IMPACT OF EXPERTS` FORECAST ON
UAH/USD EXCHANGE RATE
VOLATILITY

by

Savin Serhii

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Thesis Supervisor: ____________________________Professor Olesia Verchenko

Approved by ____

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BIS The Bank for International Settlements

Forex Foreign exchange market

FX Foreign exchange

ACF Autocorrelation function

PACF Partial autocorrelation function

CHAPTER 1. INTRODUCTION

Foreign exchange (FX) market is the largest global market, which works anytime and anywhere. Being an over-the-counter (OTC) market, it has neither centre nor physical exchange. According to the Bank for International Settlements (BIS), daily turnover in the market was about 6.6 billion USD in 2019, which is approximately by 12.5 times more than the global fixed-income market and by 50 times more than equity market. Moreover, the FX market has the highest annual market growth rate since 2000 (9.7%) in comparison to 6.3% of fixed-income and 3.7% of the global equity markets. Some analyst predicts that such tendency will remain the same in the next decade due to money velocity speed up and cross-countries trading intensification.

Considering the Ukrainian case almost 50 and 61 USD billions of exports and import respectively had to be managed in 2019. Also, some local agreements are linked to the USD or EUR exchange rate. Since Ukraine is a relatively open economy and takes 58 place within 165 countries in the global trade openness ranking, foreign currency cash flows management place a vital role for local businesses. Some companies, for example, in metallurgy, food and clothes distribution industries, are focused on regular export or import. Although usually FX risks are assigned to one counterparty, both parties are dependent on foreign exchange rate fluctuation. Moreover, the standard hedging tools such as forwards are not accessible in Ukraine. Therefore, there is a need to forecast the exchange rate.

Many kinds of research related to currency exchange forecasting have been conducted. The classic approach is to test hypotheses based on macroeconomic theory. The most common approach is Purchasing Power Parity Theory investigated by Wheatley and Ricardo and its modification. However, such models rely on unbiased expectations of market participants and overall market efficiency. However, these assumptions are questionable. Increasing mass media coverage creates space for manipulations of misleading information spreading, which shapes expectations and effect on market efficiency. Therefore, the question that has to be answered is "do expert's forecasting effect on UAH/USD Exchange Rate volatility".

The causality mechanism between news realizing and exchange rate fluctuations is a fundamental question for my research. There are two different thoughts on this. The first perspective is that news publishing shapes market participants expectations that determine fluctuations in the market. The second approach relies on the idea that news is a straightforward way to convey expectations of market participants that have shaped already. On the research, I support on the first approach. Therefore, the focus of the paper is not to define or test the causality mechanism, but investigate the link between news sentimental features and volatility of the exchange rate.

Ukrainians do not believe on the national currency, because they went through hyperinflation on 1993-1996 and double-digit inflation periods on 1998-2002, 2008-2009 and 2014-2016. The shocks came with the devaluation of local currency. Thus, Ukrainian have strong doubts on stability and reliance on the hryvnia. Looking at banking sector statistics, we may find of the statement. According to the National Bank of Ukraine data, almost 42% of deposits on January-August 2020 are in a currency other than hryvnia.

Moreover, there is a strong positive correlation (0.91) between duration of deposits and share of foreign currency at deposit portfolio. Also, banks are more willing to give credits at foreign currency. Approximately 39% of loans on January-August 2020 are in a currency other than hryvnia. The same situation is with duration, and long-term loans are mostly on US dollars or euro.

These factors have shaped a lack of confidence of Ukrainian to domestic currency. Both companies and individuals have more reasons to believe in negative rather than positive news.

To answer the research question, I have web scrapped the most popular news related to UAH/USD forecasting from Google news. There are time, title, source and text of the news were collected, which is described in Chapter 4. Afterwards, the EEGARCH model has been used to forecast the volatility of the exchange rate.

The paper is structured in the following way. Chapter 2 reviews related literature not only for exchange rate modelling and news impact but also their interaction. Chapter 3 explains the methodology description, web scrapping tools and specification of econometric models. Chapter 4 gives a descriptive statistic of the data, its primary analysis, sources, and limitations. Chapter 5 shows the key findings and insight received from the research. Chapter 6 summarizes the results, makes conclusion and recommendations based on the conducted analysis.

CHAPTER 2. LITERATURE OVERVIEW

Since the barter economy degeneration, the establishment of the trading relationship and money swap the currency exchange rate became the crucial topic in economic theory. Early studies conducted by Physiocrats and Classical political economists had lied in the exchange rate theories which prevails before the XX century (the mint parity and purchasing power parity theories).

On the XIX-XX century, the most supportive theories rely on macroeconomic fundamentals. The nominal exchange rate was modelled as a dependent variable on various macroeconomic performances such as inflations, net export and real exchange rate. However, such an approach has two critical shortcomings:

1. The minimum interval of input data is the month. Almost all macroeconomic data is reported at monthly, quarterly, or yearly basis. Therefore, focusing on monthly prediction models have limited value for companies which manage currency flows on a daily basis. Moreover, official data are published with a significant time lag, for example, estimation of quarterly GDP in Ukraine announce in 45 days after the quarter. Consequently, this approach is inflexible, considering increasing money velocity and growth in the FX market.

2. The underlying assumption about rational expectations is questionable. Most of these models assume rational behaviour and do not account the asymmetry of information and different analytical abilities among market participants.

These weak points could distort the significance of models and predictive power. The relationship among exchange rate and macroeconomic variables is highly nonlinear and lagging. Thus, developed models have lower explanatory power than a random walk. It is aptly summarised by Meese and Rogoff (1983) based on the US dollar to pound, mark, yen exchange rates. The similar conclusion was received by Kilian and Taylor (2003) who examine that long-term deviation is nonlinear and is difficult to predict due to the short time structure of the available data because they use quarterly data.

Considering such non-trivial relationship between exchange rate and macroeconomic indicators, and inability to forecast on the short period (weeks, days, hours) numerous researchers began analyzing news as an essential factor that effects on exchange rate fluctuations.

The first attempt to investigate the news impact on the exchange rate was made by Frenkel (1981). Analyzing monthly deviation of dollar to French franc and Deutschmark over 1973-1979, the scientist concluded the significance news effect. Using the VAR model, Frenkel has shown that news should be considered as a significant factor as macroeconomic variables. Also, the author links such results with expectation theory, meaning news shapes market participant expectations. However, this assumption is questionable that many other economists believe in this causality mechanism. This question remains open due to the different approach to describe market efficiency and techniques to test it. In the paper, I would like to take a deeper dive into the question.

Afterwards, economists became test news and macroeconomic variables in together. MacDonald (1983), Copeland (1984), Ito and Roley (1987), Hardouvelis (1988), Hogan et al. (1991) continued researching this topic. Usually, economists use monthly and quarterly data and analyze the positive and negative news as an additional variable within established models. Despite analyzing different currency pairs and models, many economists found the significant but not much noticeable relationship between exchange rate volatility and news publishing.

The next wave of research was focused on applying VAR and EGARCH models and their extensions. Omrane at el (2003) using 5-minute frequency data did not find a noticeable effect of the news on the exchange rate. However, it might be the case that the impact of the news has not only the short-term structure but long term as well. Thus, focusing on 5-minute interval raises a new question: does the market react to the news immediately such that all movement is captured within the next 5 minutes?

Analyzing daily data, Evans and Lyons (2008) have shown that news help to explain approximately 35% of volatility in the exchange rate. Considering that the day-to-day exchange rate of the benchmark to the US dollar over May 1 to August 31, 1996, were studied, the results may differ if we take more closer period.

Guglielmo et al. (2016) estimated a VAR-EGARCH(1,1) model for Brazil, Russia, India, China and South Africa. The model uses Bloomberg news about key macroeconomic variables (i.e., GDP, unemployment, retail sales and durable goods). Then, the authors divide all these news into two groups: "positive" and "negative", and use frequency of the news as an input variable at the model. Valuable insight from the research is that both news from developed (USA) and developing (Brazil, Russia, India, China and South Africa) countries affect exchange rates. Thus, we may hypothesize that USD/UAH exchange rate is dependent on local news. The similar research was conducted by Caporale et al. (2015) for the Czech Republic, Hungary, Indonesia, Korea, Mexico, Poland, South Africa, Thailand and Turkey FX markets. The results, based on a VAR-EGARCH(1,1) model, show a weak relationship between news and exchange rate, which becomes more robust during the crisis period.

Such a conclusion is contrary to an alternative approach, which analyses news effect based on excess impact perspective. Egert and Kocenda (2014) used such methodology in order to investigate the impact of a central bank announcement on emerging European FX markets. They use the deviation of the news from the prior expectation as the explanatory variable in an EGARCH model. Even though news from the central bank has a significant effect, the magnitude of the impact differs within crisis (2004-2007) and non-crisis periods (2008-2009). The target counties were the Czech Republic, Hungary and Poland. Therefore, I may hypothesize that we should receive similar results for Ukraine.

Diving news into positive and negative groups is a widely used approach; for example, Maserumule and Alagidede (2017) studied South African rand and US dollar exchange rate. They have shown that news lead to exchange rate volatility increase despite characteristic on the news. Also, the researchers found that negative news has a higher impact on volatility than positive news. This conclusion is exciting to test in the Hryvnia to US Dollar case.

Recent research for the Indonesian market (Badara at el. 2019) concludes that both positive and negative news have an effect on the exchange rate but with different lags. Thus, positive announcements have one lag, while negative almost three lags. However, the results were obtained relying on Blomberg news index from the USA, China and Indonesia simultaneously. Thus, the research did not account other news portals, meaning it does not represent different perspectives on the events.

Summing up the literature overview, I cloud formulate research question more details and emphasize scientific novelty and personal contribution at this sphere. In particular, I would like to investigate the link between news semantic and exchange rate volatility. Following the best practices, EGARCH models and its extensions will be used. However, contrary to common practice to use the news from some information portal (Bloomberg, Reuters etc.) I will use Google news due to two reasons. First is that news about hryvnia to the US dollar is unpopular in comparison to other currency pairs. Secondly, Google news allows us to select the most readable news and diversify content makers. It is a crucial aspect considering limited journalistic independence in Ukraine.

CHAPTER 3. METHODOLOGY

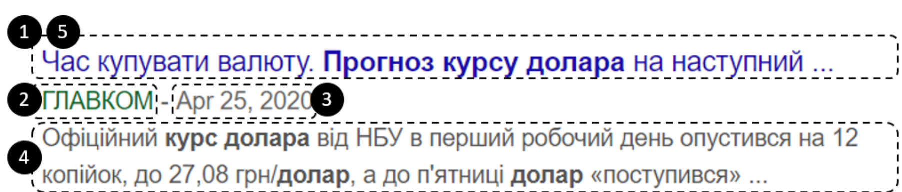
There are two steps in the research: web scrapping and exchange rate forecasting. Firstly, key information from google news about forecasting of UAH/USD exchange rate will be web scrapped using R packages. At the next stage, texts of this news will be web scrapped from the individual news webpages (Iacus 2015). Then the most common words will be grouped into considering shades of meaning. After that, the EGARCH model and its extensions will be used to estimate exchange rate volatility (Bollerslev 1986, Taylor 1986).

News collection approach

On the research, I have used Google news on search "forecasting of Dollars exchange rate" ("прогноз курса долара"). The news represents the market experts opinion on the future exchange rate. On the one have, such news are more narrow in comparison to macroeconomic news, which were used in the literature mentioned above. On the other hand, they have a more explicit link to the exchange rate fluctuation. Thus, I would like to focus on this part of the economic news.

Following automated data collection methodology (Iacus 2015), and using the R package 'rvest' I have extracted five characteristics of the news:

1. Title of the news
2. Name of newsmaker
3. Date of the news
4. First words from the news
5. Link to the news webpage (hidden in the title)



As a result, 540 news within January 29 and August 12, 2020, were collected. According to official Google information, Google news search algorithm have searched news considering language, region and personal information from past activity on Google, Google Search and YouTube. Therefore, the received list of news could be biased. In order to eliminate the issue, all personal information including cookies and cache, was deleted before the search.

At the next stage, I collected text on the news from the websites following the same methodology and using received links. Consequently, full texts of this news were collected into one database.

News analysis approach

After receiving the final dataset, I have translated information to English from Ukrainian and Russian. Then I conducted a text mining procedure using R and following Munzert's approach (Munzert and el. 2014). The adapted methodology suggests the following steps:

1. Create linguistics text corpus (sample of "real word" text)
2. Remove all numbers, non-letter signs and extra spaces
3. Remove stop words (such as articles and pronouns)
4. Stemming text (meaning combine words with the same roots into one group)
5. Divide these groups into two blocks: (1) positive and (2) negative.
6. Analyze the frequency of the words from these blocks along the period.

The outcome in the stage should be relatively frequency of the words from each block on a daily basis.

ARMA model estimation

Since the exchange rate time series is usually nonstationary, in the research, I have analyzed daily changes of UAH/USD exchange rate from January 29 to August 12 2020.

$$r_t = \ln\left(\frac{\left(\frac{UAH}{USD}\right)_{offer_t}}{\left(\frac{UAH}{USD}\right)_{ask_t}}\right)$$

Before proceeding with the EGARCH model estimation, we have to start with the ARMA model to estimate its residuals. ARMA model and its extensions are widely used for exchange rate modelling. The majority of the studies used the model as a basis for analysis due to its efficiency and convenient economic interpretation of the obtained results. I have followed and adapted Box–Jenkins methodology to ARMA models (Box and Jenkins, 1989):

1. Detect data stationarity using run sequence plot, autocorrelation function and partial autocorrelation functions. Take a difference if the data is not stationary. The possible stationarity count is observed within weekdays.
2. Detect possible seasonality. Deason data in case of significant seasonality.
3. Identify p and q for ARMA relying on Akaike and Bayesian information criteria and normality of residual distribution.

After running the model, residuals ε_t will be collected. At this stage, we have to test these residuals on the white noise, for example, using Ljung-Box test, Haar Wavelet White Noise or Q test. If the residuals are not white noise, then the model should be specified differently and reestimated. Thus, the specification will have the following expression:

$r_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{i=1}^{p} \theta_i \varepsilon_{t-i}$

, where c, φ, θ are some constant

r_{t-i} are lagging values of the independent variable

ε_{t-i} are lagging values of residuals.

After running the last model, we may estimate the effect of the frequency of destabilizing words on exchange rate volatility. Consequently, based on the γ_1 and γ_2 sings, we may conclude on the effect of the news on exchange rate volatility.

EGARCH model estimation

The next step is to construct EGARCH models with no intermediate steps. Such an approach helps us to deal with heteroscedasticity automatically. Also, we may add dummy variables to the model and test effect of the external factors on the volatility. Therefore, the model will have the following expression:

$$\log(\sigma_t^2) = \widehat{\omega} + \sum_{i=1}^{t-1} \widehat{\alpha_i} * \log(\sigma_i^2) + \sum_{i=1}^{t-1} \widehat{\beta_i} * \mathrm{g}(\mathrm{r_t}) + \gamma_1 * f_{1t} + \gamma_2 * f_{2t} + d_i$$

, where where f_{1t} is the relative frequency of words from the group of positive words

f_{2t} is the relative frequency of words from the negative words

d_i is a dummy variable

Moreover, we may test different dependent variables. Following relevant literature recommendations, the initial models have dependent variables the logarithm change of official exchange rate (next day to the current day). However, such an approach has issues with a significant lag. Today's news may affect today's market and do not affect the news days market situation. Some researchers use current day bid-ask spread as a dependent variable to deal with the lags. In the research, I would like to construct such a model in the following way:

$$\log(\sigma_t^2) = \widehat{\omega} + \sum_{i=1}^{t-1} \widehat{\alpha_i} * \log(\sigma_i^2) + \sum_{i=1}^{t-1} \widehat{\beta_i} * \mathrm{g}(\mathrm{x_t}) + \gamma_1 * f_{1t} + \gamma_2 * f_{2t} + d_i$$

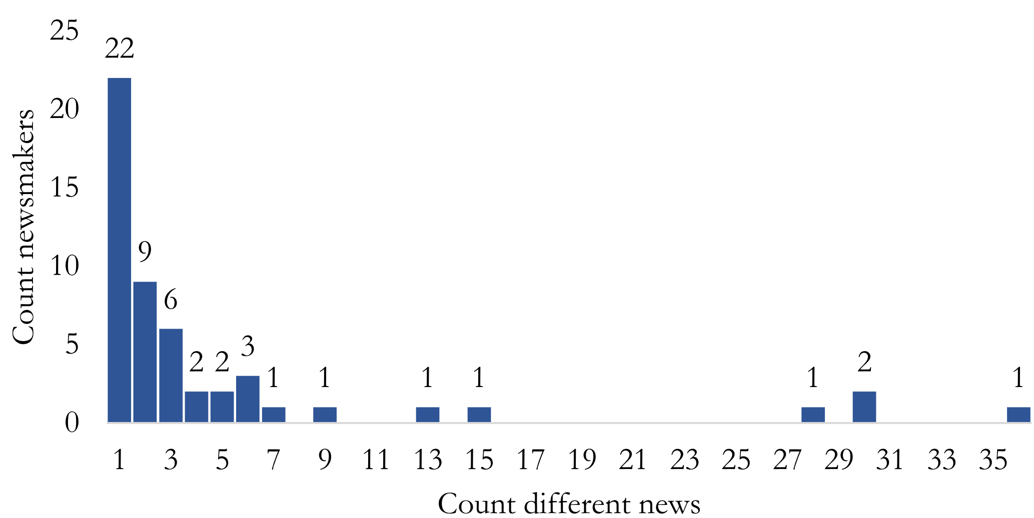
, where $\mathrm{x_t}$ is the bid-ask spread (in hryvnias) on the interbank market.

The research is based on web-scrapped news from Google news and UAH/USD official exchange rate as a bid-offer spread on the daily interbank market. Thus, I would give a data description for both news and exchange rate separately.

Descriptive statistic of web-scrapped news

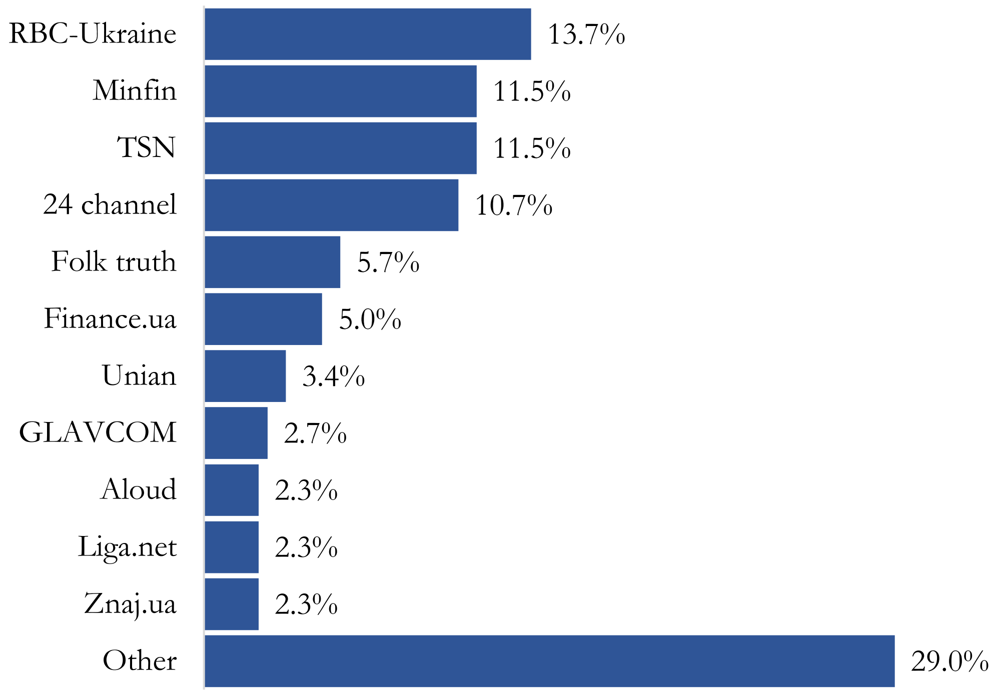
The dataset includes 540 news from 53 different newsmakers. There are five news on average per newsmakers. However, the distribution of news (depicted in figure 1) is positively skewed. Therefore, the median value is 2, meaning half of the values are less than 2. Along with this fact, the values have a Herfindahl-Hirschman index equal to 686; thus, we may conclude that the dataset is diversified and account different opinions in the market.

Figure 1: Distribution of news



Looking at newsmakers level, there are four distinct leaders in the market, who publish more than 10% of relevant news each. The remaining 52.7% are distributed within other 49 news portals. About 75% of the news was written in Ukrainian, and the rest 25% in Russian.

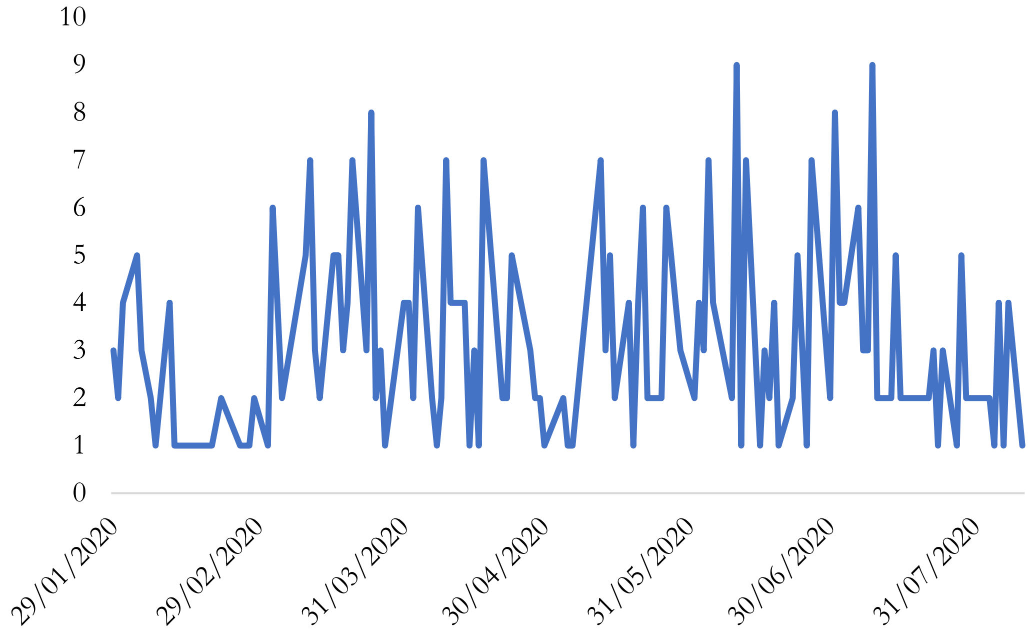
Figure 2: Distribution of newsmakers



There is 3.5 news published on average per working day during the study period. The intensity of news in the sample differs along the time. The popularity of the topic was relatively low (2.4 news per working day) before March 2, 2020. However, during the next two months, concernment of the topic increased (4.3 news per working day). Such movements coincide with hryvnia devaluation and setting lockdown due to COVID-19.

Therefore, there is a plausible economic rationale for such fluctuations. Beginning from May 2020 intensity of news publishing in this field became 2.5 news per working day.

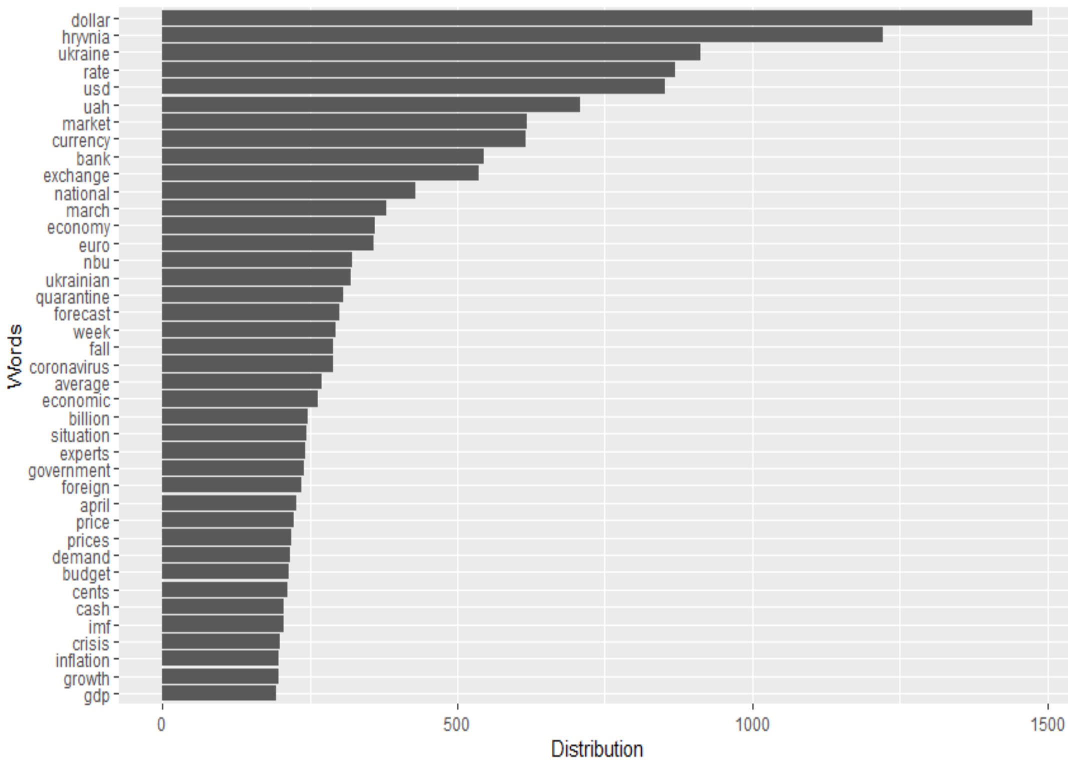
Figure 3: Dynamics of news publishing (number of news)



After cleaning the dataset and removing stop-words, we may illustrate the most frequent word in the sample (figure 4). Within the top 40 the most popular words, we could observe four groups:

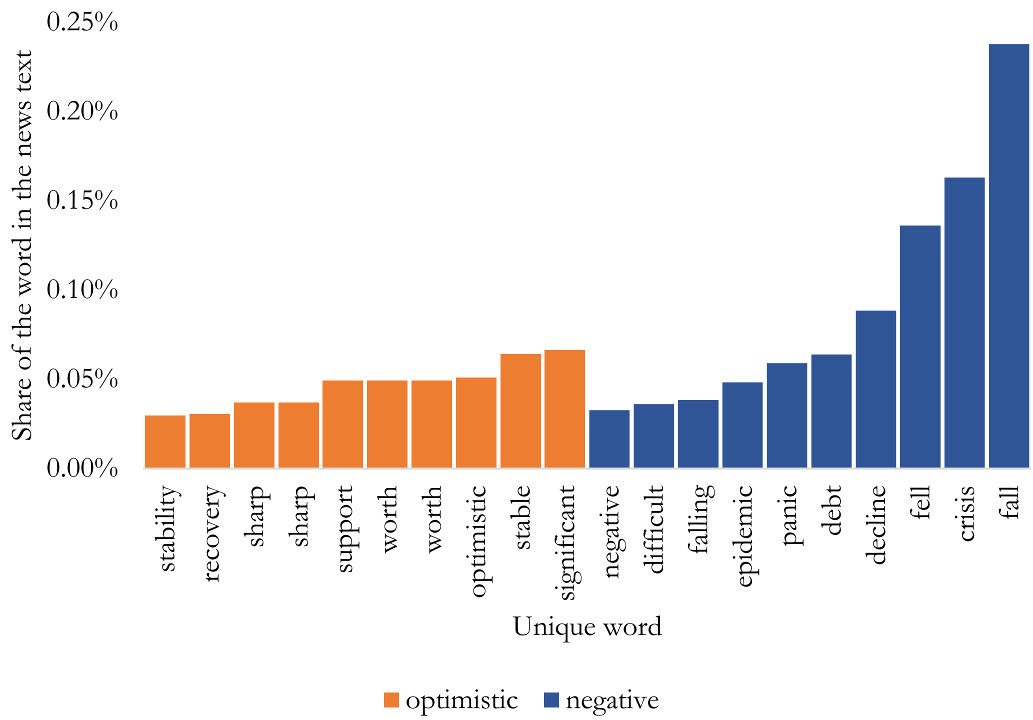
1. Currencies (dollar, hryvnia, euro)
2. Economic terms (price, inflation, demand, cash, budget, GDP, economy)
3. Institutions and organizations (bank, government, NBU, IMF)
4. Other

Figure 4: Top 40 famous words in the sample



Since the analysis is based on a division of news on positive, negative, and other, it will be beneficial to investigate the frequency of such words with specific examples. On figure 5, the most frequent positive and negative words are presented.

Figure 5: Top 10 the most frequent words in the news



From the graph above, we may observe that negative words prevail in the sample. Such negative words as "decline", "fell", "crisis", and "fall" are much more popular than the most popular positive words "stable", and "significant". Meaning newsmakers are more willing to put negative words into the news. There is 660 emotionally loaded word in the sample. Almost 59% (391 words) have a negative meaning while remaining 41% (269 words) are positive. However, considering the frequency of usage of these words, we may conclude that negative words are used more intensively. About 63% (2679) of all emotionally loaded word in the sample were negative versus to 37% (1606) of positive words. The most popular negative and positive word in the dataset is depicted in the word cloud below (figure 6).

Figure 6: The most popular positive and negative words

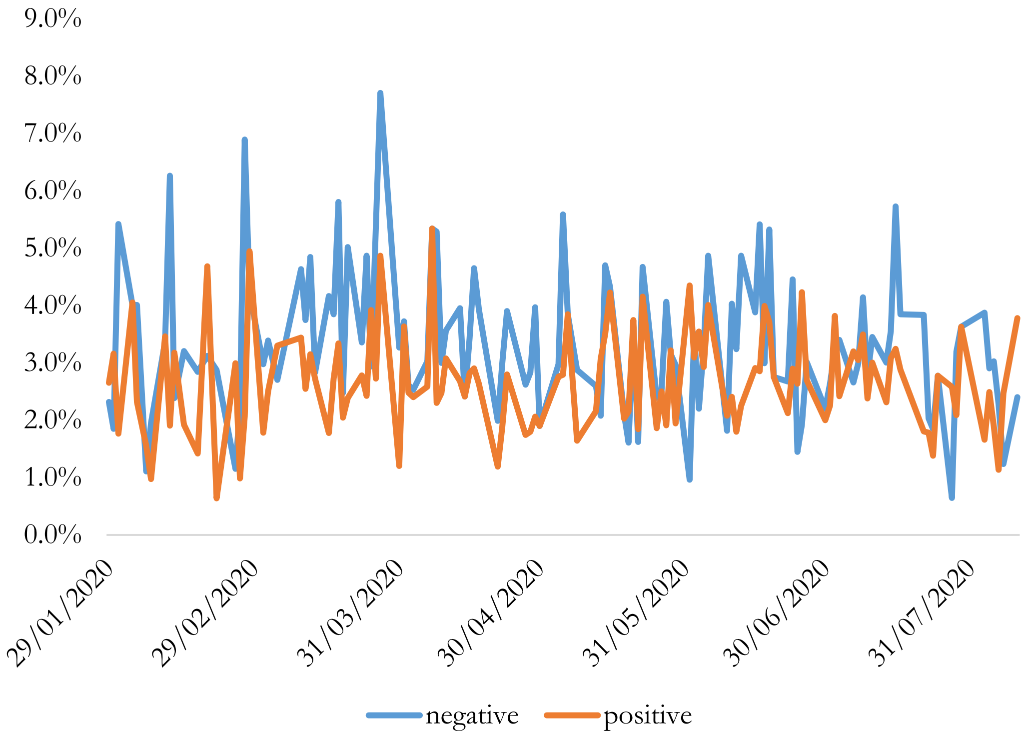
Since the topic of the news is the exchange rate, some words might have the opposite meaning. For example, "fall" or "decline" may be a positive word in case of UAH/USD exchange rate. Therefore, the following words were excluded from the sample: "fall", "fell", "decline", "falling", "fallen", "slowed", "cheap", "excessive", "increase", "positively" and "decrease".

Table 1: Descriptive statistics of shares of words in the news

Measure	Share of positive words	Share of negative words
Mean	0.026	0.041
Median	0.035	0.024
Standard deviation	0.0081	0.0122
Kurtosis	0.3928	-0.25467

Usually, newsmakers use 3.5% of negative, 2.4% of positive and 94.1% of a neutral word in the texts of news. Looking at the dynamics of using positive and negative words, we may affirm that negative vocabulary is more frequent in 86% of workdays. These frequencies are the input variables for the EGARCH model.

Figure 7: Dynamics of shares of positive and negative words in the news



Descriptive statistic of UAH/USD official exchange rate

During the study period, hryvnia devaluated by 8.5% from 24.72 to 26.82 UAH/USD. The line on figure 8 represents the official exchange rate published by the National Bank of Ukraine. Despite reasons of a rapid shift in March, such movement is associated with the higher number of news as it was discussed above.

Figure 8: Dynamics of UAH/USD exchange rate

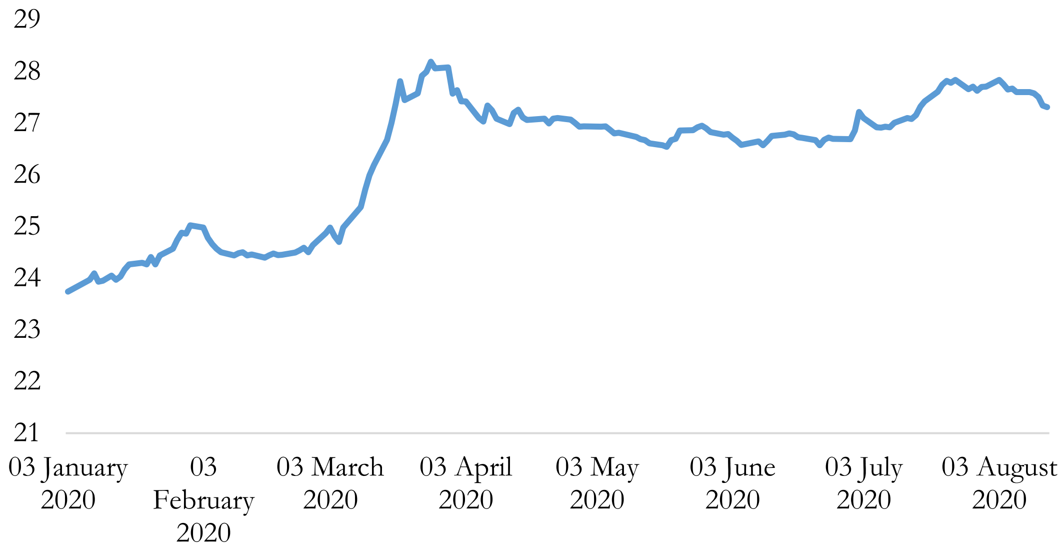
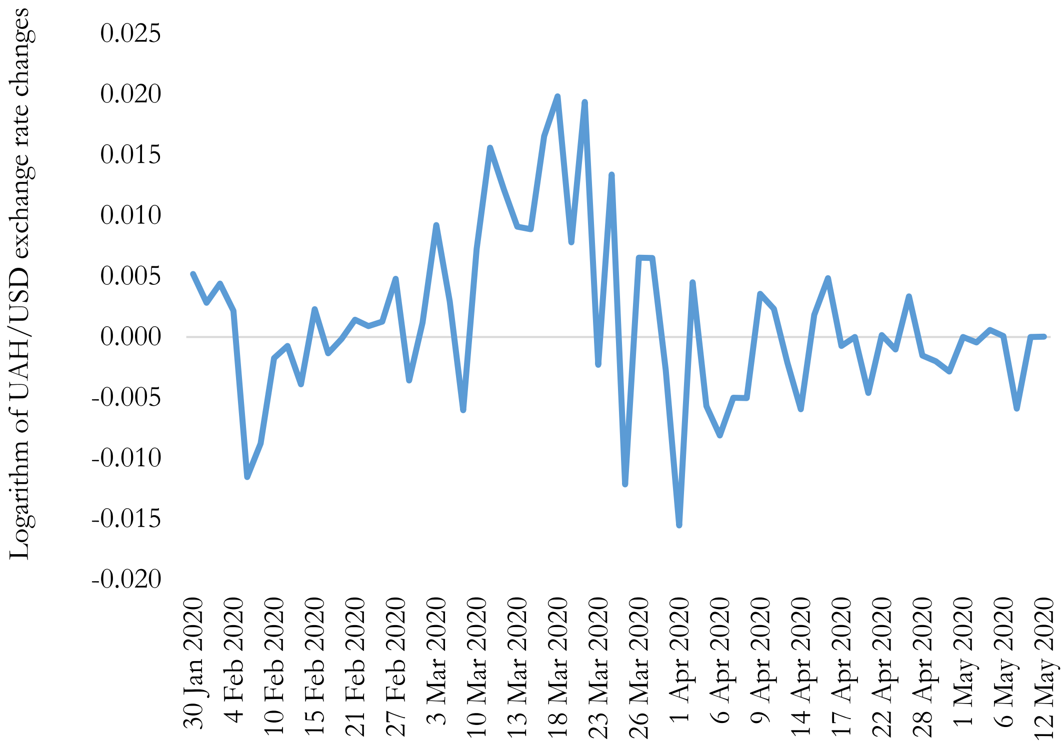


Table 2: Descriptive statistics of the natural logarithm of UAH/USD exchange rate changes

Measure	The logarithm of the exchange rate (daily term)	The logarithm of the exchange rate (annual term)
Mean	0.00127	0.32004
Median	0.00012	0.03024
Upper quartile	0.00231	0.58212
Lower quartile	-0.00118	-0.29736
Standard deviation	0.00694	0.11017

However, for the analysis, I would like to use changes in the exchange rate using the natural logarithm. This transformation makes data stationery and appropriate for ARMA model. Looking at figure 9, the average value is 0.32004 is higher than the median is 0.03024, meaning hryvnia devaluated not smoothly, but sharply with a few distinct outliers.

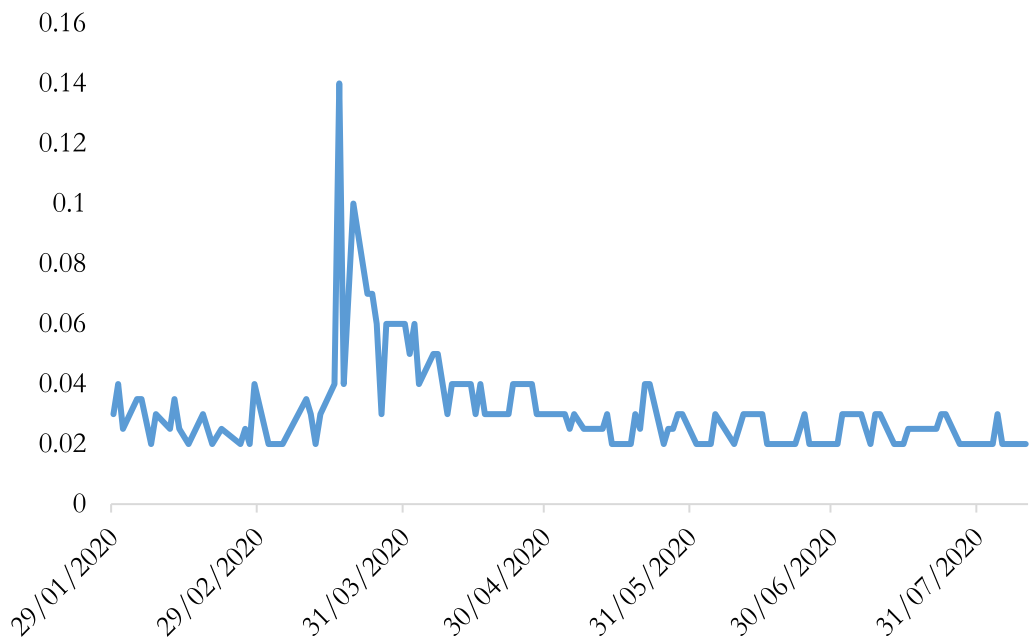
Figure 9: Dynamics of the natural logarithm of UAH/USD exchange rate changes



The magnitude of fluctuation shows the volatility in the market. Therefore, the measure will be an input variable for the ARMA model. However, the exchange rate shifted from 24.5 UAH/USD to 27 UAH/USD level during March. This movement affects modelling outcomes and may cause erroneous results. In order to eliminate this factor, we may impose a dummy variable for the period from March 6 till April 6.

Also, I would like to analyze the interbank bid-ask spread. The dynamics of the spread is presented in figure 10. From the graph, we observe the period of high volatility during March, which is in line with general currency devaluation.

Figure 10: Dynamics of the interbank bid-ask spread of UAH/USD exchange rate



However, the period of hight interbank bid-ask spread has not to affect significantly on the spread distribution. The mean and median values are close to each other (distance is 9% of a standard deviation).

Table 3: Descriptive statistics of the interbank bid-ask spread of UAH/USD

Measure	Interbank bid-ask spread of UAH/USD rate (daily term)
Mean	0.0314
Median	0.03
Upper quartile	0.02
Lower quartile	0.0325
Standard deviation	0.0164

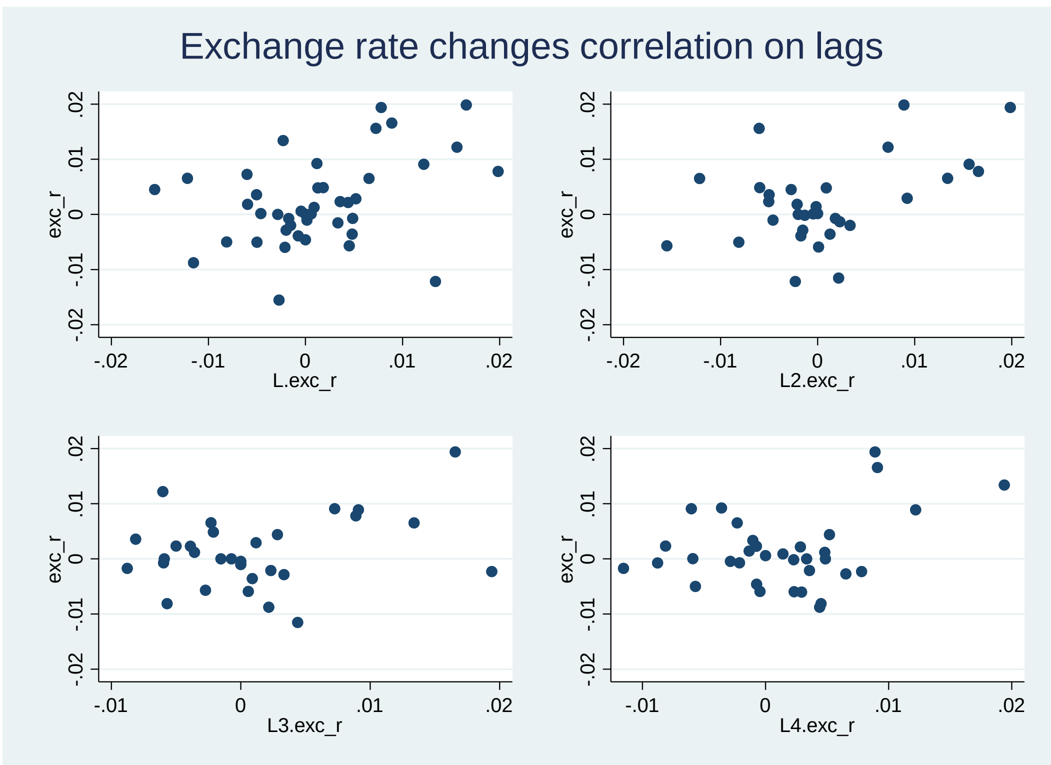
Summing up the preliminary data description, we may conclude the following statements:

1. News on the dataset are not concentrated on some individual newsmakers. Thus, they present different perspectives on the market.
2. The number of published news has not fluctuated significantly over the estimated period.
3. Negative words are prevailing in the Ukrainian news about exchange rate forecasting.
4. There is an exchange rate shifting during March, which affected an increase in both the exchange rate and interbank bid-ask spread volatilities.

Analysis of data stationarity

At the fists stage, we have to check the variable on stationarity. The validation of data stationarity is based on the combination of 3 analysis: (1) correlation with lags, (2) (partial) autocorrelation functions, (3) Dicky-Fuller test.

Figure 11: Correlations with lags of UAH/USD exchange rate changes



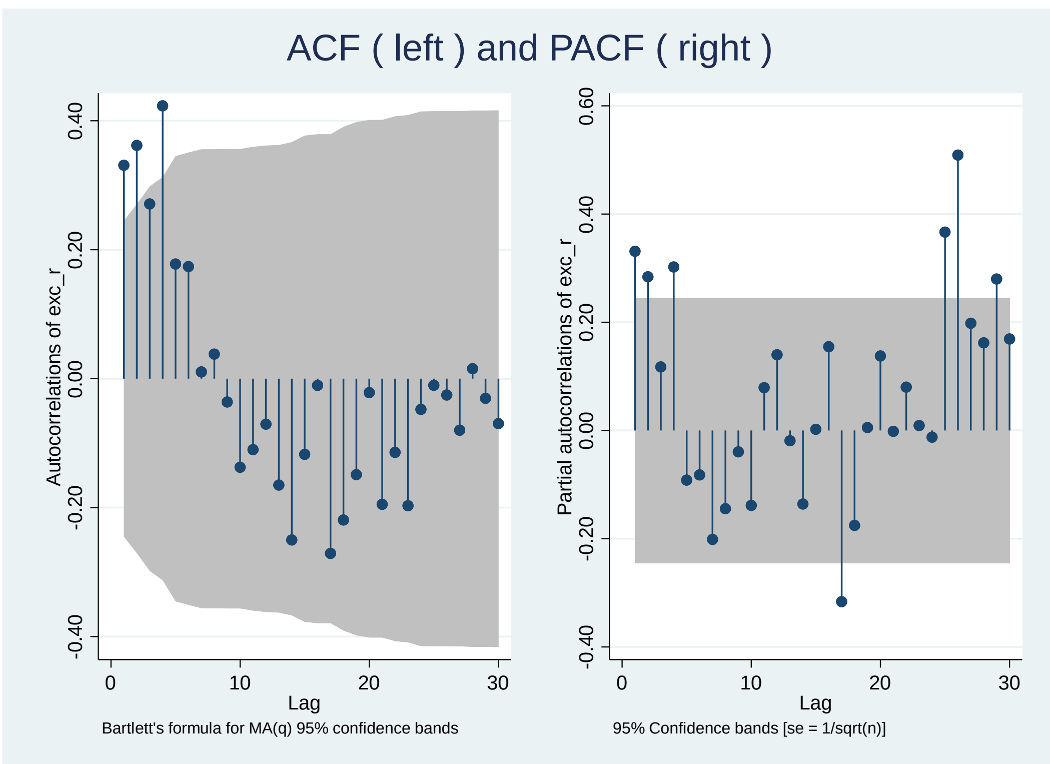
On the figure, ten correlograms with lags values are shown. There is a strong correlation with the first, second, third and fourth lagging values. On Table 1, correlation values are presented. From the table, we may conclude that none of the lag correlates greater than 0.5. Therefore, we may hypothesize that data is more likely to be stationary than nonstationary.

Table 4: A correlation matrix with lagging values

	exchange rate	lag 1	lag 2	lag 3	lag 4
exchange rate	1				
lag 1	0.3294	1			
lag 2	0.3602	0.3296	1		
lag 3	0.2747	0.3611	0.3306	1	
lag 4	0.4299	0.2749	0.3633	0.3314	1

Looking at ACF and PACF for exchange rate changes (figure 11), we observe seven values out of confidence interval at partial autocorrelation function and almost three values out of confidence interval at autocorrelation function, giving a sign of stationarity of the variable.

Figure 12: ACF and PACF for exchange rate changes



Dicky-Fuller test was conducted on four lags, shows by varcos test. Based on the Dicky-Fuller test, we reject a null hypothesis, meaning the data is stationary at a 95% confidence interval.

Table 5: Outputs of the Dickey-Fuller test

exchange rate	Coefficient	Standard error	t value	p > |t|	95% confidence interval	
constant	0.0004	0.0001	3.64	0.000	0.0002	0.0006
L1	-0.3484	0.0892	-3.90	0.000	-0.5251	-0.1716
LD	-0.3215	0.0886	-3.63	0.000	-0.4971	-0.1459
Number of observations 117 Test statistic -3.904 1% critical value -3.504 5% critical value -2.889 10% critical value -2.579 MacKinnon approximate p-value for Z(t) = 0.002						

Summing up, based on these three analyses conducted above, the variable is stationary. Therefore, we may proceed with the ARMA model. Also, there are no weekdays seasonality or trend in the variable; therefore, we may proceed without deseasoning and detrending.

ARMA model

Based on the ACF and PACF depicted in figure 11, the model should include 1 or 2 MA and 1 or 2 AR processes. In order to select the model, Akaike's information criterion and Bayesian information criterion and significance of coefficient are taken into account. In table 2, seven different ARMA specification are considered.

Table 6: Comparison of the ARMA model specification

Model	Akaike's information criterion	Bayesian information criterion	All coefficients are significant at a 95% confidence interval
ARMA(1,0)	-321.1239	-322.3425	Yes
ARMA(0,1)	-356.3230	-352.5867	Yes
ARMA(1,1)	-346.2342	-340.5146	Yes
ARMA(2,0)	-460.5767	-454.1	Yes
ARMA(0,2)	-399.6531	-397.526	Yes
ARMA(2,1)	-446.4873	-440.0579	Yes
ARMA(1,2)	-389.003	-384.7488	Yes

Therefore, we select the ARMA (1,0) model for further analysis. Also, the residuals were examined on being white noise. ACF and PACF have only one value out of confidence interval, while White test shows that values are white noise. Relying on these two analyses, we may conclude that residuals are white noise at a 95% confidence interval. Meaning the ARMA specification is plausible for further analysis.

EGARCH model

For EGARCH model squared, terms from the ARMA model were collected and checked by ACF, PACF and White test on validity for the model. The selection of EGARCH specification is based on the maximum value of the maximum likelihood function. Following this approach, the EGARCH model with one lag was selected. Based on the model output in the tables below, the model has one significant EGARCH, and ARCH lags.

Table 7: EGARCH model output (with log change of exchange rate)

exchange rate	Coefficient	Standard error	z value	p > |z|	95% confidence interval	
constant	0.0000	0.0000	0.06	0.794	0.0000	0.0001
L1	-0.6145	0.0303	-20.27	0.000	-0.6739	0.5551
positive words	-22.9572	12.7469	-1.80	0.072	-47.9407	2.0262
negative words	80.9108	10.3154	7.84	0.000	60.693	101.1286
constant from external variables	-16.65	0.5537	-30.07	0.000	-17.7353	-15.5648
Number of observations 117 Log-likelihood 684.1367						

The next step in the analysis is to construct a model with the bid-ask spread of the exchange rate on the interbank market.

Table 8: EGARCH model output (bid-ask interbank change of exchange rate)

exchange rate	Coefficient	Standard error	z value	p > |z|	95% confidence interval	
constant	0.0030	0.0011	0.27	0.789	-0.0019	0.0025
L1	-0.6138	0.02932	-20.93	0.000	-0.6713	-0.5563
positive words	-23.6659	12.4372	-1.90	0.057	-48.0423	0.7105
negative words	83.6984	10.4046	8.04	0.000	63.3058	104.0912
constant from external variables	-10.1498	0.5553	-18.28	0.000	-11.2383	-9.0614
Number of observations 117 Log-likelihood 299.4785						

From the output of the models above we may conclude that despite dependent variable selection both models lead us to the same conclusion: frequency of the positive words on the news have a marginal effect on the exchange rate volatility, while the frequency of the negative words causes an increase in the volatility.

Addressing the March high values of the dependent variable, I have constructed the model with a dummy variable for the period. The output is presented on the table below.

Table 9: EGARCH model output with dummy variable (bid-ask interbank change of exchange rate)

exchange rate	Coefficient	Standard error	z value	p > |z|	95% confidence interval	
constant	0.0000	0.0000	-0.05	0.963	0.0000	0.0000
L1	-0.704	0.0671	-10.41	0.000	-0.8365	-0.5715
positive words	17.7208	17.4184	1.02	0.309	-16.4186	51.8602
negative words	30.1503	12.9364	2.33	0.020	4.7955	55.5051
dummy	3.1123	2.3316	1.38	0.261	-1.4483	7.7156
constant from external variables	-17.3517	-0.606	-28.63	0.000	-18.5395	-16.1638
Number of observations 117 Log-likelihood 733.8207						

Therefore, the period of the exchange rate shifting does not drive the result of the model and does not lead to change the previous conclusions. Also, we may put into a model the average values of the independent variables to estimate the magnitude of the effect. Putting the average values of the independent variables into the models above we may conclude that shares of the negative words explain about 16-20% of the exchange rate volatility into the news.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

In the research, we have investigated the effect of the news on the volatility of the exchange rate volatility. Two primary data sources for the analysis were used: (1) exchange rate of UAH/USD as a bid-offer spread on the daily interbank market and (2) web-scraped Google news on the search request "hryvnia exchange rate forecast". The studied period includes all working days within January 29, 2020, and August 12, 2020. The critical question to test was "does the frequency of the emotionally loaded word in the news affect the volatility?".

Considering the news analysis, we find out that Google news could be the appropriate data source of diversified news. Especially for countries with limited news from international newsmakers (Blomberg, Reuters). Looking at the dynamics of the news publishing, we observed the correlation between the intensity of news publishing and volatility of the exchange rate changes.

From the sentiment analysis, we conclude that negative words are more frequent presented at the expert's forecasting news than positive words. Therefore, the share of the negative word in the news is not correlated with the exchange rate fluctuation.

The analysis of the changes in the exchange rate volatility has shown that hryvnia is more likely to change sharply then smoothly. Following the conducted analysis, we may conclude the following:

1. Positive words in the news have not to effect on the fluctuation of the exchange rate. Even though the coefficient is significant, the value is almost negligible. Therefore, we may conclude on the weak positive effect of positive words in the news on the volatility of UAH/USD exchange rate volatility.
2. Negative words do not affect the volatility of UAH/USD exchange rate, and explains about 16-20% of the exchange rate volatility.

Therefore, we may formulate the recommendations for businesses with frequent daily transactions with currency:

1. Do not take into account news with positive words as a primary key to the exchange rate fluctuation determinant.
2. React to the negative news as one of the factors of the possible increase in the exchange rate volatility.

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