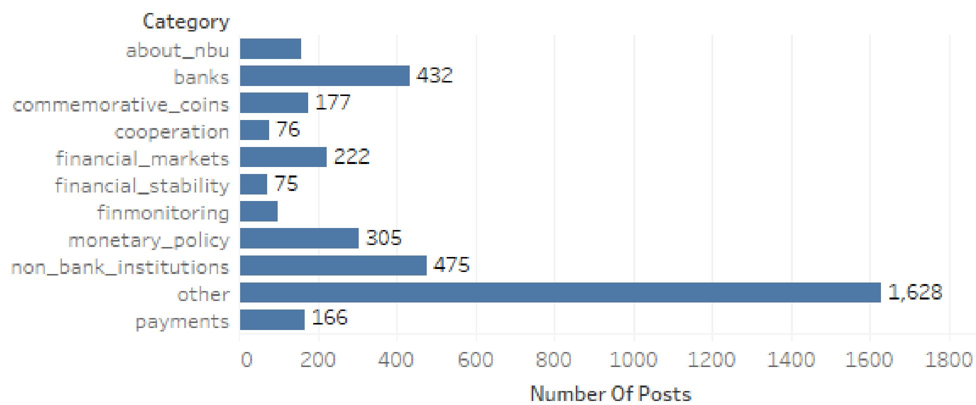

Figure 3. Distribution of topics.

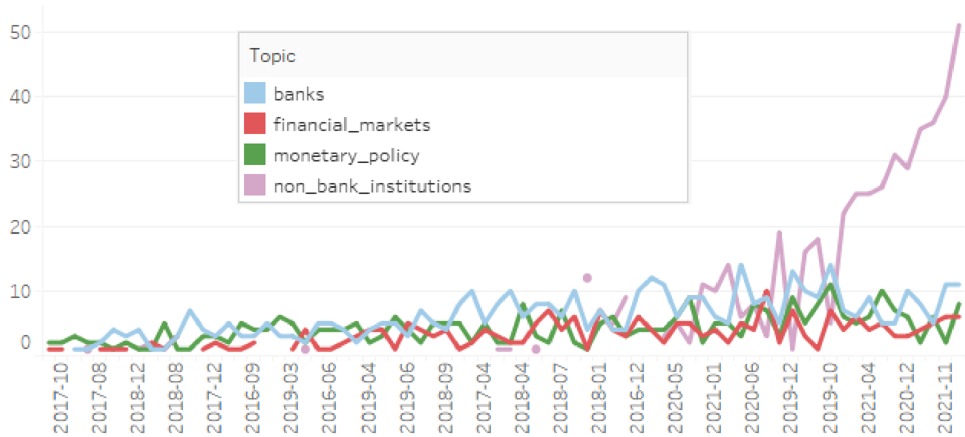

Figure 4. Evolution of the largest topics over time.

Working with categorical variables can be tricky as they need special treatment. One of the popular approaches is called label encoding, which assigns a number to each of the possible values. Although simple, this method has its limitations. The major issue is that such variables may be misinterpreted by the algorithm because numbers imply some kind of order and comparability, even though the topics themselves may not be comparable. Therefore, another approach called one-hot encoding is applied. This method simply creates a column for each possible topic and fills them with zeros except for the column which represents the existing topic. This approach is most commonly used when working with categorical variables.

4.2. Exchange rate

The second type of data used in this thesis is the exchange rate. It is a time-series dataset taken from the official NBU database. The rates are available for each day from 2016 to 2021. Figure 5 shows the dynamics of the exchange rate in the period of study (2016-2021).

The descriptive statistics for this dataset are shown in Table 3. This table also provides the descriptive statistics for log-returns of the exchange rates, which are used in the EGARCH model (as described in the previous section). As can be seen, taking logarithms normalized the data, allowing us to proceed without any additional scaling. Similar calculations will be performed later for other variables, making it possible to combine all of them in one model.

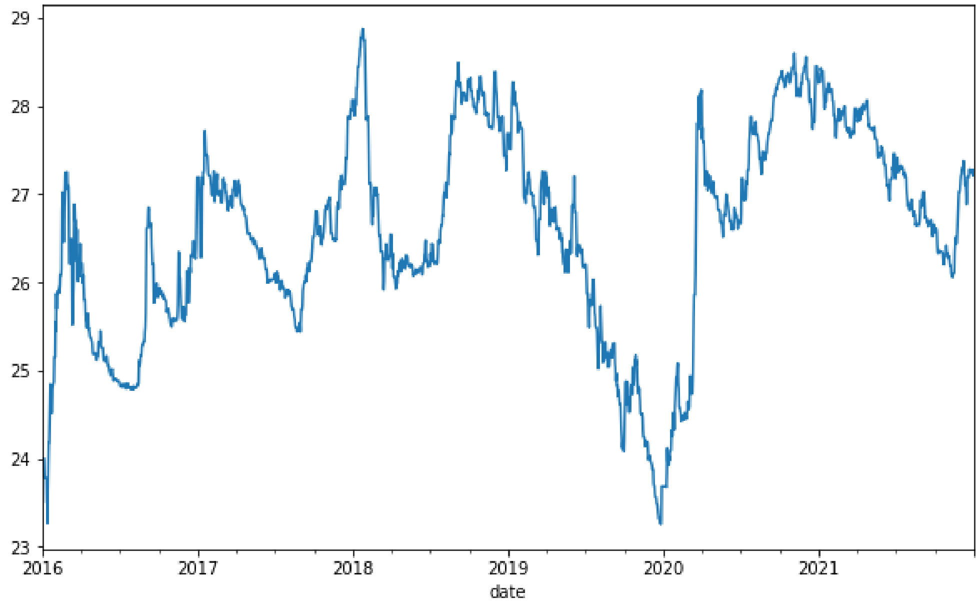

Figure 5. The dynamics of the exchange rate.

Table 3. Descriptive statistics for the dataset of exchange rates.

	Exchange rate	**Log-returns**
Number of Observations	2192	2191
Mean	26.57	0.000058
Standard deviation	1.17	0.003689
Min	23.25	-0.025670
Median	26.66	0
Max	28.87	0.027548

4.3. Control variables

Control variables are used to ensure the validity of the model. They include high-frequency data: oil prices and VIX recorded daily at the same time period (2016-2021). Control variables represent the general stance of the economy. When a certain event happens, it affects oil prices, VIX, and the exchange rate. Including this variable in the analysis allows us to diminish the possible bias caused by such effects.

Oil prices were taken from the FRED website (Crude oil prices: BRENT – Europe), VIX is available on the CBOE webpage. Figure 6 shows the dynamics of oil prices, while Figure 7 depicts the dynamics of VIX. Table 4 provides descriptive statistics for level values of both of these variables, log-returns of oil prices, and first-differenced VIX. Although oil prices and VIX serve the same purpose (to account for other economic events), it can be seen from Figures 6 and 7 that they are very different: they have opposite directions and unalike variances. This phenomenon explains the need to include both of these variables.

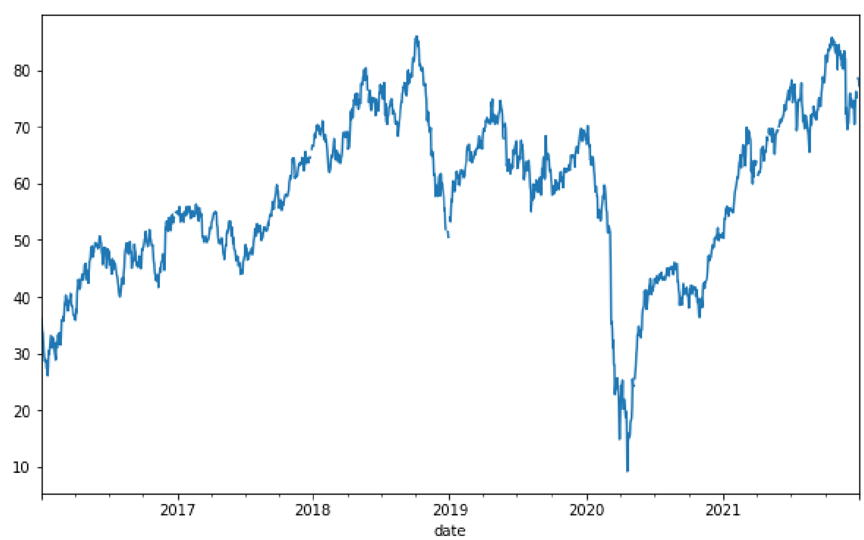

Figure 6. The dynamics of oil prices.

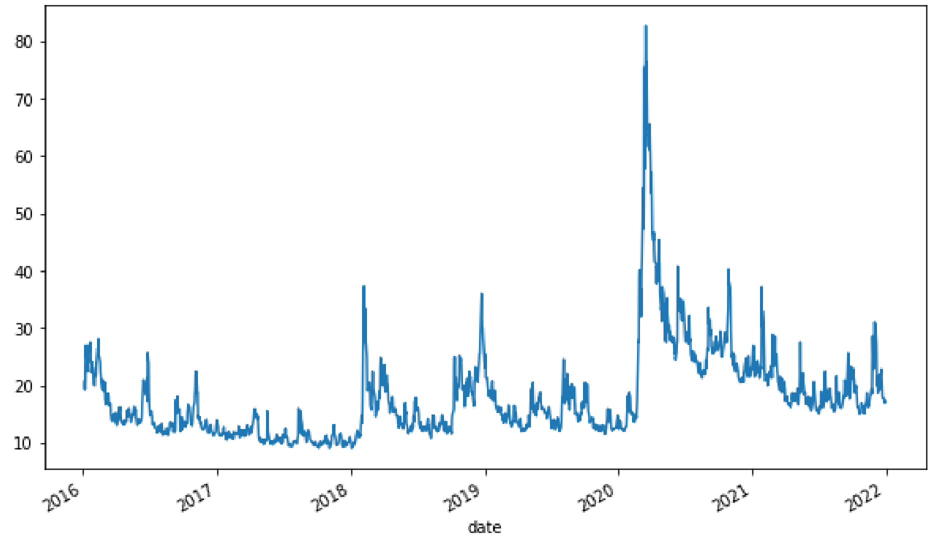

Figure 7. The dynamics of VIX.

Table 4. Descriptive statistics for the dataset of oil prices and VIX.

	Oil prices	Log-returns of oil prices	VIX	First-differenced VIX
Number of Observations	1565	1564	1511	1510
Mean	57.63	0.000483	17.98	-0.002
Standard deviation	14.21	0.034981	8.23	2.087
Min	9.12	-0.643699	9.14	-17.64
Median	59.08	0.000942	15.93	-0.1
Max	86.07	0.412023	82.69	24.86

Chapter 5

ESTIMATION RESULTS

In this chapter, I present the results of the regression analysis. But before interpreting the results, a correct model specification must be chosen. To do that, I run several different models with various numbers and orders of lags and compare how well they fit the data. Table 4 shows the AIC and BIC scores for all the models tried on a Twitter dataset, Table 5 – OW dataset.

As can be seen, GARCH(2, 2) has given us the lowest AIC values for both Twitter and OW datasets, so I will continue with this specification.

The number and order of lags can also be increased further, which might result in even better results. However, using too many lags is not very common in the literature, and 2 previous values are more than enough in our case.

Table 5. Comparison of models with different specifications (with data from NBU's Twitter page).

Model	**AIC**	**BIC**
GARCH(1, 1)	10924.9	11029.5
GARCH(2, 1)	10923.7	11033.3
GARCH(1, 2)	10924.8	11034.5
GARCH(2, 2)	10923.1	11042.7
GARCH(3, 2)	10923.8	11048.4
GARCH(2, 3)	10924.4	11049.0
GARCH(3, 3)	10927.8	11062.4

Table 6. Comparison of models with different specifications
(with data from NBU's official website).

Model	**AIC**	**BIC**
GARCH(1, 1)	15035.6	15153.8
GARCH(2, 1)	15029.9	15153.4
GARCH(1, 2)	15024.9	15148.4
GARCH(2, 2)	15016.1	15150.4
GARCH(3, 2)	15017.1	15156.7
GARCH(2, 3)	15018.1	15157.7
GARCH(3, 3)	15020.8	15171.2

After choosing the best specification, we can finally run the model and look at the results. Full outputs of both models for Twitter and NBU's OW data are provided in Appendix E and F, respectively. Tables 7 and 8 show the most important parts of the output that show the estimates, standard errors, and statistical significance for the variables of interest.

Table 7. EGARCH(2, 2) results for the drift equation
(Twitter data).

Variable	Coefficient	Variable	Coefficient
Const	-0.1372 (1.067)	crisis	-0.4390 (4.445)
exch...rns[1]	0.0990 (3.056e-02)**	inflation	-5.7372 (4.622)
sentiment	0.9333 (6.393)	intern…eserves	-10.4156 (0.168)***
vix_diff	0.3364 (0.150)*	nbu_...cation	9.1368 (4.917)*
oil_price_returns	-3.05e-04 (1.597e-03)	other	0.1149 (1.495)
about_nbu	2.9604 (4.548)	payments	0.1372 (2.539)
com…ative_coins	-0.3969 (2.763)	security	-0.7400 (4.045)
credits	5.3066 (6.163)		

*** $p<0.001$, ** $p<0.01$, * $p<0.05$, . $p < 0.1$

Table 8. EGARCH(2, 2) results for the drift equation
(NBU's OW data).

Variable	Coefficient	Variable	Coefficient
Const	-0.782 (2.77e-02)***	cooperation	-0.0641 (0.828)
exch...rns[1]	0.0632 (1.77e-02)***	financial_markets	-2.1607 (1.387)
sentiment	1.5080 (0.259)***	financial_stability	-1.1819 (2.543)
vix_diff	-0.0347 (1.16e-02)***	finmonitoring	1.7073 (1.400)
oil_price_returns	-9.53e-04 (1.85e-03)	monetary_policy	0.1946 (1.399)
about_nbu	-0.4477 (0.808)	non_...itutions	0.7094 (0.522)
banks	-0.0809 (0.788)	other	0.116 (9.20e-03)***
com…ative_coins	0.2613 (1.188)	payments	0.1798 (0.962)

*** p<0.001, ** p<0.01, * p<0.05, . p < 0.1

Statistical significance from the above tables is exactly what we need to answer the main question of this thesis: whether the tone and topic of NBU communication affect exchange rates. From the obtained results, we can see that sentiment is not statistically significant in the first case (Twitter data) but significant in the second case (OW data).

This outcome is surprising considering that Twitter data has more non-neutral posts than OW news. However, this result does not seem to be robust: when run in different specifications (for instance, without the topic), sentiment does not always turn out significant. Moreover, the coefficient on the sentiment is positive, implying that more positive news causes an increase in the exchange rate volatility. This goes against the previous work and should therefore be treated with caution.

One possible explanation for a positive estimate might be that people's response to positive news is high, and the number of exchange rate operations on the market increase. Another possible reason is the endogeneity problem: unobserved variables may affect both the sentiment and the exchange rate, making them change in the same direction. For example, in the case of inflation, when exchange rate volatility increases, NBU may try to post more positive news to mitigate the negative impact. This results in both: increasing ER volatility and more positive sentiment.

As for the topic, two categories (International reserves and NBU communication) are significant in the first case, and only one topic (Other) is significant in the second case. Such a result does not allow us to state with certainty that the topic affects the exchange rate, but we can clearly see that some relationship exists. In particular, news related to international reserves has a calming effect on the exchange rate volatility. Many other topics have similar interpretations, but they do not appear to be significant. NBU communication-related news, on the contrary, increase exchange rate volatility, which is an undesirable effect.

Chapter 6

CONCLUSIONS AND POLICY RECOMMENDATIONS

From the conducted analysis, several points should be taken:

- Given the evidence, there is likely no impact of sentiment on the exchange rate, but even if it exists, positive sentiment would only increase the ER volatility.
- News on international reserves has a calming effect on the exchange rate volatility. Other topics do not seem to be that important.
- Twitter data does not seem to be more suitable for measuring NBU's communication impact on the exchange rate.

The first result follows from varying outcomes of different model specifications. Only one of them has given statistically significant estimate and it turned out to be positive, which seems counterintuitive and goes against the results from the related literature. It implies that the higher the sentiment of the post, the larger is the exchange rate volatility. Such a behavior (if exists) might have harmful side effects; therefore, NBU's official should be cautious and stick to a more neutral style. This way, they will diminish any unwanted changes to the exchange rate.

However, since this result is not robust, we cannot claim with 100% certainty that sentiment affects exchange rate. This outcome goes in line with the work of Hansen and McMahon (2016), who also did not find a strong effect of CB communication on real economic variables. We can therefore conclude that the causal effect of sentiment on the exchange rate is weak.

The second result states that news related to international reserves tend to lower the exchange rate volatility, hence, they carry positive consequences. This result is consistent across different model specifications and confirms the hypothesis that topic (although not all of the topics) is important in NBU communication.

Finally, Twitter data does not seem to provide any additional insights compared to the news from the NBU's official website. On the contrary, some variables turned out to be completely insignificant. This implies that there is no much difference between these two data source, and Twitter cannot be treated as a better option for such an analysis.

As for the other results indicating insignificance of topics, one possible explanation is that people simply do not read and/or understand messages posted by the NBU. We cannot exclude this option since many economic terms and laws are indeed too complicated for an average citizen, and more knowledgeable persons can form their behavior even without NBU's posts. And while the former does not seem to be a problem, on the contrary, this is what central bank communication is supposed to be like, the latter may be an indicator of population ignorance of economic processes or even basic terms.

It is impossible to claim that such a situation indeed exists (since it is beyond the scope of this work), but if it does, one can doubt economic models that rely on rational expectations (and many modern economic models are exactly rational expectations-based). However, to check this hypothesis, additional research must be conducted.

Apart from that, insignificant results may have been caused by the specifics of the data source. NBU's official webpage and Twitter page are obviously not the most popular information channels, and most of the news is received through general news websites such as UKR.NET or UKRAINSKA PRAVDA. Telegram, with its many news channels, has also recently become particularly popular among Ukrainians.

Also, it is very likely that exchange rates are affected by other types of NBU communication, such as audio and videos. They can carry a significant part in forming economic expectations. Moreover, audios and videos have much more features than texts (such as gestures, intonations, etc.) that can be extremely helpful in such an analysis.

Overall, the hypothesis of NBU communication affecting exchange rates has been confirmed only partially. Not all of the results are statistically significant, some go against the results of related literature, but the existence of a relationship between NBU communication and exchange does seem to exist. More comprehensive research that would incorporate more textual characteristics and include more control variables could shed more light on this subject.

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APPENDIX A

NBU'S TWITTER: TOPIC WORD SCORES

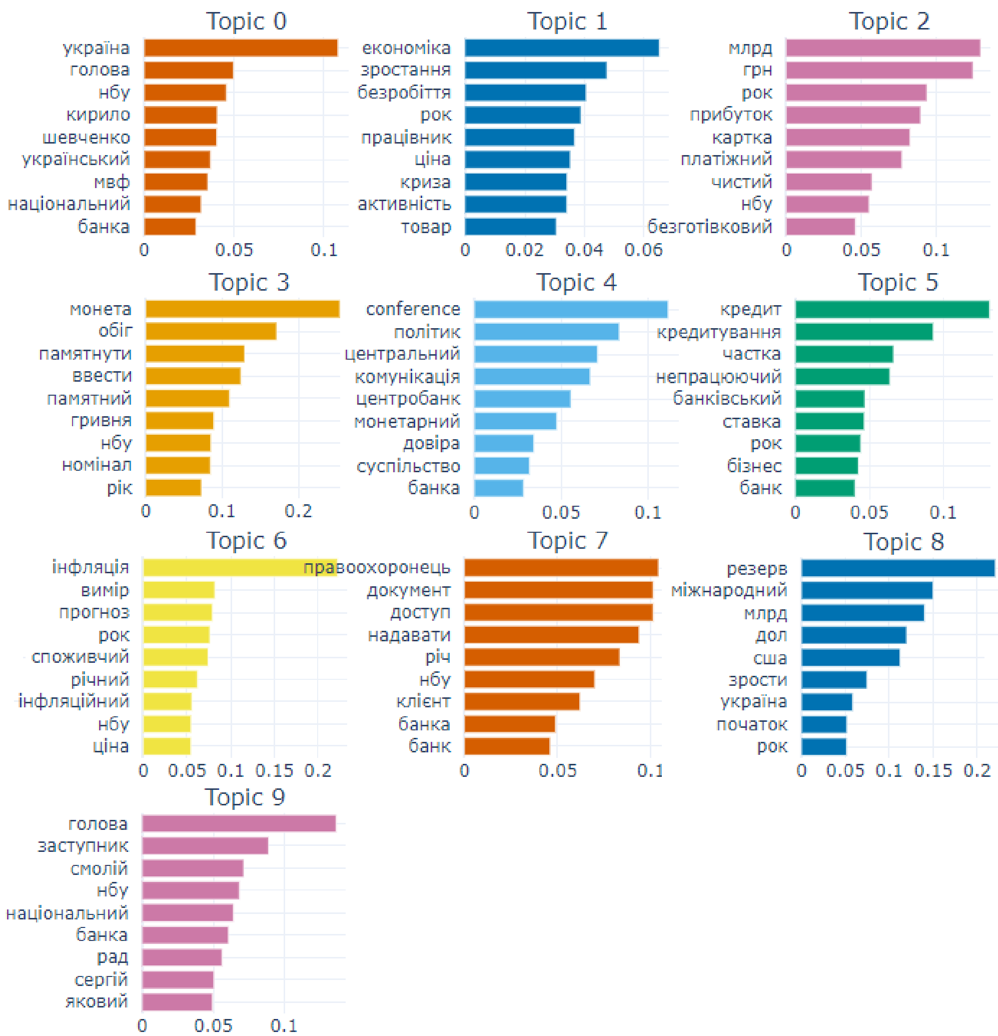

Figure 8. Most important words for each topic and their importance scores.

APPENDIX B

NBU'S TWITTER: TOPIC EXAMPLES

Table 9. Examples of tweets for each topic.

Topic	Example 1	Example 2
Інше	Фінансова система стійка, банки готові до формування буферів капіталу до початку 2024 року.	Опубліковані результати оцінки стійкості банків у розрізі банківських установ.
Криза	У листопаді бізнес очікував погіршення результатів своєї діяльності на тлі посилення карантинних обмежень.	Як почувається економіка України? Що заважає швидшому відновленню? Як зростатиме ВВП нашої країни у 2022-2023 роках?
Рахунки та платежі	За січень – вересень 2021 року фінансові компанії згенерували рекордні прибутки порівняно з аналогічним періодом останніх трьох років.	За 9 міс. 2021 року кількість пунктів продажу, які приймають платіжні картки, зросла на 11,2% – до 363,5 тис.; мережа торговельних POS-терміналів – на 11,4% до 417,6 тис.
Пам’ятні монети	Вітаємо авторів монет-переможниць!	НБУ ввів у обіг пам'ятну монету "175 років створення Кирило-Мефодіївського товариства" з 26.11.2020
Комунікація НБУ	Аскарі: "Повідомлення стосовно майбутньої фіскальної політики призводять до того, що шоки державних витрат матимуть дуже різний ефект за монетарного та фіскального режиму протягом періоду очікування".	Популізм розхитує крихку фінансову стабільність. Коливання курсу цього тижня спричинила саме політична нестабільність.
Кредитування	Вперше за 2 роки більшість (88%) банків очікує прискорення кредитування населення протягом 12 міс.	У ІІ півріччі банки знизили відсоткові ставки за кредитами для бізнесу більше, ніж подешевшали депозити населення
Інфляція	#Інфляція у вересні (7.9% р/р та 1.8% м/м) відповідала прогнозу #НБУ, що на кінець 2016 вона становитиме 12%.	У лютому споживча інфляція в річному вимірі уповільнилася до 32.7% порівняно з 40.3% у попередньому місяці
Безпека	У жовтні 2016 року #НБУ надавав правоохоронцям доступ до інформації 13 разів	Національний банк дозволив відкривати банківський рахунок з цифровим паспортом
Міжнародні резерви	У жовтні міжнародні резерви України зросли на 3,3% передусім через валютні надходження на користь уряду та купівлю валюти Національним банком на міжбанківському валютному ринку	Такий обсяг резервів є рекордним за останні дев’ять років (більший від вищезазначеного обсяг було зафіксовано ще у квітні 2012 року).
Про НБУ	Сьогодні Рада Національного банку під час засідання призначила заступником Голови Національного банку Сергія Ніколайчука.	Інтерв’ю заступника Голови Національного банку Юрія Гелетія для @zn_ua

APPENDIX C

NBU'S OFFICIAL WEBSITE: DISTRIBUTION OF TOPICS

Table 10. Topics of news from NBU's official website and their sizes.

Topic	Topic (in Ukrainian)	Number of posts
other	Інше	1247
non_bank_institutions	Небанківські установи	475
banks	Банки	432
monetary_policy	Монетарна політика	305
financial_markets	Фінансові ринки	222
commemorative_coins	Пам’ятні монети	177
payments	Платежі та розрахунки	166
about_nbu	Про НБУ	158
finmonitoring	Фінмоніторинг	97
cooperation	Міжнародна співпраця	76
financial_stability	Фінансова стабільність	75
uah	Гривня	74
courts	Суди	60
statistics	Статистика	54
research	Дослідження	40
consumer_rights	Права споживачів	29
currency_liberalization	Валютна лібералізація	29
innovation	Інновації	21
drafts_discussion	Громадське обговорення	21
coronavirus	Коронавірус	16
strategy	Стратегія розвитку	14
financial_inclusion	Фінансова грамотність	9
Inflation	Інфляція	4
refinancing	Рефінансування	4
corrective_measures	Заходи впливу	3
lending	Кредитування	3

APPENDIX D

NBU'S OFFICIAL WEBSITE: TOPIC EXAMPLES

Table 11. Examples of news for each topic from NBU's official website.

Topic	Example 1	Example 2
Небанківські установи	Національний банк дебюрократизує проведення валютних операцій для страхових компаній	Нова програма співпраці України з МВФ: НБУ має залишатися незалежним і продовжувати реформи у фінсекторі
Банки	ПАТ "Авант-Банк" віднесено до категорії неплатоспроможних	Національний банк визначив три системно важливих банки
Монетарна політика	Виступ Голови Національного банку Валерії Гонтаревої з питань монетарної політики	Національний банк залишив облікову ставку незмінною
Фінансові ринки	Національний банк оновлює підходи до розрахунку та оприлюднення офіційного та довідкового курсу гривні	Національний банк врегулював порядок проведення грошових розрахунків за правочинами щодо цінних паперів
Пам’ятні монети	У Національному банку відбулася презентація пам’ятних монет, присвячених Збройним Силам України	Набір із чотирьох срібних пам’ятних монет "Козацькі клейноди" вводиться в обіг 30 грудня 2021 року
Платежі та розрахунки	Стартувала всеукраїнська інформаційна кампанія з популяризації безготівкових розрахунків	Національний банк вітає пілотний проєкт Міністерства цифрової трансформації щодо випуску програмованих електронних грошей
Про НБУ	Департамент ліцензування Національного банку очолив Михайло Федоренко	Національний банк завершив другий етап централізації регіональної мережі
Фінмоніторинг	Національний банк спростив процедуру обміну інформацією між банками та Держфінмоніторингом	Національний банк і Міністерство фінансів обговорили заходи із боротьби з відтоком капіталу
Міжнародна співпраця	Валерія Гонтарева: Швейцарія надасть Україні 200 млн доларів США	Швейцарський національний банк надав кредит Національному банку України
Фінансова стабільність	Рада з фінансової стабільності відзначила зниження системних ризиків	Національний банк змінив підхід до оцінки банками кредитного ризику

APPENDIX E

MODEL OUTPUT: TWITTER

Table 12. Results of EGARCH(2,2) run on the Twitter data.

No. Observations:	1080	R-squared:	0.033
Df Residuals:	1065	Log-Likelihood:	-5437.56
Df Model:	15	AIC:	10923.1
		BIC:	11042.7

Mean Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
Const	-0.1372	1.067	-0.129	0.898	[-2.228, 1.953]
exch...rns[1]	0.0990	3.056e-02	3.239	1.199e-03	[3.910e-02, 0.159]
sentiment	0.9333	6.393	0.146	0.884	[-11.597, 13.463]
vix_diff	0.3364	0.150	2.245	2.47e-02	[4.269e-02, 0.630]
oil_price_returns	-3.05e-04	1.597e-03	-0.191	0.848	[-3.43e-03,2.82e-03]
about_nbu	2.9604	4.548	0.651	0.515	[-5.953, 11.874]
com…ative_coins	-0.3969	2.763	-0.144	0.886	[-5.813, 5.019]
credits	5.3066	6.163	0.861	0.389	[-6.772, 17.385]
crisis	-0.4390	4.445	-9.87e-02	0.921	[-9.151, 8.273]
inflation	-5.7372	4.622	-1.241	0.214	[-14.796, 3.322]
intern…eserves	-10.4156	0.168	-62.138	0.000	[-10.744,-10.087]
nbu_...cation	9.1368	4.917	1.858	6.316e-02	[-0.501, 18.775]
other	0.1149	1.495	7.690e-02	0.939	[-2.814, 3.044]
payments	0.1372	2.539	5.403e-02	0.957	[-4.839, 5.113]
security	-0.7400	4.045	-0.183	0.855	[-8.668, 7.188]

Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	0.5877	0.530	1.108	0.268	[-0.451, 1.627]
alpha[1]	0.7635	0.432	1.766	7.742e-02	[-8.394e-02, 1.611]
alpha[2]	-0.2093	0.691	-0.303	0.762	[-1.563, 1.144]
gamma[1]	0.3045	0.266	1.144	0.253	[-0.217, 0.826]
gamma[2]	-0.3699	0.306	-1.208	0.227	[-0.970, 0.230]
beta[1]	0.9705	0.646	1.503	0.133	[-0.295, 2.236]
beta[2]	0.0000	0.628	0.000	1.000	[-1.230, 1.230]

Distribution

	coef	std err	t	P>|t|	95.0% Conf. Int.
nu	2.0679	6.519e-02	31.722	7.82e-221	[1.940, 2.196]
lambda	0.0191	2.964e-02	0.645	0.519	[-3.89e-02,7.72e-02]

APPENDIX F

MODEL OUTPUT: OFFICIAL WEBSITE

Table 13. Results of EGARCH(2,2) run on the OW data.

No. Observations:	1588	R-squared:	0.007
Df Residuals:	1572	Log-Likelihood:	-7483.05
Df Model:	16	AIC:	15016.1
		BIC:	15150.4

Mean Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
Const	-0.782	2.77e-02	-28.16	1.74e-174	[-0.837, -0.728]
exch...rns[1]	0.0632	1.77e-02	3.57	3.56e-04	[2.851e-02,9.788e-02]
sentiment	1.5080	0.259	5.83	5.44e-09	[1.001, 2.015]
vix_diff	-0.0347	1.16e-02	-2.98	2.87e-03	[-5.75e-02,-1.18e-02]
oil_price_returns	-9.53e-04	1.85e-03	-0.51	0.608	[-4.59e-03,2.69e-03]
about_nbu	-0.4477	0.808	-0.55	0.579	[-2.031, 1.135]
banks	-0.0809	0.788	-0.103	0.918	[-1.625, 1.463]
com…ative_coins	0.2613	1.188	0.220	0.826	[-2.066, 2.589]
cooperation	-0.0641	0.828	-7.7e-02	0.938	[-1.687, 1.559]
financial_markets	-2.1607	1.387	-1.55	0.119	[-4.879, 0.558]
financial_stability	-1.1819	2.543	-0.46	0.642	[-6.166, 3.802]
finmonitoring	1.7073	1.400	1.219	0.223	[-1.037, 4.451]
monetary_policy	0.1946	1.399	0.139	0.889	[-2.548, 2.937]
non_...itutions	0.7094	0.522	1.358	0.174	[-0.314, 1.733]
other	0.116	9.20e-03	12.705	5.57e-37	[9.88e-02, 0.135]
payments	0.1798	0.962	0.187	0.852	[-1.705, 2.065]

Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	1.0470	0.971	1.078	0.281	[-0.857, 2.950]
alpha[1]	0.9825	1.118	0.879	0.379	[-1.209, 3.174]
alpha[2]	0.1593	0.304	0.524	0.600	[-0.437, 0.756]
gamma[1]	0.2688	0.326	0.824	0.410	[-0.371, 0.908]
gamma[2]	0.2614	0.327	0.800	0.424	[-0.379, 0.902]
beta[1]	0.0856	6.295e-02	1.359	0.174	[-3.782e-02, 0.209]
beta[2]	0.8670	4.120e-02	21.043	2.676e-98	[0.786, 0.948]

Distribution

	coef	std err	t	P>|t|	95.0% Conf. Int.
nu	2.0500	0.118	17.435	4.480e-68	[1.820, 2.280]
lambda	-0.0150	1.044e-02	-1.440	0.150	[-3.54e-02,5.43e-03]