1.Introduction

Since the advent of Bitcoin in 2009, public attention has been focused on the new technology. A large cluster of academic literature is devoted to analyzing the opportunities that Bitcoin opens up, - weather it is safe haven asset, a hedge, a diversifier, or just a speculative asset (Bouri et al. 2017, Klein et al. 2018). In this direction, many works have started to study the relationships between Bitcoin and other financial assets as well as the determinants of Bitcoin returns and volatility itself. Baur et al. (2021) and Klein et al. (2018) investigated Bitcoin and gold using the GARCH and correlation models but was unable to find any relationship. In contrast, Yi Zhang et al. (2023) and Urom et al. (2020) find the relation in statistical properties of two assets. Other works have studied the relationship of Bitcoin with other traditional assets, but the results of the work also varied. A particular interest is devoted to the analysis of determinants of the price of Bitcoin. To explain the behavior of Bitcoin in the literature, groups of variables responsible for the macroeconomic situation (Yu 2019, Caldera and Iacoviello, 2018), the state of the economy (Beckmann, 2024), as well as for the attention of investors were used. By using GARCH model specifications Wang et al. (2019) or Paule-Vianez et al. (2020) showed the positive impact of economic policy uncertainty index proposed by Baker et al. (2016). Guesmi et al. (2019) and Chen et al. (2020) used GARCH models to prove the relevance of different economic factors such as VIX volatility index and found strong evidence of a relationship. At the same time, since Bitcoin is driven by investors' attention, so academic literature has started to use investors sentiment analyze the returns (Kristoufek, 2018). Guégan and Renault (2021) and Burggraf et al. (2020) used public announcements and Twitter posts to show the relevance of sentiment data in Bitcoin analyze. To analyze the Bitcoin, its returns and volatility statistical models and machine learning models are typically used (Dyhrberg 2016, Baur et al. 2018, Kennard et al. 2022, McNally et al. 2018, Alessandretti et al. 2018). Both types of models show high results in terms of accuracy, but GARCH model is of greater interest due to the possibility of detailed analysis of volatility and returns because it allows them to be directly modeled. However, some papers suggest that this type of specification is irrelevant because they do not consider the possible changes of Bitcoin dynamics. Caporale and Zekokh (2019) or Akin et al. (2023) applied MS-GARCH model to Bitcoin and found clear evidence of regime switching nature.

The aim of this study is to analyze the effect of sentiment on Bitcoin returns and volatility, where the sentiment was calculated for the news from traditional and crypto-specific sources. Finally, this study contributes to the existing literature devoted to analysis of Bitcoin returns and volatility determinants in the following way:

1) By using dataset of 55409 news from Google News source from January 1, 2017 to March 23, 2024, this study investigates the influence of the sentiment component on Bitcoin returns and volatility for the most modern period.
2) This study deepens the research of influence of sentiment component on Bitcoin returns and volatility by dividing the news data on news from classical or traditional sources and news from crypto-specific sources.
3) TV-GARCH-X model with external variables that is able to account for time varying component was used in this study. Model shew that that in January 1, 2017, March 23, 2024 time window Bitcoin returns can be modelled with 1 transition.

The rest of the research is structured as follows: the subsequent section reviews literature on related topics formulates hypotheses. Section 3 describes the methodology and presents the results. Section 4 concludes the research.

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2.5.Hypothesis

In the modern academic literature, many works are devoted to the study of the influence of sentiment on the movement of various asset groups. Both existing indexes calculated from various sources are used, as well as sentiments calculated directly from discussions and posts on social networks, news from their various sources. In general, the possibility of using sentiment to predict asset movements is justified through The Weak Form of Efficient Market Hypothesis (EMH) (Fama, 1970), which assumes that the price of an asset fully reflects all available information. At the same time, Fama (1998) reflected that investors have the opportunity to achieve excessive returns in the short term. These conclusions were supported in such works as Nguyen et al. (2022). At the same time, a large number of studies focused on the behavior of asset prices, so in Clark (1973) presented a model where profitability and volume are influenced by variables reflecting events taking place in the market. The development of these theories led to the emergence of other hypotheses concerning information on the market. Copeland (1976) presented Sequential Information Arrival Hypotheses (SIAH), suggesting that information on the market is perceived by individuals in a random but consistent manner. This theory has been repeatedly investigated. For example, Jennings et al. (1981) observed that shocks to emerging information tend to increase yield volatility.

The idea of the possible influence of information content on market movements has given rise to works exploring the influence of various kinds of news, as well as new methods of analyzing text and obtaining its quantitative characteristics. Research on the influence of sentiment on the cryptocurrency market has also gained wide popularity. Chen et al. (2020) in their work investigated the influence of sentiment on the price of Bitcoin. The sentiment was based on Twitter posts, as this site was the most popular among American users. The results of the analysis showed a strong relationship between the variables. The study of the influence of sentiment on the cryptocurrency market often specializes in the study of a specific kind of news or events. In the work of Corbet et al. (2018) the impact of macroeconomic news on profitability and Bitcoin was investigated and a stable positive relationship was once again shown. Nevertheless, the work also showed that an increasing amount of negative news can be correlated with higher returns on the market in certain periods of time. Chen et al. (2020) also investigated the impact of sentiment and news about COVID-19 on the Bitcoin market. The indicators of the frequency of occurrence in Google trends, as well as the VIX index, were taken as additional variables. In Guégan and Renault (2021) comments and Twitter posts were used as the basis for calculating sentiment. In this work, prices with a high frequency of intraday observations were taken as data on Bitcoin. Based on sentiment data in the work of

Burggraf et al. (2020), an index was built and applied to the analysis of cryptocurrency volatility using various models. The work revealed a strongly significant influence of sentiment on the volatility of the cryptocurrency. In addition to classic news from publicly available sources, the works also often explore sentiment based on certain reports. For example, Akin et al. (2023) investigated the impact of announcements regarding the introduction of digital currencies in China on the profitability and volatility of Bitcoin. Based on reports issued by the central bank, the authors collected announcements and news about digital currencies and showed that this news have a positive relationship with profitability, since they generally speak about the process of acceptance of digital assets by society.
In general, in most studies that investigated the influence of sentiment based on news or other sources of information about cryptocurrency, a significant effect of this indicator on the volatility or profitability of Bitcoin was found. This paper will also explore the impact of sentiment based on news from publicly available sources on Bitcoin volatility.

Hypothesis 1. News sentiment can influence Bitcoin returns

Sapkota (2022) investigated the influence of sentiment on the volatility of Bitcoin returns. The sentiment was based on the news from the LexisNexis database. This source contains a large number of magazines in various categories. The author used the "Major Newspaper" category and received more than 17,000 news items on the "Bitcoin" request for the period from 2012 to 2021. Having built a sentiment, the author showed the presence of a positive relationship between the sentiment index and the volatility of Bitcoin's profitability.
In the work of Tang et al. (2024) more than 1,400 different news sites have been used to get news about Bitcoin. At the same time, the database of sites contained financially specialized sources, which, however, specialize more in traditional financial assets than in cryptocurrency. Similarly, Yu-Sheng Kao et al. (2024) investigated the influence of sentiment on volatility prediction, but sentiment was built on the basis of news downloaded from certain sources from Google News. In the academic literature, it is customary to take a large number of sources for research, however, these sources are mainly magazines or websites traditional for stock markets or other classic assets. This article will show the expansion of existing methods of sentiment research. The analysis will be based on news from Google News, with the sources divided into classic and crypto-specific.

Hypothesis 2. A quantitative assessment of sentiment based on news from classical sources will have a significant effect on the returns of Bitcoin.

Hypothesis 3. A quantitative assessment of sentiment based on news from crypto-specific sources will have a significant effect on the returns of Bitcoin.

The further part of the work is devoted to the description of the methods and steps carried out to test the hypotheses. The data and models used for the analysis will be described, as well as the results obtained.

3.Methodology

3.1. Sentiment calculation

In the academic literature, there is a large number of approaches to calculating sentiment of text. The most common approaches include methods based on machine learning or software for analyzing the linguistic characteristics of a text. All methods are based on NLP algorithms for text analysis and processing (Mitra, 2020). One of the most popular and easy-to-implement methods for obtaining sentiment is the NLTK Python library. This library provides access to lexical resources such as WordNet and SentiWordNet (Janani et al. 2016). This method allows to get a positive, negative, and general sentiment score of the text. The process itself consists of determining the sentiment of each individual element of the text, after which the total sentiment for the entire fragment is calculated (Mitra, 2020). In Bonta and Janardhan et al. (2019) the process of calculating sentiment using the NLTK library was described, and it was shown that in the process of operation, this method transforms the text in such a way as to achieve higher accuracy in calculating sentiment. First of all, this process involves the process of text tokenization, where the raw text is divided into smaller and easier to analyze chunks. The next step involves the removal of stop words. Python's NLP library contains ready-made dictionaries for various languages that contain a list of words that do not carry meaning but are cohesive. These words are removed to leave only meaningful parts of the text. Finally, another important part of text preprocessing is Lemmatization and Stimming, which involves bringing different word forms into a uniform form. Another popularly used library for sentiment counting based on machine learning is the Python library TextBlob. This library uses Naive Bayes methods, calculating the relative probabilities of words falling into a sentiment group (Amin et al. 2020). This method was used by Bose et al. (2020) or Suanpang et al. (2021), where it showed 89% accuracy on a test and training text dataset.

Another group of methods for analyzing sentiment involves the direct application of ready-made dictionaries to the processed text to obtain an overall score. In Sapkota (2022), the author collected a dataset of news items from the LexisNexis portal and applied four ready to use dictionaries to them. These dictionaries were divided into groups according to the principle of finance specific dictionaries and psychological dictionaries. Having obtained the sentiment score using each of the dictionaries, the author evaluated their impact on financial indicators. The next group of methods involves the use of neutron networks to calculate the sentiment. One of the most popular models for sentiment calculation is the BERT model. The advantage of these methods is that they are pre-trained on large datasets and do not require training during the study. These models have separate specifications that have been trained on data with a certain slant. For example, Zou and Herremans (2023) uses the FinBert model, which is a modification of the BERT model trained on a financial dataset. In addition to neutron networks and machine learning libraries, there are other models that can analyze sentiment without first training the model. One such method is the VADER (Valence Aware Dictionary for Sentiment Reasoning) method, which was first introduced in Gilbert (2014). This method was originally proposed as a model for initial sentiment processing in social media. In the task of analyzing news, Twitter, social networks and other informational sources, this method has been applied in works such as Borg et al. (2020) and was shown to be highly precise. VADER works on the basis of a lexical classifier. For each particular text passage, the model counts its sentiment score in the range from -1 to 1, on the basis of which it can finally calculate the score of the whole text passage. When using this method, special attention is paid to reinforcing words, such as "very", as well as punctuation marks indicating the emotional coloring of the text. The VADER model contains a large dictionary built on English words, on the basis of which the recognition is performed. To classify words into groups, the model uses a scale according to which a total score of less than -0.05 classifies the text as negative, from -0.05 to 0.05 as neutral and more than 0.05 as positive. In this paper, the VADER model was also used to analyze sentiment. Before using it, text processing will be performed, in which atypical characters were removed from the text, as well as stop words of the English language.

3.2. TV-GARCH-X model

The most common in terms of volatility modelling autoregressive conditional heteroscedasticity model (ARCH) is decomposed as (Engle, 1982):

$$u_t = \sigma_t \eta_t, \qquad \sigma_t > 0, \qquad \eta_t \sim iid(0,1), \qquad t = 1, \ldots, n \tag{1}$$

Where ${\sigma_t}^2$ is the conditional variance of u_t and η_t is an innovation term with zero mean and unit variance. This model became popular with financial application because u_t could be regarded as returns of an asset and hence ${\sigma_t}^2$ is a volatility of returns conditional on the past information that is available due to time t. Classical approach assumes the conditional variance process defined as ${\sigma_t}^2 = E({u_t}^2 \mid \mathcal{F}_{t-1})$ to be stationary so the unconditional variance is constant. Hence, the GARCH(1,1) model proposed by Bollerslev (1986) states the following:

$${\sigma_t}^2 = \omega + \alpha {u_{t-1}}^2 + \beta {\sigma_{t-1}}^2, \qquad \alpha, \omega > 0, \qquad 0 \leq \beta < 1 \tag{2}$$

Most extensions are able to work with volatility clustering but still assumes unconditional variance to be constant. Model TV- GARCH proposed by Amado and Terasvirta (2013, 2017) offers the option of working with unconditional variance. The model expands equation (1) by stating:

$$u_t = \sigma_t \eta_t, \qquad \sigma_t > 0, \qquad \eta_t \sim iid(0,1), \qquad {\sigma_t}^2 = g_t h_t, \qquad t = 1, \dots, n \tag{3}$$

Where g_t is a TV component and h_t is a rescaled GARCH term. Following the works of Amado and Terasvirta (2013, 2017) the g_t component with a single transition in unconditional volatility is described as:

$$g_t = \delta_0 + \delta_1 G\left(\gamma, c; \frac{t}{n}\right), \; 0 < \delta_0, \; -\delta_0 < \delta_1 \tag{4}$$

$$G\left(\gamma, c; \frac{t}{n}\right) = \frac{1}{1 + \exp -\gamma\left(\frac{t}{n} - c\right)}, 0 < \gamma, c \in (0,1) \tag{5}$$

In equations (4) and (5) γ stands for speed of transition of the volatility. So, the bigger it is the sharper will be the transition. c is a locator for transition expressed as a number between 0 and 1 to show in fraction manner where the transition has happened. Finally, for equation (5) G is a logistic function varying from 0 to 1 in order to specify the transition size δ_1 in equation (4). If δ_1 is estimated to be 0 for the particular data then g_t is equal δ_0, which is set by the model to be greater than 0 in order to have g_t positive. Finally, following Amado and Terasvirta (2013, 2017) the h_t is stands for rescaled GARCH(1,1) which is the modification of equation (2) stated as:

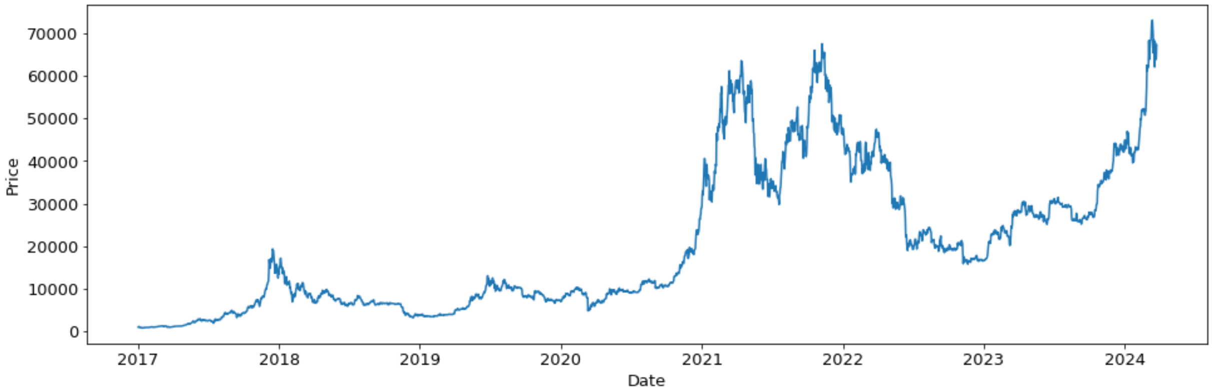
$$h_t = \omega + \alpha {\phi_{t-1}}^2 + \beta {h_{t-1}}^2, \qquad \phi_t^2 \equiv \; {u_t}^2 / g_t \tag{6}$$

This term in particular allows for inclusion of external variables that is stands for X in TV-GARCH-X model. In Campos-Martins and Socarras (2024) the implementation of the model proposed by Amado and Terasvirta (2013, 2017) was illustrated using the tvgarch R package. This work will also use tvgarch to investigate the influence of sentiment data on Bitcoin and to test the hypothesis proposed by this study.

4.Data description

To analyze the relationship between news sentiment and cryptocurrency volatility the data on Bitcoin closing price from coinmarketcap.com was used in this research. Daily data span from January 1, 2017, to March 23, 2024, with a total of 2639 observations. The dynamic of Bitcoin price in this window presented on the Figure 1.

Figure 1. Bitcoin price (USD)



There are several of the most common ways to calculate returns based on financial data - arithmetic and logarithmic. Following Akin et al. (2023) for the purposes of building models in this paper the return of Bitcoin is obtained using the natural logarithm of arithmetic returns. This method allows to obtain a stationary and ergodic time series. These characteristics are important for building GARCH models because they allow to get reliable estimates and results. The graph of the returns is shown in Figure 2 and the formula is the following:

$$R_i = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln(P_{t-1}) \tag{7}$$

Following such papers as Guesmi et al. (2019) or Chen et al. (2020) in addition to sentiment, the VIX index will be used as explanatory variable in this work. VIX index is a volatility index developed by the Chicago Board Options Exchange (CBOE) in 1993. This indicator reflects traders' expectations for fluctuations in the S&P 500 broad market index for the next 30 days - its implied volatility. VIX was shown to act as a significant explanatory factor in analyzing Bitcoin volatility. In Beckmann (2024) this index, along with other indicators, has been used to explain Bitcoin's volatility. The VIX index has shown the most consistent results in terms of significance in various models. Similarly, Guégan and Renault (2021) found a significant relationship between VIX as well as other financial and macroeconomic factors and Bitcoin returns and volatility. Thus, this paper will also explore the impact of this index on Bitcoin volatility. The data for this index was downloaded from investing.com for the same timeframe as Bitcoin price. Figure 3 shows the dynamic for VIX index in a chosen timeframe.

Figure 2. Bitcoin returns

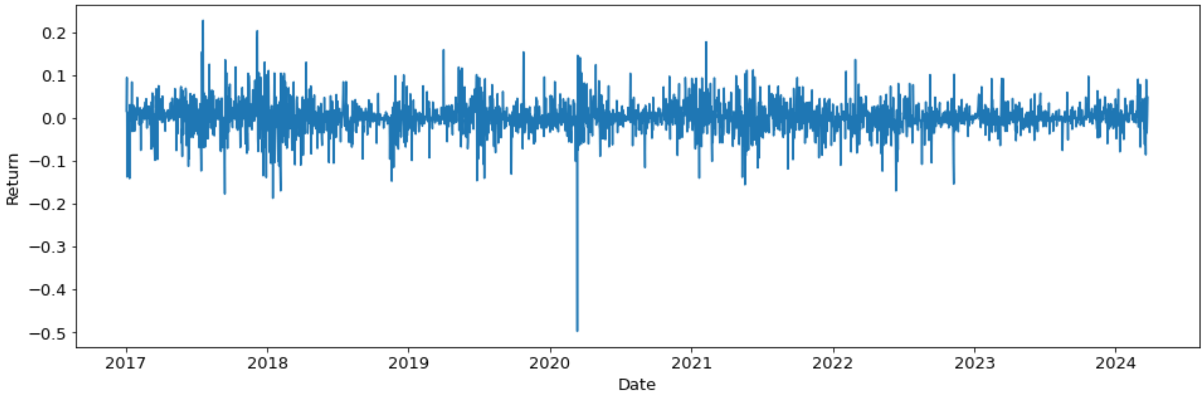
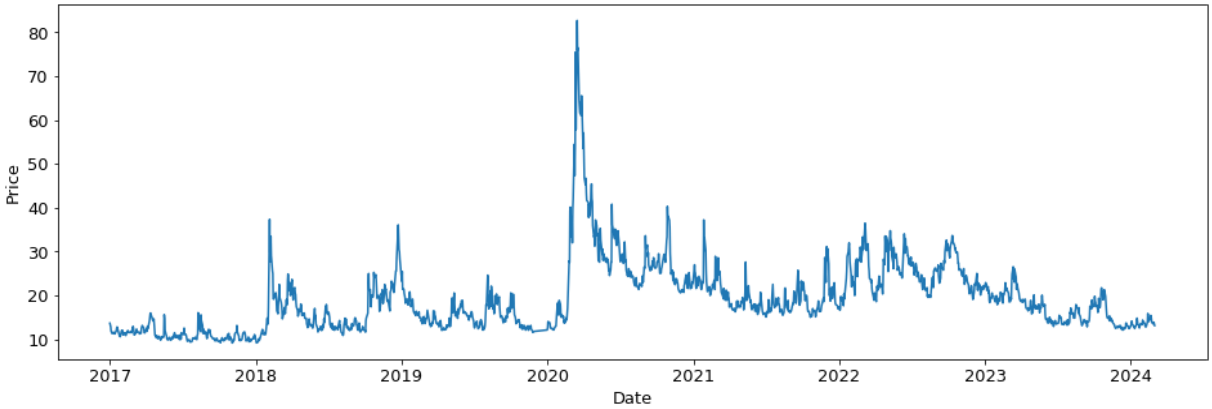
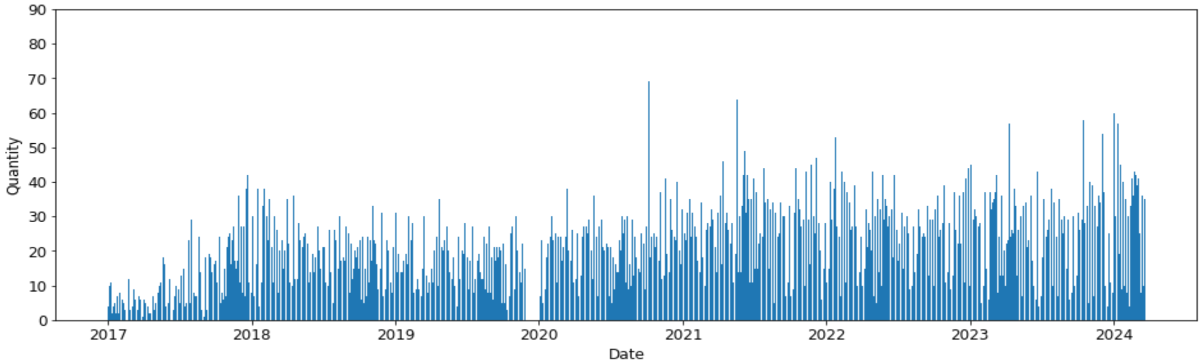


Figure 3. VIX index (USD)



To calculate the sentiment data daily news from Google News was obtained for the period from January 1, 2017, to March 23, 2024. In order to download the data, the keywords "Bitcoin" and "BTC" were used as the name of the cryptocurrency ticker. The news on the Google News resource is suitable for studying the influence of sentiment because this resource aggregates news from different sources and is also international in nature, which allows to analyze the effect as a whole, without reference to a specific country. Such open Python libraries for parsing as Requests, BeautifulSoup and Seleneum were used to get the news. The total of 55409 news was downloaded for the chosen timeframe. Figure 4 shows the number of news items in the sample by day. For some days and periods, there was no news, but in general, the average amount of news per day in the sample is 20.

Figure 4. Number of news items per day



This work involves building a sentiment separately for news from classical sources and for news from crypto-specific sources. Google News allows to capture the name and link to the source when parsing. Using Python tools, the source data was extracted from each news item and classified. The classification was performed by searching for a specific word or its form from a list containing crypto related words. This list includes words such as ‘Crypto’, ‘Coin’, ‘Blockchain’, names of exchanges and the most popular sites, and more. In total, the downloaded sample contains 3070 unique sources, of which 147 belong to crypto-related sources and 2923 to classical ones. After classifying into two types of news sources, it turned out that the sample contains 30605 news from classical sources and 24804 news from crypto-specific sources. The distribution of the amount of news for both type of sources presented on the Figure 5 and Figure 6.

Figure 5. Number of news items per day for crypto-specific sources

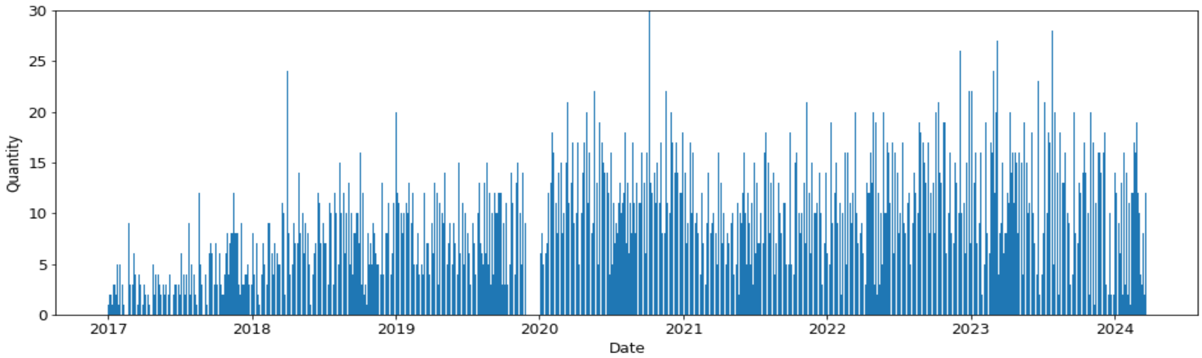
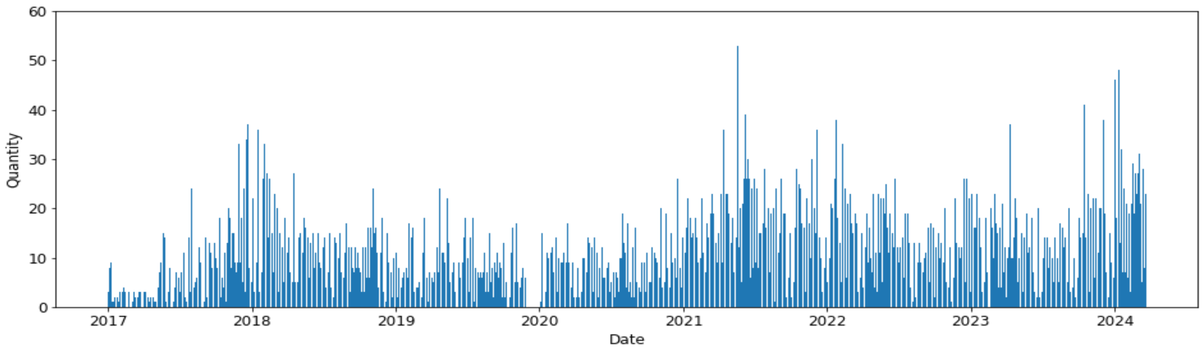


Figure 6. Number of news items per day for classic sources



For the purpose of a more in-depth analysis of the available data, news distributions by source were also obtained for both groups. The distribution data for the top 20 sources are shown in Figure 7 and Figure 8. As can be seen from the figures, both types of sources are characterized by high concentration. Approximately 3-4 of the largest sources in both groups contain the majority of each sample, respectively. The sample also includes sources that contain less than 10 news items for the entire period under review. Nevertheless, these sources were not removed from the dataset for a more realistic analysis.

Figure 7. Top- 20 sources for classic news sources

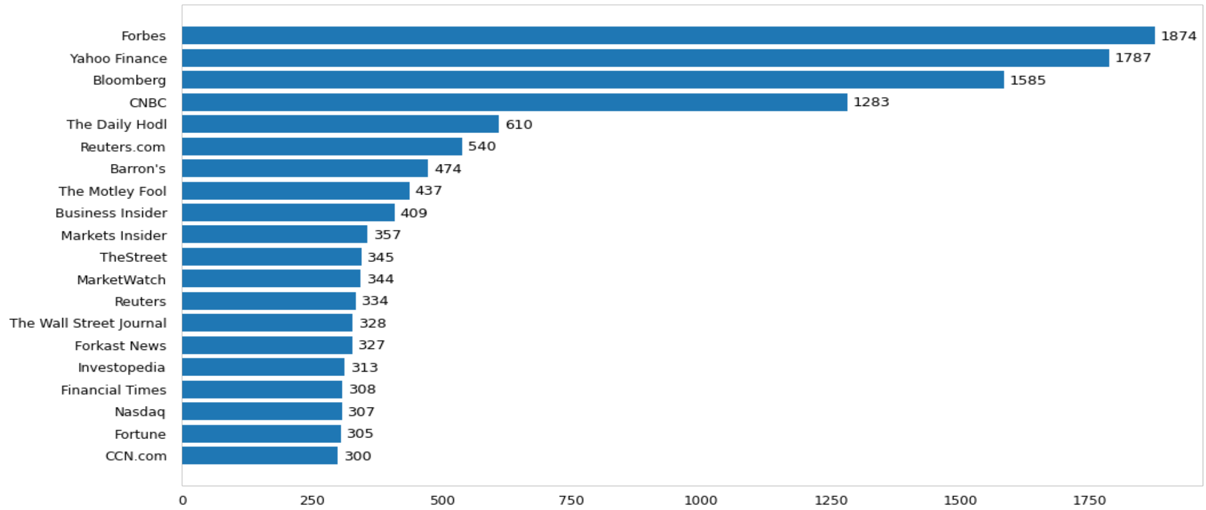
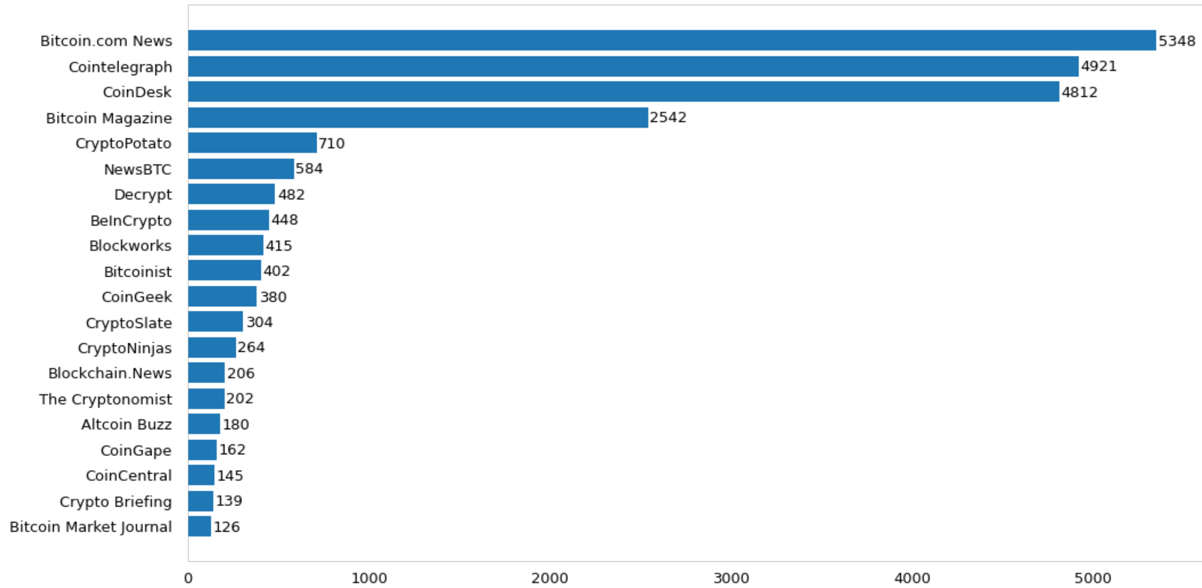


Figure 8. Top- 20 sources for crypto-specific news sources



For the primary analysis of the text, word clouds on the Figure 9 were built using the R library wordcloud2. After preparing the text and applying the VADER model, the final sentiment for the news from classic and crypto-specific sources was calculated. An averaging mechanism was used to calculate the sentiment of a particular day. The sentiment score of all individual news items during the day was summed up into a single value and then divided by the number of news items released that day. So, the following formula was applied, where i indicates the particular day and t indicates the news belonging to a specific day:

$$Sentiment_i = \frac{\sum_{t \in i} Sentiment_t}{n} \quad (8)$$

Figure 9. Wordclouds for classic and crypto-specific news

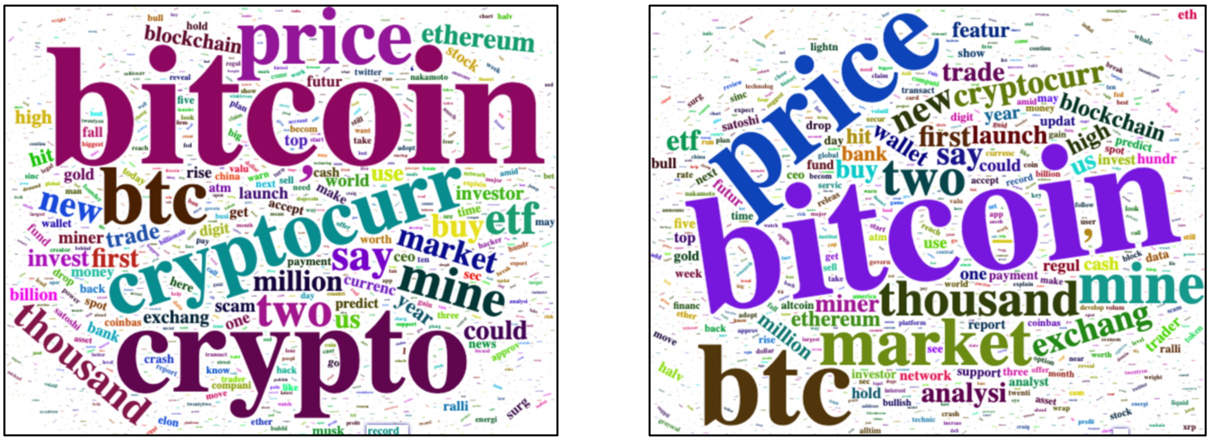


Fig 9. Wordclouds for classic news (left) and crypto-specific (right) news datasets obtained through Wordcloud2 package in R.

After preparing the data and calculating the sentiment, a method of working with omissions, namely interpolation, was applied to each of the data sets, including data on the VIX index and sentiment. Interpolation allows to use a linear model for filling gaps in the data and at the same time specify a limit on the maximum number of consecutive fills in order to preserve the properties of the sample.

Figure 10. Sentiment scores

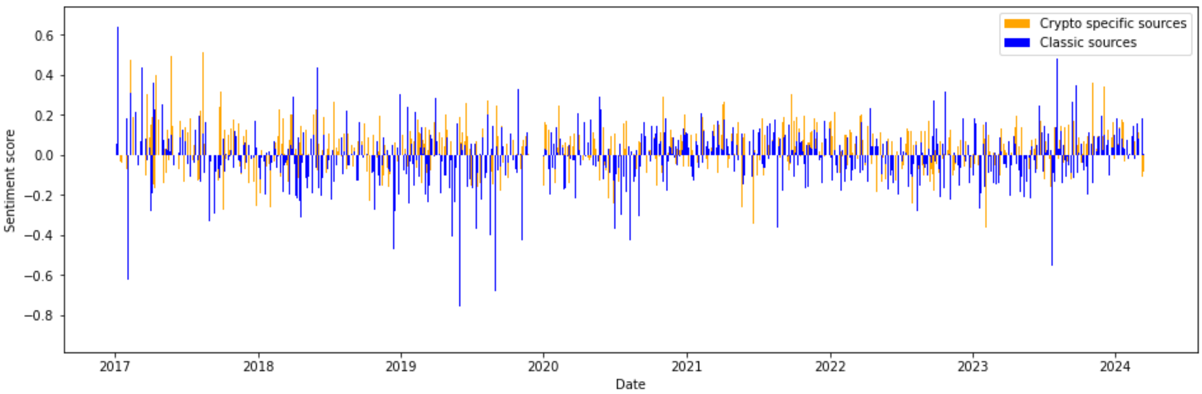


Table 1 shows summary statistics for the final dataset. Jarque-Bera test for normality of distribution was conducted for all the variables. It was found that at 1% level of significance the null hypothesis is rejected for all the variables so the data in not normally distributed. The next step of investigation is a test for stationarity or the presence of unit root, Augmented Dickey-Fuller test was used to test the null hypothesis of non-stationarity of the time series. As a result, the test shew that variables employed in models are stationary at 1% and 5% level.

Table 1. Summary of Statistics.

	BTC Returns	VIX
Mean	0.1658877	19.27
Median	0.1469	17.59
Maximum	22.76	82.69
Minimum	-49.7278	9.14
Std. dev.	3.948229	8.057212
Skewness	-0.8157778	2.269691
Kurtosis	15.82308	12.91627
Jarque-Bera	17524***	12474***
ADF	-51.7***	-1.98**
Observations	2517	2517

Note 1: BTC Returns, Sentiment classic, Sentiment crypto and VIX represents Bitcoin log returns, sentiment for news from classical sources, sentiment from crypto sources and VIX index respectively.
Note 2: The null hypothesis for Jarque-Bera is the normality of distribution and the null hypothesis for ADF test is stationarity.
*Note 3: ***, **, * represents the significance of the test for 0.01, 0.05 and 0.1 significance level, respectively.*

From Figure 2 it is clear that there is a presence of volatility clustering in the returns. Large (small) returns tend to be followed by small (large) so the conditional variance may not be constant. The next evidence is that returns are systematically more volatile during some periods of time which could be the evidence of unconditional variance being not constant as well. Following procedures presented in Yu-Sheng Kao (2024) residuals of ARMA(p,q) mean model were extracted and tested using Box-Ljung test. The test was applied to squared residuals so as to capture the autocorrelation, because the methodology assumes that is residuals are heteroscedastic then squared residuals are autocorrelated.

Table 2. Box-Ljung test results.

	X-squared	df	p-value
BTC returns	18.126***	1	2.067e-05

Note 1: The null hypothesis for Box-Ljung assumes that the data is independently distributed.
*Note 2: ***, **, * represents the significance of the test for 0.01, 0.05 and 0.1 significance level.*
Note 3: optimal ARIMA(p,d,q) for extracting residuals was found using R method "auto.arima".

The results of the test presented in Table 2 clearly indicates the rejection of the null hypothesis of the independently distributed data at 1% level of significance. Therefore, the use of the GARCH(1,1) model is justified for the analysis of volatility in data.

As it was stated in Campos-Martins and Socarras (2024) equations (4) and (5) make us to know the number of transitions (changes in unconditional variance) in order to properly specify equation (5). To test the number of transitions, tvgarchTest command was applied to the returns on Bitcoin, the results of the test presented in the Table 3. The test procedure was also proposed by Amado and Terasvirta (2013, 2017). The test utilizes the sequence of LM tests with the initial hypothesis of unconditional variance being constant. B3, B2, B1 are referred to as a potential transition so the hypothesis in presented in Table 3 makes it possible to identify the final number using p-values from the tests.

Table 3. Test for number of transitions.

	NonRobTR2	p-value	RobTR2	p-value
H0:B3=B2=B1=0	7.3549	0.0614	8.6440	0.0344
H03:B3=0	0.1799	0.6714	0.2902	0.5901
H02:B2=0|B3=0	1.3469	0.2458	1.1424	0.2851
H01:B1=0|B3=0|B2=0	5.8317	0.0157	7.6550	0.0057
No. of locations (alpha = 0.05) = 1				

Note: The null hypothesis refers to applicability of GARCH(1,1) while the alternative of TV-GARCH

The p-value for H0 is 0.0344 meaning that the unconditional variance is not constant. The only rejected hypothesis from H03, H02 and H01 is H01 meaning that B1 term is not equals 0. Finally, the TV(1)-GARCH(1,1)-X model was built using the VIX index as an external regressor.

Thus, at this stage, all the necessary variables have been obtained, and a model has been defined to test hypotheses. To test the hypothesis of the study the following final specification with one transition will be used:

$$h_t = \omega + \alpha \frac{y_{t-1}^2}{\hat{g}_{t-1}} + \beta h_{t-1} + \theta\_0 * VIX_{t-1} + \theta\_1 * Sentiment\_classic_{t-1} + +\theta\_2 * Sentiment\_crypto_{t-1} \tag{9}$$

$$g_t = \delta_0 - \delta_1 G_1(\gamma, c; t/n) \tag{10}$$

In equation (9) $Sentiment\_classic$ refers to the sentiment built on news from traditional news and $Sentiment\_crypto$ refers to the news that was built on crypto-specific news. To test the hypothesis 1 it is needed for θ_1 or θ_2 to be significant in order to proof that in general the idea of the sentiment analysis makes sense. To test the hypothesis 2 and 3 it is needed to investigate the significance of θ_1 and θ_2 respectively.

5.Empirical results

5.1.Hypothesis testing

Table 4. TV(1)-GARCH(1,1)-X estimation results.

	(1)	(2)	(3)	(4)
intercept.g (fixed)	18.952	18.952	18.952	18.952
Size	-13.273***	-11.884***	-11.818***	-13.18***
Speed	2.518***	3.142***	3.115***	2.576**
Location	0.723***	0.762***	0.756***	0.727***
Intercept.h	0.068*	0.055***	0.06**	0.067**
ARCH	0.065**	0.066***	0.066**	0.066**
GARCH	0.865***	0.869***	0.867***	0.864***
Sentiment_classic(θ_1)	0.011*			0.210**
Sentiment_crypto(θ_2)		0.094		0.035
VIX (θ_0)	0.217***	0.010***	0.01**	0.011***
Observations	2517	2517	2517	2517
BIC	13673	13726	13710	13681

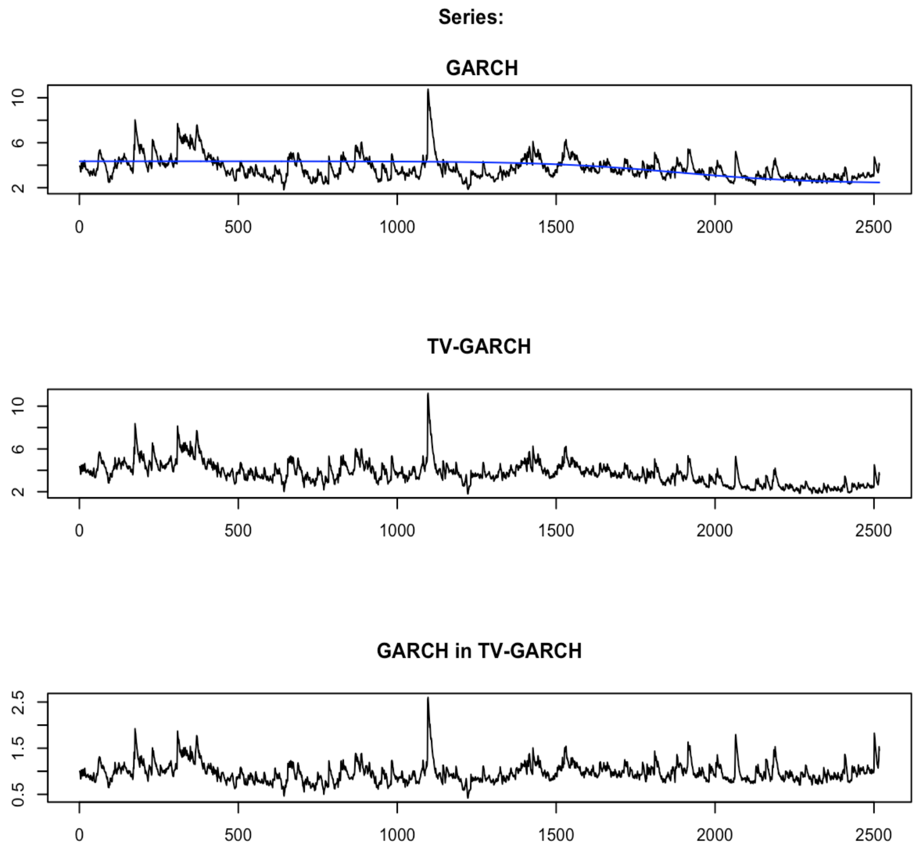
*Note 1: ***, **, * represents the significance of the test for 0.01, 0.05 and 0.1 significance level, respectively. Note 2: Sentiment_classic, Sentiment_crypto stand for sentiment extracted from classical sources and crypto sources respectively, first lags were used.*

Table 4 presents the main results of the analysis of in-sample model estimation. P-values for the coefficient estimations were calculated using standard errors. The terms *Size*, *Speed* and *Location* refer to TV(1) component from the equations (4) and (5). For all four specifications of tested models, TV(1) components are significant indicating that Bitcoin returns are indeed could be described by the model and that unconditional variance is not constant. ARCH and GARCH components are also significant for all the models.

This indicates that modelling conditional variance for returns is appropriate and volatility clustering is presented in the data. Finally, external regressors are showed to have significant relationship with Bitcoin returns except *Sentiment_crypto* which is referred to the first lag of the sentiment calculated on the news from crypto-specific sources. Table 3 also demonstrates a sustainability in coefficient estimates. For specifications (1) and (4) *Sentiment_classic* is positive and significant while for specifications (2) and (4) the *Sentiment_crypto* is insignificant. VIX index is also showed to have a significant and stable relationship with Bitcoin returns. Overall, results in terms of investigation of sentiment and VIX impact are consistent with such works as Guesmi et al. (2019) or Chen et al. (2020) who shew that VIX is relevant in Bitcoin returns analysis, and with works as Corbet et al. (2018), Guégan and

Renault (2021) or Burggraf et al. (2020) who shew that sentiment is a strong factor in the analysis.

Figure 11. Standard deviations from the TV(1)-GARCH(1,1)-X .



Note 1: upper plot contains GARCH standard deviation (black line) and TV(1) component (blue line), middle plot is the standard deviation from the TV(1)-GARCH(1,1)-X model, lower plot is the GARCH from TV-GARCH standard deviation obtained by dividing by root of TV term. Note 2: x axis of the plots represents the sequence of observation from the dataset.

From the point of view of hypothesis testing, it can be said that hypotheses 1 and 2 were confirmed, while hypothesis 3 was rejected. The coefficients for classical sentiment turned out to be significant, while for crypto-specific sentiment they were not. The results are in fact coincides with such works as Sapkota (2022) or Tang et al. (2024) who used the dataset of news from classical sources and verified their significancy. Regarding the sentiment built on crypto-specific news it is not possible to compare the results with other works, as such a division has not been applied to Bitcoin news before. At the same time, there are several reasons why news from crypto sources could potentially be insignificant. First and foremost is the quality of the news. In traditional sources, news can be pre-screened before publication

and is therefore more reliable. Moreover, cryptocurrencies and Bitcoin are usually not the main topic in traditional sources, which means that if magazines and websites publish news about Bitcoin, these are significant events that can affect the movement of Bitcoin.
Finally, Figure 11 presents the results of estimation of conditional standard deviation. The TV-GARCH plot (middle) specifies the conditional standard deviation from the TV(1)-GARCH(1,1)-X model and the estimated conditional standard deviation from the GARCH(1,1)-X component of TV(1)-GARCH(1,1)-X which is obtained by dividing returns by the root of TV(1) component. To compare the outcomes GARCH plot (upper) contains the conditional standard deviation from the GARCH(1,1)-X (black line) model assuming unconditional variance to be stationary as well as conditional standard deviation from TV(2) (blue line) (Campos-Martins and Socarras, 2024). As we can see from the lower plot, the component became more stable within the GARCH in of TV(1)-GARCH(1,1)-X model which once again confirms the applicability of the model. Additional considerations regard the date of transition. The R package allow users to extract the date of transition using special commands (Campos-Martins and Socarras, 2024). In this model transition occurred smoothly so the model allows to extract the mid date of general transition. In this data transition corresponds to the 1819 observation which is the March 10, 2022.

5.2.Robustess check

In order to check the robustness of the results obtained from model building, robustness evaluation was performed. The TV-GARCH-X model with the inclusion of regressors has shown its applicability in the previous section, but now we should compare this model with the classical GARCH and TV-GARCH models without regressors. Table 5 shows the results of the estimations of the TV(1)-GARCH(1,1)-X model with VIX index and classic sentiments as external regressors and control (specification (1)), simple GARCH(1,1) model (specification (2)), and TV(1)-GARCH(1,1) model without external regressors (specification (3)). These specifications were added to the analysis in order to verify that TV(1)-GARCH(1,1)-X model is indeed the best in terms of in-sample fit and that it is not enough to just build simple GARCH(1,1) model. The BIC measure was used in the analysis to choose between different models (Campos-Martins and Socarras, 2024). As it could be seen from the tables 4 and 5 TV(1)-GARCH(1,1)-X with sentiments and *VIX* is the best fitted model in terms suiting the data. BIC criterion uses likelihood meause and number of parameters to give the evaluation and so in this way the model TV(1)-GARCH(1,1)-X has shown the lowest BIC value.

Table 5. Models comparison.

	(1)	(2)*	(3)
intercept.g (fixed)	18.952		18.952
Size	-13.273***		-11.625***
Speed	2.518***		4.388***
Location	0.723***		0.785***
Intercept.h	0.068*	0.521	0.072***
ARCH	0.065**	0.058**	0.082***
GARCH	0.865***	0.905***	0.842***
Sentiment_classic	0.011*	0.816*	
VIX	0.217***	0.149**	
Observations	2517	2517	2517
BIC	13673	13725	13722

*Note 1: ***, **, * represents the significance of the test for 0.01, 0.05 and 0.1 significance level, respectively. Note 2: (2) stands for simple GARCH(1,1) model by setting transitions component to 0. Note 3: specification (3) stands for TV(1)-GARCH(1,1) without external regressors.*

6.Conclusion

In this paper, an analysis of research on the topic of Bitcoin and its returns was carried out. Due to the fact that this asset has been gaining popularity in recent years, many academic and practitioners are concerned about finding the best method of modeling cryptocurrencies. In addition to applying various statistical and machine learning models, various variables are included in the work to explore the relationship of Bitcoin with the macroeconomic environment (Wang et al. 2019., Yu, 2019., Caldera, and Iacoviello, 2018), the state of the economy (Guesmi et al. 2019., Beckmann, 2024) or investor's sentiment (Chen et al. 2020., Burggraf et al. 2020). Due to the fact that the investor sentiment towards Bitcoin is one of the most significant in its analysis, many works are engaged in the study of the influence of sentiment (Kristoufek, 2018). This work contributes to this class of literature by further investigating the idea of using public sentiment in order to model and explain the volatility of Bitcoin returns. Sentiment was calculated from a large set of news from public sources with the VADER model. The results showed that in general news sentiment affects Bitcoin returns positively leading to hypothesis 1 being not rejected. This result coincides with findings of Sapkota (2022), Tang et al. (2024) or Yu-Sheng Kao et al. (2024) who also showed the presence of strong relationship between quantitative measure of sentiment and Bitcoin movements. In addition, this work deepens the analysis by separating the news dataset on news from classical sources (Figure 7) and news from crypto related sources (Figure 8). The results of model construction shew that nearly all specifications used in this study considered sentiment build on news from crypto related sources as unsignificant, which lead to the rejection of the 3d hypothesis in this study. This result again matches with works on the same topic as Sapkota (2022) or Tang et al. (2024) which used news from traditional sources in their studies and shew the sentiment significance. Although, there may be several possible explanations for the fact of insignificance of sentiment built on crypto-specific sources. The first sing is again an attention of investors and users of Bitcoin. Despite the fact that Bitcoin is gaining popularity, most of its users can use it exclusively as a means of investment and are not deeply interested in the ecosystem. That's why traditional news sources may be simply more suitable from them and in this way traditional news sources simply has more users so the sentiment built on them is more representative in terms of investors sentiment and attention to Bitcoin. The next thing is the quality of the data. Since traditional news sources have a higher reputation and are more responsible for the published content, news from traditional sources can again be more representative in terms of investors sentiment. They are less likely to publish unverified content or news that relate to cryptocurrency but do not relate to significant events which can influence the price. Traditional news usually publishes only the most high-profile events regarding cryptocurrency, since in general, cryptocurrency is not the central topic of these sources. These considerations can explain the result according to which sentiment from crypto-specific sources turned out to be insignificant.

This study also contributes to the literature trying to utilize time varying models to Bitcoin returns. While traditional statistical and volatility models assume unconditional volatility of Bitcoin to be constant, in works of Caporale and Zekokh (2019) or Akin et al. (2023) authors applied model that account for volatility instability. These works used MS-GARCH model and shew that it can give better results that simple stationary frameworks. This work's finding again coincide with previous research. By utilizing TV-GARCH model proposed by Amado and Terasvirta (2013, 2017) it was shown that Bitcoin returns indeed gives signs of variability in terms of unconditional variance. By comparing different model specifications TV(1)-GARCH(1,1)-X model turned out to the best in terms of in-sample fit.

At the same time, there are areas that may require additional study. Future research may primarily focus on more adapted methods for quantifying sentiment from the raw news data. Some of the news that came across in the process of detailed analysis of the dataset had positive tendencies, at the same time, the model gave out an understated sentiment in their regard. In addition, future work may use a broader set of explanatory variables in order to consider possible hidden effects in the data.

This study has some limitations in terms of comparing findings. In the academic environment, there are practically no works devoted to comparing different types of news sources in the task of sentimental extraction for Bitcoin returns analysis, so it is impossible to compare the results. This however also create a direction for the potential future research that could repeat the analysis using different methodologies or news sources.

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