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ARE ALL TEXT NEWS JUST A NOISE FOR INVESTORS? IMPACT OF ONLINE TEXTS ON BITCOIN RETURNS

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Abstract: The paper demonstrates the power of alternative data. Relying on the indicators obtained by mining online publicly available news articles, authors analyze their impact on Bitcoin returns. This research shows that in the first quarter of 2022 Bitcoin returns could be explained by the sentiment of information obtained from news published on online portals. However, we find negative relation between Bitcoin news sentiment and its returns. Such result can be explained as anomaly of researched period which is characterized by inception of global political crisis caused by the war in Eastern Europe and turmoil on crypto market. Our research also confirms that the news about Ethereum, Bitcoins' investment substitute, affected Bitcoin's returns as well. On the other hand, the obtained results show that there is no relation between the lexical readability of the news (i.e., the clarity with which the text is written, measured by the fog index) and the returns on Bitcoin in the analyzed period. Collected evidences speak in favor of Bitcoin's market inefficiency. In this paper we also demonstrate that returns forecasts based on online news are more accurate in comparison to those generated by ARMA-GARCH model, a conventional financial tool for predicting returns.

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1. Introduction

Development of modern technology brought an entirely new category of useful data that did not exist before. Common name for all data obtained from non-traditional sources (such as: satellites, mobile phones, various cards, social networks, etc.) is *alternative data*. This paper relies on an alternative data source – publicly available news from internet portals. We employ collected news to analyze their impact on the movement of Bitcoin returns and their predictive power. By doing so, we also examine the applicative power of online news articles as alternative data source in financial researches.

When it comes to impact analysis, we extract three potential returns predictors from collected news utilizing our own text mining algorithm. Goal of our analysis is to check whether any of the three extracted predictors can explain Bitcoins returns in the first quarter of 2022. First analyzed predictor is the investors sentiment estimated from the text of Bitcoin news. One should bear in mind that cryptocurrencies don't possess some intrinsic value and they aren't backed by any collateral nor government guarantee. Under these circumstances investors sentiment could have strong impact on Bitcoin's value, and, consequently on its returns. Introduction of the second predator is inspired by one of the basic postulates of microeconomic theory. It is well-known fact that the value of an asset can be affected by market's opinion on its substitutes. We address this phenomenon by extracting the sentiment of articles about Ethereum as the second potential predictor. We have picked Ethereum since it is the second largest cryptocurrency (by both market capitalization and the number of users). As the last predictor, we use level of Bitcoin news articles' readability. This might be an important predictor since a partial or incomplete understanding of text can have an unpredictable effect on the behavior of investors and other members of interested public.

Results of impact analysis will show whether news published through online portals affect Bitcoin's returns in the observed period. In this way, we indirectly examine the cryptocurrency market efficiency. According to Fama (1963, 1965), the market is considered efficient if the prices already incorporate all publicly available information, including those published through online portals. Consequently, the existence of a relation between Bitcoin's returns and textual indicators would speak in favor of cryptocurrency market inefficiency in the case of Bitcoin.

The period observed in this research includes the beginnings of the Russian-Ukrainian crisis. The crisis initiated the negative phase of the business cycle in global economy and, at the same time, shocked cryptocurrency market. This is the first time in history that we have global crisis and the crisis on cryptocurrency market at the same time. As documented in Sarkodie et al. (2022), COVID19 pandemics spurred cryptocurrency market which at that time experienced one of its biggest market booms. Therefore, the impact analysis of textual news sentiment on cryptocurrency returns in such crisis conditions is still an underexplored field which we would like to enlighten.

Secondary aim of this research is to examine the predictive power of news articles. Based on conducted impact analysis, we select only those predictors whose impact on Bitcoin returns is proven to be significant. Identified significant predictors are then used to train an ensemble algorithm for predicting future Bitcoin returns. Algorithm's predictive power is judged based on benchmark analysis. As benchmark we have used predictions obtained via ARMA(p,q)-GARCH(m,s) model. We chose it as a benchmark since it is a conventional financial tool for prediction of financial assets' returns. In this way we directly compare predictive power of alternative and traditional data sources.

Technically, we organize this research as a three step procedure. The first of the three steps represents the preparation of the research. It includes data collection and estimation of sentiment weights for all words according to Jegadeesh and Wu (2019) methodology. At the end of the first step we are able to measure sentiment of any text, since we possess sentiment of each word.

In the second step, from collected news we compute the three discussed potential predictors of Bitcoin returns. They are: sentiment of Bitcoin news, their readability and sentiment of Ethereum news. Goal of this step is to determine which of these predictors were relevant for explanation of the Bitcoin returns in the first quarter of 2022. Predictor's significance is examined through a regression model. We regress Bitcoin returns on a constant, on their previous value and on three news-based predictors whose significance we examine. Predictor's impact on Bitcoin returns is analyzed through-out estimated regression parameters. At the same time, discuss implications of our results on Bitcoin's market efficiency.

The third and the final step is reserved for analysis of news articles predictive power. Based on the results from previous step we train an ensemble algorithm for Bitcoin returns prediction (described in section 5.3.2). Simultaneously, we estimate appropriate specification of ARMA(p,q)-GARCH(m,s) model. Both tools are then used to predict Bitcoin returns. Quality of obtained predictions is compared by Diebold-Mariano's test. Assuming that news-based predictors should provide us with more accurate estimates of future Bitcoin returns, we test whether prediction errors are smaller in case of ensemble model.

Thematically, this paper consists of 6 sections. The first section is introductory. In the second section we give literature review. In the third section data sources will be discussed. The methodology will be presented in the fourth section. Finally, the fifth section will present the final results, while the sixth section will give the closing remarks.

2. Literature review

The most interesting application of text mining related to cryptocurrencies is the work of Sapkota & Grobys (2023). Authors analyzed the sentiment of the content of so-called whitepapers. Their research showed that the success of whitepaper's content to raise optimism among investors, remove their fears and explain them the functioning of a given cryptocurrency is an important factor for success in raising funds during the initial public offering. In contrast, the existing literature is flooded with examples in which sentiment is assessed from posts on social networks, primarily Twitter. This phenomenon can be simply explained by the fact that texts for analysis can be easily found on social networks. This approach was chosen by Mai et al. (2015) in the case of Bitcoin, Kraaijeveld & De Smedt (2020) in the case of Ethereum, Şaşmaz and Tek (2021) in the case of Neo, as well as many others. Incomparably fewer papers assess investor sentiment in cryptocurrencies from the news. Among them, two approaches are distinguished. According to the first approach, the impact of general (i.e. macroeconomic) news is analyzed. Such news is more common and therefore more accessible to researchers than news closely related to individual cryptocurrencies. However, their predictive power is much weaker. Corbett et al. (2020) showed that only news about unemployment and the durables' production have a negative effect on the movement of Bitcoin (they stimulate investors to invest in other forms of financial assets). In the case of news about other macroeconomic variables, no statistically significant relationship was found. A similar result was obtained by Entrop et al. (2020), showing that macroeconomic news has no influence on the movement of Bitcoin futures.

The second approach involves the analysis of news about the cryptocurrencies themselves. This news is more specific and mostly transmitted by portals that are dominantly oriented towards cryptocurrencies. In order to get to the texts, it is often necessary for the researcher to have a good prior knowledge about relevant media as well as knowledge on programming techniques for downloading online content. In addition, this approach offers fewer texts on a daily basis than a social network-based approach. Finally, researches based on social networks are more attractive because of the popularity that social networks themselves enjoy today. These are all reasons why research based on texts from online portals is less numerous. Regardless, the usability of texts from online portals is extremely high, as evidenced by the dispersion of their applications. Lmon et al. (2017), Vo et al. (2019) and Anamika (2022) analyzed cryptocurrency returns regarding news sentiment. Bernardi et al. (2017) showed that Value at Risk can be more accurately estimated if news sentiment is taken into account. Analyzing the volatility of Bitcoin, Cankaya et al. (2019) and Shapkota (2022) came to the conclusion that the risk can be more precisely assessed when the sentiment of the news is taken into account. An interesting research with a specific idea was conducted by Rognone et al. (2020). The authors tried to answer whether cryptocurrencies behave more like a means of payment (i.e. fiat currencies) or like financial assets (instruments from the financial market). The authors looked at the volatility and returns of cryptocurrencies and their reactions to text news by comparing them to those of foreign exchange rates and common stocks. The results showed that cryptocurrencies currently behave more like financial assets than as means of payment.

According to the market efficiency hypothesis, developed independently by Samuelson (1965) and Fama (1963, 1965), the market is efficient if prices reflect all available information. Consequently, price movements must be unpredictable (i.e. can be described as a random walk). In other words, no technical and fundamental indicators could predict future price changes. In light of the new evidence that the literature has provided, we must ask whether financial markets are really efficient. In the last thirty years, there have been papers that claim that prices do not follow a random course, and that they are predictable to a certain extent and in a certain period (Lo and McKinley 1988, Butler & Malaika 1992, Kavussanos & Dockery 2001, Gallagher & Taylor 2002, Qian & Rashid 2007 and others). In addition to the above, the success of certain market actors in achieving abnormal profits also suggests that markets are not as efficient as considered in the conventional literature. This led certain authors such as De Long et al. (1990) or Barberis et al. (1998) to develop new models of the financial economy. The authors relax the assumption of rational investors and allow a number of actors in the economy to be driven by current sentiment. This type of investor does not make decisions rationally but trades according to his current attitudes, moods and emotions. This creates a herd effect that puts pressure on the price so that it can deviate from the fundamental value in the short term. Due to the persistence of pressures in the short term, but also due to other limiting factors, the price correction will not occur immediately, as suggested by the market efficiency hypothesis. De Long et al. (1990) conclude that the price is influenced by two groups of factors: fundamental factors and market attitudes, i.e. investor sentiment. Consequently, the market behaves inefficiently in the short term in which it is possible to predict price changes. Additional argumentation was provided by Le Baron et al. (1999) which defined algorithm based on artificial intelligence which simulates market described by De Long et al. (1990). One explanation of this phenomenon was offered by Gidofalvi & Elkan (2003). The authors advocate the theory of the twenty-minute window of opportunity, in which trading based on sentiment is possible and profitable. Such results have led a number of researchers who deal with sentiment analysis to look at the validity of the hypothesis about market efficiency in modern conditions as part of their research. Their conclusions were based on attempts to predict the movement of returns based on sentiment, on checking the significance of the relationship between these two quantities, or on causality tests. Authors including Bollen et al. (2011), Schumaker et al. (2012), Qasem et al. (2015) presented results suggesting that the analyzed financial markets are not efficient in the short term, while the same conclusion was reached by Vo et al. (2019) and Kraaijeveld & De Smedt (2020) for cryptocurrency markets. In contrast to them, Reno (2020) failed to make satisfactory returns predictions based on sentiment, and points out that his results speak in favor of full market efficiency. The presented evidence suggests that instead of the classical hypothesis about market efficiency, it is more appropriate to talk about the so-called alternative hypothesis about market efficiency established by Lo (2004). According to this hypothesis, in modern conditions markets are not permanently efficient, but they are adaptive and competitive. The level of their effectiveness will depend on changes in the environment, the investor population and their attitudes. For this reason, in modern conditions there are periods when the market behaves efficiently, as well as those in which it behaves inefficiently. Therefore, the adaptive market efficiency hypothesis allows rationality and behaviorism to co-exist which is perhaps a good framework to describe the cryptocurrency market.

Two factor primarily distinguish our work from the present literature. Firstly, we examine news impact on Bitcoin returns, its consequences on efficiency of Bitcoin's market and predictiveness of Bitcoin returns in very specific time period. Observed period is characterized by simultaneous global economic crisis (i.e. beginning of negative sequence in global business cycle) and crisis on crypto market. Such circumstances are significantly different from those in period of COVID19 pandemics and our research aims to shed more light on them. Secondly, in our research we include impact of Ethereum sentiment on Bitcoin returns. To the best of our knowledge this is the first attempt in existing literature to analyze impact which investors' sentiment about asset's substitute (i.e. competing alternative investment) has on asset's returns. Besides that, our research contributes to better understanding of Bitcoin, discussion on efficiency of modern markets and applicative power alternative data.

3. Data sources

For the purposes of this research, over 20,000 texts written in English about the cryptocurrencies Bitcoin and Ethereum were downloaded. Downloaded texts were published in the period 01.01.2021. – 22.03.2022. on the *cryptonews.net* portal. Texts were download automatically via web scrapping algorithm designed by authors. Algorithm accesses English version of *cryptonews.net* website. From its text database it searches for texts about Bitcoin and Ethereum separately. In case of Bitcoin, algorithm artificially inserts keyword "Bitcoin" in website's search engine and runs the search. From search results algorithm retrieves only those webpages on which are stored texts published within the researched period. Finally, from each identified webpage algorithm will extract only article's text (without images, advertisements, links to other pages, other textual content which is not part of article etc.). The same procedure is repeated for keyword "Ethereum". As output we get all texts about Bitcoin and Ethereum published on *cryptonews.net* in researched period.

When it comes to returns, we exploit well-known American online financial platform – *YahooFinance*!. From it, we download Bitcoin's daily prices within the researched period. Next, from obtained prices we compute logarithmic returns, r_t:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

where P_t is price on date t.

3.1. Why CryptoNews.net?

Portal *cryptonews.net* is news aggregator. It publishes the most important news (for each cryptocurrency separately) taken in full from other relevant sources. Each day portal's international and multicultural team of experts manually tracks over 300 sources[1] of news in the field of cryptocurrencies, blockchain and FinTech[2]. News articles are selected in such a way that they cover breadth variety of topics. The "something for everyone" approach made it possible for all members of the interested public, regardless of their goals, to be informed in the same place. Topics such as: innovation in the technology that accompanies the mining process, stock exchange events, technical analyzes of price movements, the use of cryptocurrencies in practice around the world, gossip and discussions related to the debate "for and against" cryptocurrencies, etc., are just a part of what *cryptonews.net* offers. These are the reasons why platform is considered as a well-diversified, unbiased and relevant source of information.

Another important issue is portal's popularity. Popularity is proof that published news will reach general public. *CryptoNews* has set the goal of being the best and the most comprehensive digital means of informing for the public interested in cryptocurrencies around the world[3]. Such highly set goals, availability of the portal in the form of smartphone application and its translation of published texts into four world languages contributed to the portal gaining a large population of readers all over the planet. Besides that, a special contribution to the popularity of the portal is given by the breadth of topics covered by the portal, as well as by popularity of its sources.

Additional benefit of using news aggregator is that analysis is more efficient. Researches get news from diversified sources by defining just one web scrapping algorithm.

4. Methodology

In this section we briefly present all the necessary inputs for empirical analyses which are carried out in the next chapter. Each methodological concept is presented in separate subsections.

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[1] Among monitored sources are some of worldwide famous platforms like: *NewsBTC*, *CryptoGlobe*, *CoinGecko*, *CoinTelegraph*, *AMBCrypto*, *Forbes*, *TheBlock*, *U.Today*, *CoinGape*, *CryptoDaily*, *CoinDesk* and many others.

[2] According to editors: *https://cryptonews.net/about-app/*

[3] According to portals craters: *https://cryptonews.net/about/*

4.1. Text mining

Text mining is the process of transforming unstructured text into a structured format from which important information and insights can be obtained through further analysis. Text mining is a relatively young procedure for which still there are not many developed standards. For this reason, many researches had to design their own text mining algorithms relying on resources available in different programming languages (e.g. Schumaker et al. 2012, Mai et al. 2015, Şaşmaz and Tek 2021, Sapkota 2022 etc.). The same is done in this research. Here we list some of the operations that the mentioned algorithm performs:

- recognizes and removes links, addresses, tags, proper names, dates, unsuccessfully removed remnants of HTML code when downloading text, emoticons, etc.;
- replace abbreviations and acronyms with the words behind them;
- removes parts of the text that are not written in English;
- connects Latin phrases and expressions with their closest synonyms in English;
- recognizes numerical values that represent monetary amounts;
- takes care of semi-compounds that cannot be treated as two separate words;
- takes care of capitalization, cleans identified words of redundant symbols and takes other steps to perform lemmatization correctly;
- carries out lemmatization (i.e., transform each word found in text to its basic form) by combining already existing functions implemented in Python with the lexicon created by authors (which significantly reduces the possibility of errors during lemmatization and includes crypto neologisms);
- low-frequency words (those that appeared a small number of times in the entire oeuvre of about 20,000 downloaded texts) are combined with the closest synonyms in terms of meaning (which is also done through the previously mentioned lexicon created by authors);
- recognizes currency names, vulgarisms, written numbers and digits, etc.

As a result of mining, each text will be transformed into a vector of concepts (words), on the basis of which further analyzes were carried out.

4.2 The Fog index

The message that the text carries, as well as the attitude and tone with which it is written, cannot influence the behavior of the readers if they are not clear to them. In other words, if the text is written in such a way that it is not understandable to the average reader, its effect will be small, inconsistent or even the opposite of what was expected. Here we do not talk about physical readability (which, for example, appears in case of illegible handwriting), our focus is on the lexical readability of the test. By lexical readability we mean the clarity with which the text is written. It is influenced by writing style, storytelling and explanation skills, word choice, sentence complexity, level of expertise and other aspects. Due to the influence that readability has on the understanding of the text (and therefore on the individual's decisions), techniques for readability measurement have been devised. Here we present one such measure – the fog index. This indicator was developed by Gunning (1952) for linguistic purposes. The basic premise of its construction is that texts containing long sentences with a lot of polysyllabic (or complex) words (words with more than two syllables) are not easy for the average person to read. In this regard, Gunning defines the fog index as follows:

$$FI = 0.4(ASL + PoCW) \tag{2}$$

where: *ASL* is the Average Sentence Length (calculated as the average number of words per sentence in the text), and *PoCW* is Proportion of Complex Words (i.e. share of polysyllabic words in the total number of words in the text).

The higher the value of the index, the more "fogy" the text is to the reader. Consequently, the messages it carries will not reach the reader in full. Readability is considered good if the value of this index is around 7 or less. On the other hand, if the value of this index is over 12, the text is difficult for the average person to understand. Understanding of such texts requires higher education and/or expertise in the given field.

In this research we use the Fog Index to check whether there is a relationship between confusingly or clearly written articles about Bitcoin from the previous period and the future movement of Bitcoin returns.

4.3 Jegadeesh and Wu's model for estimating sentiment weights

The conventional approach in evaluating the sentiment of a text involves classifying words (either through an a priori created lexicon, or through some of the techniques of machine learning and statistics) into positive, negative and neutral, after which a conclusion about sentiment would be reached by counting the words in each of these three categories of the text (i.e. whether the text is positive, negative or neutral). Examples of researches in which this approach is represented are numerous (among others: Tetlock 2007 or Feldman et al. 2010).

However, this classification of words implies that all words of the same type carry with them the same level of sentiment. In other words, it would mean that all positive words are equally positive, and that all negative words are equally negative. However, it is more likely that this is not the case. For example, the reader is left to (subjectively) compare the weight of the following negative words: "bankruptcy" and "debt", "kill" and "wound", "unbearable" and "unpleasant", etc. It is evident that the classification of words according to sentiment into 3 groups would be too rough. In this regard, the literature turns to text sentiment evaluation methods that recognize the difference in weights between words of the same type. One such model was offered by Jegadeesh and Wu (2019). The authors define sentiment as a weighted sum of the relative frequencies of each word in the text.

$$S_{i,t} = \sum_{j=1}^{J} w_j \frac{f_{i,j,t}}{a_{i,t}} = \sum_{j=1}^{J} w_j rf_{i,j,t} \tag{3}$$

where: $S_{i,t}$ is sentiment of i-th text ($1 \leq i \leq N$, where N is total number of downloaded texts) published on date t ($1 \leq t \leq T$, where T is last date in sample), w_j is sentiment weight[4] of j-th word ($1 \leq j \leq J$, where J is total number of unique words), $f_{i,j,t}$ absolute frequency of j-th word in i-th text published on date t, $a_{i,t}$ total number of words in i-th text published on date t, and $rf_{i,j,t}$ is relative frequency of j-th word in i-th text published on date t.

Jegadeesh and Wu started from the assumption that the sentiment of the texts affects the economic variables (more specifically, returns) about which the texts are written. Consequently, it is possible to estimate following regression equation:

$$r_t = \alpha + \beta S_{i,t} + \epsilon_{t,i} \tag{4}$$

where: alpha and beta are the regression parameters, r_t is return on the financial asset that the texts write about, and $\epsilon_{t,i}$ residuals.

Since the sentiment of the texts is not known a priori, Jegadeesh and Wu propose the following modification of equation (4):

$$\begin{aligned} r_t &= \alpha + \beta \left(\sum_{j=1}^{J} w_j rf_{i,j,t} \right) + \epsilon_{t,i} = \alpha + \sum_{j=1}^{J} \beta w_j rf_{i,j,t} + \epsilon_{t,i} = \\ &= \alpha + \sum_{j=1}^{J} B_j rf_{i,j,t} + \epsilon_{t,i} \end{aligned} \tag{5}$$

where $B_j = \beta w_j$ are sentiment weights containing measurement error equal to the impact of sentiment on returns, i.e. parameter β.

Jegadeesh and Wu proposed that instead of the true values of the weights, i.e. w_j, the weights measured with error, B_j, should be estimated using equation (5) as the classic multiple linear regression model. However, in order to clean up the error, the authors propose standardization of the estimated parameters:

[4] *Sentiment weight* is the original name that Jegadeesh and Wu used for level of sentiment for each word. They can be both positive and negative, and they don't have to sum up to 1 (for more details see Jegadeesh and Wu 2019).

$$z_j = \frac{B_j - \bar{B}}{std(B_j)} \tag{6}$$

As a consequence of the noise in the data, one can often obtain the estimates of some small number of standardized weights, z_j, which are too extreme values. In order to exclude the effect of that noise from further analysis, Jegadeesh and Wu proposed Winsorization of estimates. Winsorization is a statistical technique for increasing the precision of estimates by replacing extreme values from either ends of the sample with some value that the researcher considers adequate. For the purposes of this paper, all standardized weights whose absolute value is greater than 3 will be winsorised.

4.4 ARMA-GARCH

Financial time series are conventionally modeled by ARMA-GARCH system of equations, since it provides good theoretical framework for some empirically observed properties. System assumes that returns are characterized by inertia in their movement (autoregression component), "limited memory" of shocks from the past (moving average component) and conditional heteroskedasticity. The first equation in the model describes returns, while the second equation describes their conditional variance. The general form of the model is given by equations (7.1) and (7.2):

$$r_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i} + e_t - \sum_{j=1}^{q} \theta_j e_{t-j} \tag{7.1}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i e_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \tag{7.2}$$

where: ϕ_i is the autoregression parameter at the i-th lag ($1 \leq i \leq p$, where p is the last included autoregression lag), θ_j is the moving average parameter at the j-th lag ($1 \leq j \leq q$, where q is the last included moving average lag), e_t is a series of random errors ($1 \leq t \leq T$, where T is the last date in sample), r_t is an analyzed time series of returns at time t, σ_t^2 is the conditional variance at time t, while α_i ($1 \leq i \leq m$, where m is the last included lag of volatility shocks) and β_j ($1 \leq j \leq s$, where s is the last included volatility autoregressive lag) are the parameters of the second equation.

The maximum likelihood method with numerical optimization is used for estimation of the ARMA-GARCH model, since parameters of both equations need to be estimated simultaneously and the objective function is highly nonlinear.

4.5 Forecast quality checking

Modern statistics offer several indicators that monitor the quality of the forecast. Measure particularly popular in the field of machine learning is the root mean square error of the forecast (RMSE). This indicator is defined as follows:

$$RMSE = \sqrt{\frac{1}{g}\sum_{t=1}^{g}\left(r_{T+t} - \hat{r}_T(t)\right)^2} \qquad (8)$$

where: g is the total number of periods for which we make a forecast, T is the last period included in the modeling sample, r_{T+t} is the true value of the analyzed variable at time $T+t$ and $\hat{r}_T(t)$ is the value predicted by the model at time $T+t$.

Bear in mind that RMSE represents just a point estimate of the forecast quality. It is often necessary to use a statistical test to check whether one model gives more accurate forecast than another. For these purposes, we use the Diebold-Mariano test. The testing procedure begins by defining a new time series given by expression (9):

$$rg_t = \left(r_{T+t} - \hat{r}_{T\ I}(t)\right)^2 - \left(r_{T+t} - \hat{r}_{T\ II}(t)\right)^2 \qquad (9)$$

where: rg_t denotes the newly obtained time series which represents the difference between squared forecast errors of this two models at each point in time from forecasting sample, while the labels I and II denote respectively the first and second models that are compared by the test. The test examines the validity of the following hypotheses:

$$H_0: E(rg)=0$$

$$H_1: E(rg)\neq 0$$

In order to examine the validity of the previously stated hypotheses, a regression in which the differences between squared forecast errors are regressed only on a constant is estimated. If the estimated constant is statistically significantly different from zero, one can conclude that there is a constant difference in the forecast quality of the two models in favor of one of them. Alternatively, if the estimated constant is not statistically significant, there is no difference in the forecast quality of the two models. The classic t-test is used for testing.

In case that test show that there is a statistically significant difference between predictions of two models, better performing model is determined based on sign of estimated constant. If constant is positive, from expression (9) it is clear that the second model outperforms the first since it yields lower forecasting errors. If the constant is negative conclusion is opposite.

Since in the Diebold-Mariano test analyzed time series is regressed only on a constant, there is a high probability that the estimated regression equation will be characterized by the presence of autocorrelation and/or heteroscedasticity. The presence of these two problems results in the standard errors bias. We overcome this problem by applying the Newey-West correction (see Newey and West 1987).

5. Modeling results

The research is divided into three stages. Within the first stage, sentiment weights were estimated according to the Jegadeesh and Wu methodology. Having sentiment of each word we are able to measure sentiment of any text. In the second stage, we compute three news-based potential predictors of Bitcoin returns: sentiment of Bitcoin news, their readability and sentiment of Ethereum. After that, we analyze impact which each of these predictor has on Bitcoin returns. In the third stage, we compare predictive power of news with conventional financial tools. Using only significant predictors, we construct an ensemble forecasting algorithm. Simultaneously, we estimate appropriate representation of the ARMA-GARCH model. Finally, the forecast errors of ARMA-GARCH model were compared with the forecast errors of the forecasting algorithm based on text analysis. Below we discuss each of the three stages separately.

5.1 The first stage – estimating sentiment weights

After texts are downloaded by web scrapping algorithm, the entire sample of texts and returns was divided into three subsamples. The first sub-sample consists of texts for training (that is, estimation) of the sentiment weights. This sub-sample includes texts and returns from the period 01.01.2021 – 31.12.2021. Based on this data, vectors of words are mined via algorithm described in section 4.1. Then, obtained vectors of words were transformed into mathematical (numerical) vectors of relative frequencies. Each numerical vector represents one text. Length (number of elements) of each such vector is equal to the total of J identified unique words (in this research J=5213). Each element of this vector represents the relative frequency of one unique word in that text. If we join all such vectors into a matrix we obtain matrix of quantified texts.

$$
\begin{array}{c c}
 & \begin{array}{cccc} text\ 1 & text\ 2 & \cdots & text\ N \end{array} \\
\begin{array}{c} word\ 1 \\ word\ 2 \\ \vdots \\ word\ J \end{array} & \begin{pmatrix} rf_{11} & rf_{12} & \cdots & rf_{1N} \\ rf_{21} & rf_{22} & \cdots & rf_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ rf_{J1} & rf_{J2} & \cdots & rf_{JN} \end{pmatrix}
\end{array}
\tag{10}
$$

From this matrix one has to remove two type of vectors: vectors of unsuccessfully downloaded texts (zero vectors) and vectors of duplicate texts. Otherwise the obtained matrix will be singular. Here we briefly discuss both problems. Unsuccessful downloading of texts occurs when, instead of the text, only a link which leads to some different portal is provided by *cryptonews.net*. This happens in cases when *cryptonews.net* do not obtain permission from text's original source to publish text on its webpage. The appearance of duplicates can occur for two reasons. The first reason is texts congruence. Namely, there are texts written about both considered currencies, Bitcoin and Ethereum, at the same time. For example, text can compare performances of these two currencies in past period. Second reason is the consequence of the human factor. In particular, the platform can accidentally publish two identical texts on the same day, at approximately the same time. The occurrence of these problems does not affect the outcome of this research for two reasons. First, both Bitcoin and Ethereum are cryptocurrencies with high frequencies of published articles in a single day (around 50), so by omitting one of them we do not lose generality. Second, mentioned two problems occur rarely, i.e. in very small number of cases (specifically, in this research, they have occurred in only 2.48% of cases).

When the two mentioned problems are eliminated, the final matrix of numerical vectors is obtained. The resulting vectors were used as regressors to estimate the equation given by expression (5). The obtained estimates of slope parameters were standardized according to formula (6). Finally, Winsorization was carried out. In this way, sentiment weighting scores, z_j, were obtained for each identified word. Table 1 presents some of the most negative and most positive words identified by the model:

Table 1: Overview of the most negative and most positive words identified by the model

The most positive words	assimilate	blond	buddy	cavalry	concise
The most negative words	abysmal	bed	brown	boo	medieval

5.2 The second stage – analysis of the texts' impact on returns

The second sub-sample aims to estimate a regression model based on which relevant predictors of Bitcoin returns will be identified and therefore their influence on returns analyzed. The potential predictors considered in this paper are: previous level of returns, sentiment of Bitcoin texts, sentiment of Ethereum texts and readability of Bitcoin texts. It is clear that each of the highlighted potential predictors can have an impact on the Bitcoin returns, and the aim of this subsection is to examine whether these impacts really existed during the analyzed period.

Such choice of potential predictors creates a problem of publication frequencies inconsistency. Free, publicly available returns data can be obtained once a day. Conversely, a large number of different articles on Bitcoin and Ethereum can be published within the same day. In addition, the number of published texts changes from day to day for both cryptocurrencies. Besides that, within the same day, the number of articles published about Bitcoin does not necessarily equal the number of articles published about Ethereum. This represents a specific form of MIDAS problem (*Mixed Data Sampling*) well-known in both statistical modeling and machine learning. In particular, what makes this form of MIDAS problem specific is the change in the number of published texts from day to day (i.e., the change in publication frequency). This paper will offer a simple solution for this problem which is suitable for machine learning. Before the aforementioned solution is presented, we put forward one additional hypothesis. We assume that the previous day events can affect what will happen today. With this hypothesis in mind, we proceed with the model setup. Each article about Bitcoin will be considered as one observation. This means that the total number of observations during the analyzed period is equal to the total number of texts (*N*) and can be represented as follows:

$$N = \sum_{t=1}^{T-1} n_t \tag{11}$$

where n_t is the total number of Bitcoin articles published on day *t*.

To each text we add the return that was achieved the day after the text was published. This means that the vector of *T* returns needs to be redefined into a vector of *N* returns, so that the return obtained on day *t* corresponds to every text published on the previous day. The new return vector is represented by expression (12).

$$r = \left.\begin{pmatrix} r_T \\ \vdots \\ r_T \\ r_T \\ \vdots \\ r_3 \\ \vdots \\ r_3 \\ r_3 \\ r_2 \\ \vdots \\ r_2 \\ r_2 \end{pmatrix} \begin{matrix} n_{T-1} \\ \vdots \\ 2 \\ 1 \\ \vdots \\ n_2 \\ \vdots \\ 2 \\ 1 \\ n_1 \\ \vdots \\ 2 \\ 1 \end{matrix}\right\} N \tag{12}$$

Additional problem arises in the case of texts about Ethereum. Besides the fact that publication frequencies of Ethereum and Bitcoin articles are not the same, they cannot even be uniquely linked. In other words, it cannot be determined which one out of the $n_{t,ETH}$ Ethereum texts published on day *t* should be paired with the i-th ($1 \leq i \leq n_t$) Bitcoin text published on the same day. In order to overcome this problem, the average level of Ethereum's articles sentiment on the observed day is calculated. In this way, we get a vector of T elements. Now, it is possible to unambiguously pair one element from the vector of Ethereums average sentiments to each of the N observations. The matching procedure will be almost the same as in the case of returns. The only modification is that we now take the average Ethereum sentiment on the same day as day on which observed Bitcoin text was published. The newly obtained vector is given by expression (13):

$$\mathrm{X}_{ETH} = \left.\begin{pmatrix} \bar{S}_{ETH,\mathrm{T}-1} \\ \vdots \\ \bar{S}_{ETH,\mathrm{T}-1} \\ \bar{S}_{ETH,\mathrm{T}-1} \\ \vdots \\ \bar{S}_{ETH,2} \\ \vdots \\ \bar{S}_{ETH,2} \\ \bar{S}_{ETH,2} \\ \bar{S}_{ETH,1} \\ \vdots \\ \bar{S}_{ETH,1} \\ \bar{S}_{ETH,1} \end{pmatrix} \begin{matrix} n_{T-1} \\ \vdots \\ 2 \\ 1 \\ \vdots \\ n_2 \\ \vdots \\ 2 \\ 1 \\ n_1 \\ \vdots \\ 2 \\ 1 \end{matrix}\right\} N \tag{13}$$

where $\bar{S}_{ETH,t}$ is the average sentiment level of the Ethereum texts on day t.

When it comes to the fog index we do not have the problem of mismatched frequencies. This indicator is calculated for each text about Bitcoin separately, so the number of calculated fog index values will be equal to the number of texts about Bitcoin (i.e., N), so it is not necessary to modify the obtained vector in any way.

The decision to bring down the frequencies of all variables in the model via adequate transformations to the frequency of texts about Bitcoin is guided by data maximization principle. In this way the model will have incomparably[5] more observations for training. In an alternative approach (i.e., in the case of bringing down the frequencies of all variables in the model to returns frequency), the lack of observations could be compensated by a significant expansion of the sample. However, such a decision runs into two problems. First, going back too far in the past decreases the relevance of the results. In case of sample expansion, estimates of relations between returns and predictors would be affected by values from a period significantly distant from the period of interest. Second, the popularity of cryptocurrencies in earlier periods was not at the level it is today. The public interested in this financial asset was a much smaller part of the general population,

[5] If we base model on returns frequency we will have one observation per day, while we have n_t per day when model is based on BTC news frequency.

and there were also fewer portals and texts related to cryptocurrencies. Therefore, the strength of the observed relations would not be the same.

Taking all of the above into account, we set up the following regression:

$$r_t = c + \beta_1 r_{t-1} + \beta_2 S_{BTC,i,t-1} + \beta_3 \bar{S}_{ETH,t-1} + \beta_4 FI_{i,t-1} + \varepsilon_{i,t} \quad (14)$$

where: $S_{BTC,i,t}$ is the sentiment of the i-th text about Bitcoin ($1 \leq i \leq n_t$) published on the t-th day ($1 \leq t \leq T$), $\bar{S}_{ETH,t}$ is the average sentiment of the Ethereum texts published on the t-th day, $FI_{i,t}$ is the fog index of the i-th Bitcoin text published on the t-th day.

Based on a sub-sample covering the period 01.01.2022. – 28.02.2022. model (14) was estimated. The result is given by expression (15). In parentheses below the model are p-values.

$$\underset{(0.0000)}{r_t = -0.0313} + \underset{(0.0000)}{0.1547 r_{t-1}} - \underset{(0.0906)}{0.0012 S_{BTC,i,t-1}} - \underset{(0.0000)}{0.0121 \bar{S}_{ETH,t-1}} + \underset{(0.9391)}{0.00003 FI_{i,t-1}} + \varepsilon_{i,t} \quad (15)$$

The obtained model suggests that the readability of texts measured by the fog index did not significantly determine the movement of Bitcoin returns in the observed period. For this reason, this variable will be omitted from further analysis. Nevertheless, texts fogginess deserves further analysis. It is important since the text clarity is a prerequisite that must be met in order for the sentiment of the texts to have a full impact on a reader. The average readability level for the entire sample of texts was 8.09, with an average deviation of ±2.77. On the other hand, the variation interval is very wide since the most legible text had the fog index level of 3.44 while the most illegible text had the fog level of 57.27. This spread clearly indicates the presence of outliers of unreadable texts. This is supported by the fact that the share of texts that are easily readable by an ordinary person (have a fog index below 7) is 36.44%, while the share of texts that are unreadable by an ordinary person (have a fog index above 12) is only 5.81%. We can conclude that the presented data indicate a decent readability of texts about Bitcoin at the level of the entire sample.

By removing the texts fogginess from equation (14), the final model was obtained and the relevant returns predictors were identified. They will be retained in the third stage of the research. The final model is given by expression (16):

$$\underset{(0.0000)}{r_t = -0.0310} + \underset{(0.0000)}{0.1547 r_{t-1}} - \underset{(0.0906)}{0.0011 S_{BTC,i,t-1}} - \underset{(0.0000)}{0.0121 \bar{S}_{ETH,t-1}} + \varepsilon_{i,t} \quad (16)$$

In the previous equation, an anomaly of the period covered by the research is easily visible. The relationship between Bitcoin returns and the sentiment of articles written about it was negative. Nevertheless, it is to be expected that positive news will have a positive impact on the returns, i.e. that there is a direct positive relationship between them. However, due to the beginning of the war in Eastern Europe and tightening of relations on the international stage, panic reigned among the public interested in cryptocurrencies. This have devastated the cryptocurrency market. Specifically, in the case of Bitcoin, this led to a large price drop. At the beginning of the observed period, Bitcoins price was approximately \$38,000, while at the end of this period it was approximately \$26,000. In such times of crisis, even positive news did not raise the morale of the market. On the contrary, they had small and the opposite effect. This might be anomaly of researched period caused by crisis inception. This relation is statistically significant (at a significance level of 10%). Results suggest that news sentiment can explain Bitcoin's returns, thus this information is not encompassed in prices. Similar result is obtained by Schumaker et al. (2012) in case of equity stocks. Authors also explained unexpected sign of this relation as anomaly of researched period.

The sign next to the average sentiment on the Ethereum texts was negative, as it was expected. Articles that spoke positively about the direct substitute further contributed to the decline in Bitcoin's value in the eyes of the market. Again, since Bitcoin prices react on information about its substitute (i.e. alternative investment option), we have additional argument in favor of Bitcoin's market inefficiency. Besides that, autoregressive parameter is highly significant, which also deviates the week form of efficient market hypothesis. All evidences speak in favor of Bitcoin's market inefficiency in researched period. Our results support findings from present literature. Consequently, it might be the case that Lo's adaptive market efficiency hypothesis is more appropriate framework for an analysis of cryptocurrencies.

5.3 Third stage – comparison of forecast errors

By identifying the relevant predictors of Bitcoins returns, the conditions for starting the third stage of the research were met. The goal of this stage will be to examine whether a model obtained from alternative data sources (more specifically, from text analysis) can produce a more accurate prediction of the future returns movements compared to predictions generated by conventional time series analysis. For these purposes, the last sub-sample covering the period 01.03.2022 – 22.03.2022 will be used. In the following text, we first present an estimated ARMA-GARCH model. Next we discuss the machine learning algorithm for forecasting returns based on text analysis. Finally, at the end we compare the forecast quality of these two approaches.

5.3.1. Estimated ARMA-GARCH model

Based on second sub-sample (01.01.2022 – 28.02.2022.), the GARCH model of Bitcoin's returns was estimated. The resulting return equation has the form of a reduced ARMA (0,7) model, while volatility was modeled with the most common specification in financial researches – GARCH(1,1). The results are represented by expressions (17.1) and (17.2):

$$r_t = \mathrm{e}_t + 0.212215e_{t-2} + 0.416986e_{t-5} + 0.322440e_{t-7} \qquad (17.1)$$

$$\begin{array}{c} (0.0416) \qquad (0.0000) \qquad (0.0097) \\ \sigma_t^2 = 0.000128 - 0.105843 e_{t-1}^2 + 0.985683 \sigma_{t-1}^2 \\ (0.0953) \qquad (0.0163) \qquad (0.0000) \end{array} \tag{17.2}$$

The resulting model was used to predict the future values of all returns in the third sub-sample on a one-day-ahead basis. More precisely, for each day t from the third sub-sample, the model would take the values realized in the previous 7 days as known (because the order of the largest lag in the model is 7), include them in equations (17.2) and (17.1) made a prediction of return for the observed day.

5.3.2. Prediction algorithm based on text analysis and machine learning

The following algorithm from ensemble family will be used to predict return on day t from the third sub-sample based on text analysis and machine learning:

1. In the first step, the algorithm selects all the texts that were published up to the two months before the day for which the prediction is made. This set of texts should not include those published on the previous day to the day for which predictions are made, since, according to equation (14), they determine the returns on the day for which the prediction is made.

2. Based on the selected texts, the model from equation (14) is estimated. In modelling were used only the predictors identified as significant in section 5.2 (i.e. constant, returns from the previous period and earlier sentiments of the texts about Bitcoin and Ethereum).

3. After that, we select all texts published on the omitted day, i.e. on the day preceding the day for which the prediction is made.

4. Suppose there were n_{t-1} articles about Bitcoin on the observed day. By inserting these observations into the estimated model from the second step of this algorithm, we will get n_{t-1} predictions of possible values of tomorrow's returns.

5. The final prediction of tomorrow's returns will be the arithmetic mean of all n_{t-1}predicted values.

6. After successfully made prediction, algorithm will start next prediction. For that, it is necessary to move the algorithm forward by 1 day, according to the principle of rolling windows, and repeat the entire procedure. The algorithm ends when the predictions for all days from the third subsample have been created.

It is to be expected that this approach will give more precise results since for each prediction new model is estimated and each prediction is obtained from the n_{t-1} potential predictions. Here we again point out that the period in which the predictors are examined and selected should not be too far from the period for which the predictions are made. The choice of the predictor should be revised upon a certain period of time, since set of predictors must reflect the relevant factors that determine the movement of returns around the period for which the forecast is made.

5.3.3. Comparing qualities of obtained forecasts

The estimated ARMA-GARCH model yielded predictions whose root mean square error of forecast was 0.028540. On the other hand, algorithm described in sub-section 5.3.2 made far smaller forecasting mistakes, since its RMSE was significantly lower, i.e. 0.018422. Although a more precise model can be easily determined based on this point estimates, an additional confirmation of this result is formal Diebold-Mariano test. For testing purposes, a new time series is defined. It represents the difference in squared forecast errors between the algorithm presented in section 5.3.2 and the ARMA-GARCH model presented in section 5.3.1. In anticipation that algorithm offers a more accurate prediction than APMA-GARCH model, test examines whether the constant in the regression described in Section 4.6 is negative and statistically significantly different from zero. The estimated value of constant from Diebold-Mariano's regression is -0.0015, and the associated p-value is 0.001. Thus, the Diebold-Mariano test confirms the initial assumption that the algorithm from section 5.3.2 is more accurate than the conventional model build upon traditional data.

6. Conclusion

Authors examined impact of news on Bitcoin returns and their predictive power in the first quarter of 2022. Research showed that Bitcoin prices can be explained by sentiment of publicly available information published in news from online portals. Besides news about Bitcoins, news about Ethereum, as Bitcoin's substitute and main rival, could also be used to explain movement of Bitcoins returns. Simultaneously, news readability failed to explain Bitcoin's returns in the observed period. Besides sentiment, autoregressive behavior could also explain Bitcoin's movements in researched period. Importantly, all relations were examined at the time of global crisis caused by war in Eastern Europe which has transmitted itself on crypto market as well. Our paper is one of pioneering researches in analysis of cryptocurrencies behavior at time of such dual crisis (turning point in global business cycles and crypto market turmoil). Our results are evidences of Bitcoin's market inefficiency. Consequently, the adaptive market efficiency proposed by Lo (2004) might be more appropriate framework for analysis of cryptocurrencies. Research also demonstrates that, using information retrieved from textual data, it is possible to build machine learning algorithm which predict Bitcoin's returns more accurately than classical econometrical tools. Quality of these forecasts are checked with formal statistical test. By doing so, this research makes a unique contribution to the popularity of alternative data sources, especially among Serbian public.

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DA LI SU SVE TEKSTUALNE VESTI SAMO ŠUM ZA INVESTITORE? – UTICAJ ONLAJN TEKSTOVA NA PRINOSE BITKOINA

Apstrakt: Rad demonstrira upotrebnu moć alternativnih izvora podataka. Oslanjajući se na indikatore dobijene rudarenjem onlajn javno dostupnih članaka, rad analizira njihov uticaj na prinose Bitkoina. Ovo istraživanje pokazuje da su u prvom kvartalu 2022. godine prinosi na Bitkoin mogli da se objasne sentimentom informacija dobijenih iz vesti sa onlajn portala. Međutim, pronašli smo da je veza između sentimenta vesti o Bitkoinu i njegovih prinosa negativna. Ovakav rezultat se može objasniti kao anomalija istraživanog perioda koji karakteriše začetak globalne političke krize izazvane ratom u Istočnoj Evropi i previranja na kripto-tržištu. Naše istraživanje takođe potvrđuje da su se i vesti o Iterumu, Bitkoinovoj investicionoj alternativi, odrazile na prinose Bitkoina. Sa druge strane, rad nije uspeo da pronađe vezu između leksičke čitljivosti tekstova (tj. jasnoće sa kojom je tekst napisan, što je mereno indeksom zamagljenosti) i prinosa na Bitkoin u analiziranom periodu. Prikupljeni dokazi govore u prilog postojanju neefikasnosti na tržištu Bitkoina. U ovom radu takođe demonstriramo da su prognoze budućih prinosa na bazi tekstualnih vesti preciznije od onih dobijenih ARMA-GARCH modelom, konvencionalnim alatom za predviđanje prinosa.

Ključne reči: Bitkoin, rudarenje teksta, predviđanje, analiza sentimenta, čitljivost, prinosi, kripto valute

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Aleksandar Damjanović was born in Pristina in 1996. In 2007, he moved to Belgrade, where he completed primary and secondary school, as well as the Faculty of Economics of the University of Belgrade (basic and master academic studies). During his undergraduate studies, he graduated from the study program for Statistics, Informatics and Quantitative Finance (statistics module), while within the framework of the International Master's Program for Quantitative Finance (English: International Master in Quantitative Finance - IMQF), he obtained his master's degree with the topic "Volatility Trading". During his undergraduate and master's academic studies, he stood out as the best student in his generation within his study program. Since September 2019, he was employed as a demonstrator at the Faculty of Economics in Belgrade, where he taught several statistical and financial subjects. From 2021, he works as an assistant at the Faculty of Computer Science, where he also teaches several subjects, while from 2022 he also teaches at the Banking Academy. At the time of writing, the dissertation was in the application process.

Mikica Drenovak has significant experience in financial research and teaching quantitative methods. He has published his research results in the world's leading academic journals for finance and operational research. He taught courses related to quantitative methods in finance at the Faculty of Economics, University of Kragujevac, HEC Faculty, University of Lausanne, Switzerland, and Faculty of Economics, University of Belgrade. He participated in several domestic and international research projects. For 10 years, he has been a reviewer of the Commission for Accreditation and Quality Control, Serbia, in charge of quality assurance assessment of higher education institutions and evaluation of study programs. He graduated in mathematics at the Faculty of Mathematics, University of Belgrade, master's degree in quantitative finance and PhD in economics at the Faculty of Economics, University of Belgrade.