Does Elon Musk's tweets influence Bitcoin market value? : A sentiment anaylsis approach

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Abstract

[1] Elon Musk, one of the world's wealthiest people, is regarded as a technical visionary with a social media following of over 79 million followers on Twitter. He uses his social media presence to discuss a variety of topics, including cryptocurrency such as Bitcoin and Dogecoin. We examine how Musk's Twitter engagement influences short-term cryptocurrency price and volume using an event study approach. After examining 4787 tweets containing 68676 words, posted from December 2011 to January 2021, and rigorously controlling other determinants, we found that the tone of the world's wealthiest person can drive the Bitcoin market. In addition, Musk is likely to use positive words in his tweets, with "trust" and "anticipation" as the most frequent sentiments expressed. This results are also confirmed by applying the same sentiment approach on a different temporal subset of Tesla CEO's tweets (starting from January 2020, when Musk's popularity unquestionably gained momentum). However, we did not find evidence to support linkage between Musk's sentiments and Bitcoin volatility. Our results are strenghtened by similar findings when analyzing Dogecoin trend: in both cases we confront the timestamp of Bitcoin or Doge-related tweets and key breaking points (i.e. sudden movements of the average currency value) showing the absence of evidence to support the linkage between Musk's sentiments and the Bitcoin (Dogecoin) volatility. s

Literature review

One of the most useful social media platform to conduct data mining on is Twitter. It comes to no surprise the fact that its top users, i.e. the most followed ones, are celebrities and mass media companies. Such a result is further supported by a finding by Kwak et al.(2010), according to whom the level of reciprocity on Twitter following is as low as 22.1%. This is the reason why most of the research activities are carried out using data coming from Twitter.

The first data mining activities were conducted around 2013 with the scope of highlighting how Twitter played a central role in spreading awareness after a natural disaster occured[8]. Further steps involved using Twitter's data to predict the happening of those same phenomena[6, 16, 13]. Similar analyses have been performed to forecast political election's results[9] and are now being applied to the cryptocurrency and stock markets.

In particular, at the base of these predictions is a well tested hypothesis according to which investors are not rational, despite what classical theories have been arguing[Fama 1970]. Behavioural researchers have indeed shown that the market is driven by investor's psychology. [De Longhi et al, 1990] referred to the strategies followed by noise traiders as positive-feedback strategies, that are reflected in the tendency of buying stocks when prices are increasing and selling them when they are decreasing, following a so-called herd behaviour.

Such a trend cannot be reverted, despite the presence of rational investors who could potentially trade against noise traders. A similar strategy has proven to be ineffective for different reasons. The two most relevant according to Shiller [2003] are represented by short-selling constraints and risk aversion of the investors themselves. On the bright side, rational arbitrageurs can still exploit this condition of theirs to their advantage: they can indeed anticipate the trend, contributing to an even higher effect in price change. In this sense, investigating the noise traders' moods is crucial in predicting the market development. Schwarz 1990 studied the correlation between mood and risk and found out that people in positive moods perceive the risk as an opportunity, whereas people in negative moods are more likely to see the danger. [17] was able to correlate the change in some public's mood dimensions like calmness to a shift in DJIA values within a time lag of 3-4 days, thus suggesting a possible tracking of these factors and prediction of future stock prices. The question, though remains on the accuracy of such predictions and the reversion of these effects. @noferUsingTwitterPredict_2015 found evidence that follower-weighted social mood levels can predict share returns, even though this was not true if simple aggregation of mood states was performed. Indeed, they hypothesized the reason behind such a behavior could be explained in light of emotional contagion, according to which individuals influence each other based on their active network. in 2019[7] another research was conducted in this field and it was demonstrated that relevant information could be found on Twitter, in particular regarding analyst recommendation changes, target price changes, quarterly earnings surprises and IPO opening prices. Besides this conclusion, that was in line with other papers, they also studied another factor with relevant implications in terms of stock return quality of predictions. Specifically, they found that Twitter sentiment analysis constituted a stronger predictor for smaller firms, i.e. firms less covered by analysts. Last but not least,Porshnev, Lakshina, and Redkin [14] studied the contribution of emotional makers to the ARMAX-GARCH model and demonstrated they provided both a smaller BIC and improved likelihood function.

Inspired by the literature on stock return predictability, researchers are now studying the predictability of a new asset class: cryptocurrency. One of the fundamental differences with respect to stocks is that, just like any other currency, cryptocurrency has no fundamental value. On the other hand, it has a similar pattern when it comes to investor's decision taking process, characterized by the so called "herding behavior". [4, 5, 15]

Based on this hypothesis Naeem, Mbarki, Suleman; Vinh Vo5 and Shahzad [11] have conducted a research to investigate the predictability of cryptocurrencies, using the Twitter happiness sentiment. The study revealed a significant non linear Granger casuality across the sample and it indicated that the Hapiness Sentiment was a significant predictor, except for Dash. They also recognized the relevance of some factors in delivering an accurate and reliable prediction: market condition (bearish, normal, or bullish) and the strength of the sentiment (high/low). In 2018 Naseking and Chen [12]used machine learning techniques to construct sentiment indices and adding those values they were able to improve the predictability of logreturns both in and out the sample. They also used an IGARCH approach and were able to build an accurate model for the volatility prediction, adding a squared sentiment predictor. Other works and researches included Mai et al. (2018) and Cheuque Cerda and Reutter (2019).

With our work we intend to bring more evidence to the predictability of cryptocurrency prices, in particular Bitcoins.

#Sentiment analysis

"If you are not paying for it, you're not the customer; you're the product being sold." This is a famous quote by Andrew Lewis and is especially true for apps based on user generated content. The data here produced are made available in the form of unstructured data, i.e. data not stored in a structured database. They encompass text, emails, images and so much more. As the majority of the data come in this form new techniques have emerged that allow for them to be analysed and exploited. These techniques are part of the so called "text mining", a research branch that focuses on "extracting the data, transforming it into information and making it useful for various types of decision making". [2] The process is characterized by different steps: first in line is data clearing and organizing to best suit the goals of the research. After that, relevant words are extracted, the so called N-grams, and relationship between them are analysed with the objective of dividing words into categories. Such a partitioning allows for research questions to be addressed and conclusions to be drawn.

Some of the text mining techniques include classification and clustering, sentiment analysis and natural language processing. The latter represents a broader technique that performs different types of analysis, namely summarization, part of speech tagging, text categorization and sentiment analysis.

Particularly relevant to our research is the latter, as emotions have been proved to be key drivers in the process of investing. "Sentiment analysis is a series of methods, techniques, and tools about detecting and extracting subjective information, such as opinion and attitudes, from language."[10] It has historically focused on polarity, meaning the positivity or negativity expressed in a text, but is now moving to a more accurate detection of different emotions (frustration, joy, anger, sadness, excitement).

The first paper using sentiment analysis dates back to 1940, where opinions on various public issues were investigated. A similar analysis was performed a couple years later on countries that mostly suffered during WW2. But it is not until the early 21st century that more and more papers were published. In 2010 Sitaram Asur and Bernardo A. Huberman used data from Twitter to build a linear regression model to predict box-office revenues of movies in advance of their release. The predictor used was rate of chatter, but they highlighted how a sentiment analysis improved predictions after a movie was released. In particular, they constructed a sentiment analysis classifier to distinguish positive, negative or neutral texts. They then created two factors: Subjectivity and Polarity. With the first they were able to confirm their hypothesis, according to which "there were more sentiments discovered in tweets for the weeks after release, than in the pre-release week". The polarity factor, i.e. polarity= Tweets with Positive Sentiment divided by Tweets with Negative Sentiment was used to correlate positive sentiments with revenue increases.

In 2012 Younggue Bae,Hongchul Lee examined the positive or negative influence of popular twitterers on the sentiment of audience. They started out by selecting 13 popular users and for each of them they identifies their audience, i.e. those people "who reply to, mention, or retweet about the popular user".[3] Using lexicon-based sentiment analysis they were able to divide the audience into two groups: those who are in favour and those who are against the popular user. They then proceeded on investigating the relationship between the user sentiment and his audience one. The results showed a general positive correlation between the two, meaning that positive Tweets of a popular user were followed by positive retweets and viceversa. This result constitutes an important assumption for our research: we can generalize an audience mood by investigating the polarity and sentiment of a popular user, which facilitates our data collection and analysis. Last but not least, they investigated the relationship between real-world landscape and influence of popular users and found a strong casuality correlation. This too appears to be an important result: Twitter can be used as a predictor of real world landscape. # Introduction

On January 29, 2021, Elon Musk, at that time the richest person in the world (Klebnikov, 2021), unexpectedly changed the bio1 of his Twitter account to #bitcoin. The price of Bitcoin rose from about 32,000$ to over 38,000$ in a matter of hours, increasing the asset's market capitalization by 111 billion $ The relevance of Musk's tweets for financial markets has already become apparent in other contexts. Musk's endorsement of the encrypted messaging service Signal (Musk, 2021a) led to investors purchasing the unrelated Signal Advance stock, increasing the latter's market valuation from 55$ million to over 3$ billion (DeCambre, 2021). These events clearly show the impact that leadership in social networks can have on financial markets and the decision-making behavior of (individual) investors. While the market may read Musk's tweets on Tesla as "true news," his tweets regarding cryptocurrency reflect moods or personal sentiment, which have been shown to influence financial market pricing (Bollen et al., 2011; Gabrovek et al., 2017; Schumaker and Chen, 2009). Musk declared that Bitcoin is "on the threshold of gaining broad acceptability" in a talk on social media site Clubhouse, and admitted that he is "late to the party but[…] a fan of Bitcoin." He also said in the event that his tweets about the cryptocurrency Dogecoin are just jokes (Krishnan et al., 2021). This is consistent with Musk's tweet from May 2020, in which he stated that he "only own[ed] 0.25 Bitcoins" (Musk, 2020). Tesla, on the other hand, spent $1.5 billion in Bitcoin between January and March 2021 (US Securities and Exchange Commission, 2021), implying that the Bitcoin-related tweets were more than "just jokes." Musk's tweets appear to effect the cryptocurrency market, regardless of whether they are meant in fun or in earnest, which is our incentive to look into the topic further and analyse its consequences. While Musk is far from the only public figure to speak out on social media regarding cryptocurrency or financial markets, he is undoubtedly one of the most influential. In strategic contacts between prominent individuals such as managers, journalists, or financial analysts and stakeholder groups, social media plays a key role (Heavey et al., 2020; Pfarrer et al., 2010). By communicating directly with customers (Alghawi et al., 2014), controlling the timing of disclosure (Jung et al., 2017), or establishing trust with investors or communities, these individuals can use their social networks to shape their own reputation and identity, or that of a related company (Deephouse, 2000; Zavyalova et al., 2012). (Elliott et al., 2018; Grant et al., 2018). Strategic leaders' social media activities, on the other hand, can generate a lot of ambiguity. For example, it may be difficult to tell whether a message is simply expressing a mood or conveying specific company-related information. It could be hard to ascertain whether a message is merely expressing a mood or conveying specific company-related information. Furthermore, stakeholders may be overwhelmed with irrelevant information that diverts their attention away from the main concerns (Huang and Yeo, 2018). A person's or a company's reputation might be harmed as a result of critical behaviour. Because of the extremely quickly nature of social media, any such harm can occur in an instant (Wang et al., 2019). Several research have looked into the relationship between cryptocurrency markets and social media activity, particularly on Twitter. Short-term Bitcoin liquidity is increased by an increase in the number of Bitcoin-related tweets (Choi, 2020), the number of Bitcoin-related tweets can explain Bitcoin trading volume and returns (Philippas et al., 2019; Shen et al., 2019), and Twitter sentiment can predict cryptocurrency returns (Philippas et al., 2019). (Kraaijeveld and De Smedt, 2020; Naeem et al., 2020; Steinert and Herff, 2018). According to Mai et al. (2018), social media users with less prior cryptocurrency-related involvement drive cryptocurrency effects, which makes sense because their actions are uncommon or unexpected. If Elon Musk tweeted about cryptocurrencies multiple times a day, the market would most certainly treat it as noise. While several studies have looked into the impact of individual tweets on stock market returns (Brans and Scholtens, 2020; Ge et al., 2019—both relating to stock market-related tweets by Donald Trump), to our knowledge, very few researchers have examined into the impact of individual tweets on cryptocurrency returns and trading volume.

This research seeks to determine how one of the world's most powerful persons' social media activities affects cryptocurrency price levels. We take Elon Musk's cryptocurrency-related tweets and categorise them as unanticipated happenings. The research looks at how leadership, engagement, and information via social media, particularly Twitter, influence investor attention and behaviour in cryptocurrency markets. Of course, Elon Musk is an outlier, which is why our approach might almost be termed a case study. In an ideal world, the findings and implications could be applied to other people and markets, allowing us to better understand the likelihood of social media personalities influencing cryptocurrency markets and whether or not this is a problem.

Conceptual background: Financial market efficiency

"Prices fully represent all available information," according to the efficient market hypothesis (EMH) (Fama, 1970). The price of an item is determined by the intersection of a supply and demand curve, which satisfies both consumers (such as Bitcoin investors) and producers (e.g. Bitcoin miners). As additional relevant information becomes available, the curves adjust. A tweet from Elon Musk could be considered such new knowledge, and is priced appropriately if it is deemed important. However, the EMH's validity has been questioned because it is primarily reliant on market players' preferences and conduct. The adaptive markets hypothesis (AMH), a variant of the EMH, claims that the degree to which information is represented in prices is determined by market conditions as well as the quantity and characteristics of market participants: market effiency is context-dependent. The quality of the information provided is a critical part of the impact of individuals on financial markets. According to signalling theory, an actor can employ high-quality signals to reduce market information uncertainty (Spence, 1973). While such signals are typically used in an agent's own interest, such as when applying for a job (Spence, 1973) or seeking entrepreneurial financing (Ante et al., 2018), it appears possible that a tweet from a very influential or reputable person is interpreted by a significant number of market participants as a signal of the quality of the object of the tweet, even without an ulterior motive or even unintentionally. Every tweet is motivated by something, even if it's just a passing mood. In this situation, having faith in the signal and its quality is critical. A signal must usually be coupled with direct or indirect expenses in order to be trustworthy or credible (Connelly et al., 2011). The costs in the instance of Elon Musk's tweets are indirect, and they include the potential damage to his reputation as a technological innovator and successful entrepreneur (i.e. his influencer status) or the reputation of the companies with which he is connected (Wang et al., 2019). There's also the possibility of counter-signaling, in which other agents broadcast contradictory or critical messages. If the market discovers, for example, that Musk's tweets are noise rather than quality signals, it should disregard the information as unimportant.

Research questions

We raise the following research questions to address the issue of effciency in cryptocurrency markets and the attention their participants devote to influencers since Elon Musk and other influential individuals are likely to continue publicly commenting on cryptocurrency for the foreseeable future.

RQ1: DO Elon Musk's cryptocurrency-related tweets sentiments have an effect on the pricing and trading volume of cryptocurrency?

The answer to this issue can reveal whether tweets can be considered quality signals in general or whether the market effects seen were purely coincidental. Second, the AMH predicts that a cryptocurrency that is less efficient or liquid will be more affected by Musk's tweets.

RQ2: Do sentiments and polarity of Musk's cryptocurrency-related tweets differs by considering different time-frames and currencies?

By answering these two study questions, we will be able to measure and better understand the impact of social media influencers on cryptocurrency markets, as well as draw some implications about how to interpret future events. Market participants will be able to better assess the significance of Musk's tweets and possibly other (social media) influencers in this way. Furthermore, the findings may contribute to broader study on the function of social media leaders in influencing investor behaviour, determining the quality of influencer content in the context of signalling theory, and determining influencer relevance for financial market efficiency.

Data and methods

Popularity analysis

The analysis is based on tweets by Elon Musk (twitter.com/elonmusk) between Jan 2011 to 2022. A data extraction has been conducted via python since some of its functions were more suitable for our purposes. The code used can be seen in the **Annex** section. Our dataframe resulted in total of 4787 tweets containing 68676 words over a time-span of 10 years. As stated in the previous section, popularity and influence are critical factors to be assessed from market participants in order to assign a certain degree of reliability to the information they receive. That's why a first investigation has been conducted in this direction. Elon Musk's influece has been skyrocketing throughout the years, mainly due to the achievements linked to his companies (namely Space X and Tesla) proving wrong many opponents who considered his goals too ambitious to be reached. On top of his professional achievements, his uncommon behavior, his funny character and his inspiring vision and leadership made his influence to grow sistematically. We used three proxies to quantify his popularity: namely, the *numbers of likes*, *number of replies* and *number of retweets* on Musk's tweets. These variables has been grouped by year in order to identify the trend clearly. As expected, his popularity has gained momentum especially after *2016*, when Tesla Model 3 was launched, some companies were renovated and gained momentum (i.e. SolarCity embedded in Tesla itself) and others were founded (i.e. Neuralink).

Crypto-related tweets

In a second step, a subset of the total population of tweets was made, in order to extract only tweets containing the word *bitcoin* **and** *cypto* so to direct our focus to Musk's influence on cryptomarkets Bitcoin-related. Exploiting the embedded time-stamp of these peculiar type of tweets, it could be possible to visualize in time when his tweets (events of interest) were located in respect to the Bitcoin market capitalization trend.

At first sight, considerable variations can be highlighted after these events and further considerations will be found in the **Result** section. Diving deeply, we proceed investigating any differences in how Musk's audience reacts to three categories of tweets: namely, the first obtained through grouping by the word *crypto*, the second grouping by *bitcoin* and the third by *dogecoin*.

Sentiment Analysis

Once obtained these data, they represented the input for our models: Sentiment Analysis and Polarization analysis were conducted, supported by wordclouds (in order to determine which were the most tweeted words). Through score assignment it has been possible to detect which were the most frequent sentiments in Musks's tweets, as well as the duration of these emotions. The results obtained through this first model helped us to understand the gradient of emotions provoked by Tesla CEO's tweets and therefore assessing those as drivers to his popularity and eventually his influence on cryptomarkets. This approach has been applied to a subset of Musk's tweets obtained by the following criteria: all the tweets starting from January 2020 and not containing the word *AMP*. We believe that removing the most frequent tweeted word and looking at a more recent timespan would strengthen our study highlighting any peculiar differences or similarities among the two datasets.

Testing for stationarity

Finally, we wanted to investigate the presence of linkages between Elon Musk's sentiment and Bitcoin volatility: which means testing for stationarity. We repeat the same process for Dogecoin volatility. First of all an Augmented Dicky Fuller test was used to evaluate how strongly a time series is defined by a trend.

Hypothesis

Null Hypothesis (H0) : Null hypothesis of the test is that the time series can be represented by a unit root that is not stationary. *Alternative Hypothesis (H1)*: Alternative Hypothesis of the test is that the time series is stationary.

Why is Stationarity Important?

Stationarity can be defined in precise mathematical terms, but for our purpose we mean a flat looking series, without trend, constant variance over time, a constant autocorrelation structure over time and no periodic fluctuations (seasonality). For data to be stationary, the statistical properties of a system do not change over time. This does not mean that the values for each data point have to be the same, but the overall behavior of the data should remain constant. If the data is non-stationary (meaning it has a trend), we need to remove it in order to proceed with the analysis. Various tecniques can be used to solve the issue of non-stationarity: after some attempts, the most succesful one has been to rely on the *log difference* of time values in Bitcoin price.

From non-stationarity to stationarity

Once obtained significant p-values assessing the non-stationarity of the selected time series, we try to achieve a stationary trend by doing a log difference among two subsequent values in the cryptocurrency value obtaining satisfying results. Eventually, we confront key breaking points where the average value undergoes a relevant change between two time points and the timestamp of the crypto-related Musk's tweet in order to visualize any linkages between the two phoenomena.

Results

Elon Musk's influence

As can be seen in the summary table below, Elon Musk's influnece has grown widely over the years. In 10 years, **number of replies** per tweet has grown up to more than 3 million, **number of retweets** up to more than 4 million and **number of likes** up to the astonishing numbers of more than 50 million. As of December 31st 2021, Elon Musk's follower amounted to 71.5 mln, which means a very high coverage of $72,2$.

We can visually understand the exponential trend in the growing popularity of Tesla CEO's. It comes as no surprise that when *"Elon Musk speaks, investors listen"*. His influence derives from his large audience, prone to process the majority of the information coming from him as good quality information, influencing their (financial) decision-making process.

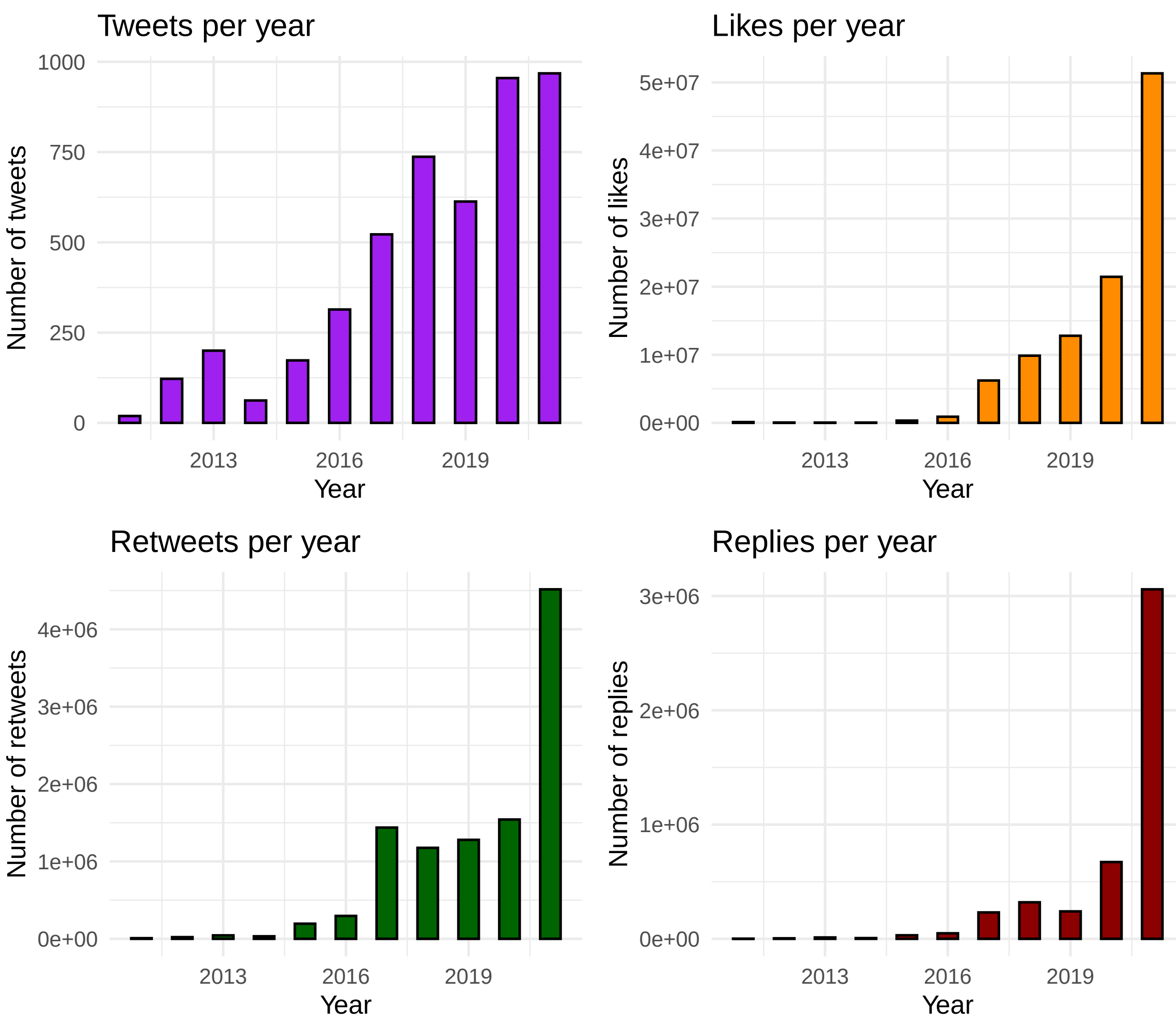


Figure 1: Elon's twitter interaction over time

Activty of crypto-related tweets

In this section we want to compare how Elon Musk's audience react to different type of tweets containing respectevely words related only to *dogecoin*, *Bitcoin* and *cypto*. As in the first section, we use the *number of likes*, *number of retweets* and *number of replies* as proxy to popularity and high network activity more generally. The first two categories are the most popular, and between the two BTC-related tweets generate slightly more interaction, coherently with the central importance that Bitcoin has in the crypto scenario. The third category seems less "popular" but this is only due to the specific address to certain currencies by the Tesla's CEO.

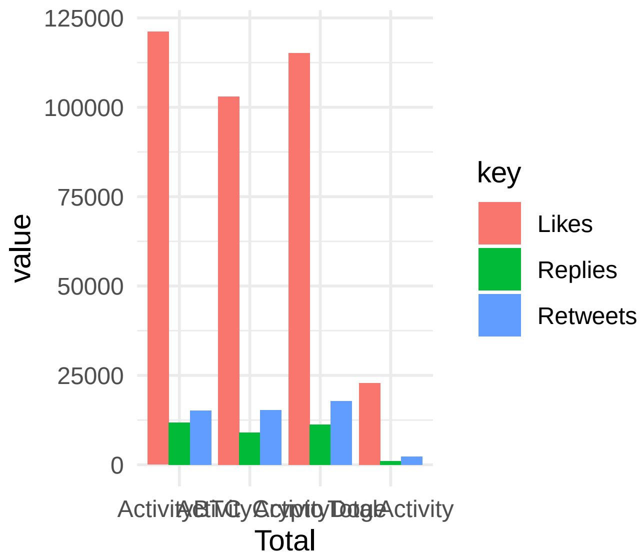


Figure 2: Crypto-related content interaction

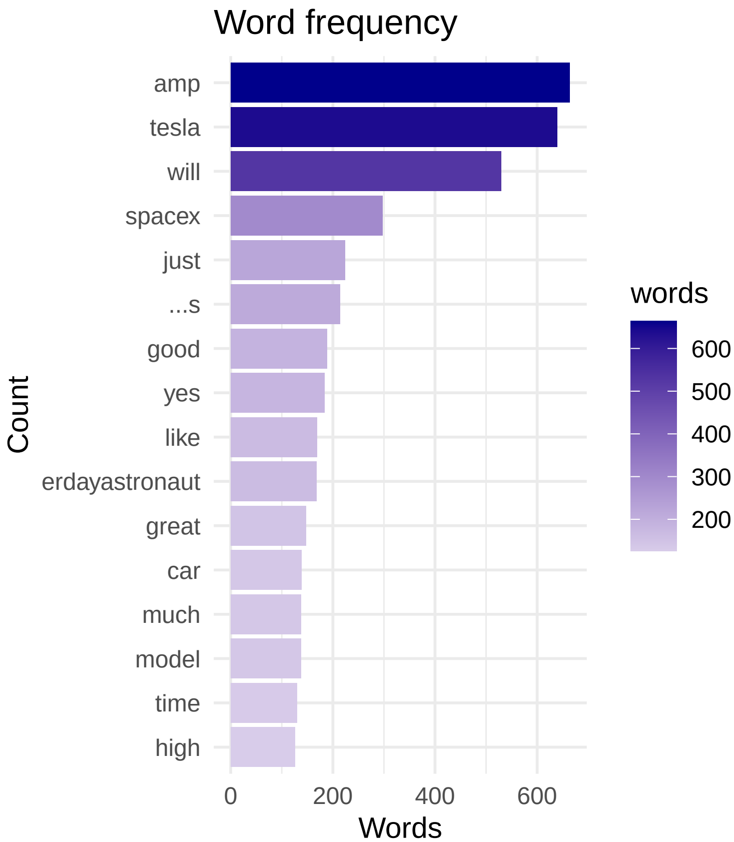
When Elon Musks tweets, investors listen

Once quantified Elon Musk's influence, it is essential to understand the extent of this influence on the cryptomarket. Which is the width of Bitcoin price volatility once a crypto-related tweets is published? We managed to extract the tweets which only cointained the words *bitcoin* and *crypto* and connected their time-stamp to the Bitcoin market capitalization trend. The pink points on the graphic represent the moment in time when a crpyto-related tweet was published: there is clear evidence suggesting a relationship between the Bitcoin volatility and Musk's trend however, it is still unclear at this stage whether it's Elon Musk's direct influence on Bitcoin price change or the other way round. It cannot be assessed a clear causality relatioship. This issue will be further addressed in this paper.

Sentiment Analysis : Model I

While the market may interpret Musk's tweets about Tesla as "accurate news", his tweets about cryptocurrency at least to some degree represent moods or personal sentiment. In this section we want to further analyze the nature of this sentiments, the most frequent words and the emotions associated to them.

The graph below shows the most used word and their frequency. It appears that the three most used words are *amp*, *tesla* and *will*. We find the presence of more than 600 words for the firsts two, while more than 500 words for the latter. It goes without saying that we expected **tesla** to be one of the most frequent word in Musk's tweet, and our interpretation of the word **will** lies in that this verb shows his strong willingness and decisive, goal-oriented character as well as his inclination towards the future sustained by visionary statements. It can be less clear why **amp** is among the most frequent word, therefore we opted for a further explanation.



AMP

Amp is a universal collateral token designed to facilitate fast and efficient transfers for any real-world application. When using Amp as collateral, transfers of value are guaranteed and can settle instantly. While the underlying asset reaches final settlement, a process that can take anywhere from seconds to days, Amp is held in escrow by a collateral manager. Once the transaction successfully settles, the Amp collateral is released and made available to collateralize another transfer. Amp exists to serve as universal collateral for anyone and any project. (*Source [(https://docs.amptoken.org/)]*). Besides being a collateral for individuals and DeFi platforms, Amp is used as a collateral for payment networks: Flexa uses Amp to enable instant, fraud-free payments to merchants across its digital payment network. Apps that integrate Flexa stake Amp to ensure all payments can be settled in real-time regardless of the asset or protocol used. Since AMP Token was to be integrated with Tesla's payment rail for crypto, it is understandable why it's been one of the most tweeted words by Elon Musk, being this news shocking the crypto-lovers panorama and the future of Tesla. The news of Tesla about the willing to accept crypto as payments and the investment in over 1.5 BLN USD in Bitcoin (February 2021), made the price of Bitcoin to skyrocket. On the other hand, a plethora of enviromental activists opposed this decision due to the high levels of electric energy which are used to mine and sustain the crypto network and highlighted the controversial nature of the Tesla CEO's choice: this led Elon Musk to no longer accept payments in Bitcoin. The impact on the crypto-currency value has been devastating has shown in the following graphic showing once again, how much "investors listen to Elon Musk".

Here follows a wordcloud which helped us to visualize the most frequent words in Elon Musk's tweets. The higher the word's size displayed, the most frequent the word would appear in his tweets.

Sentiment scores and density

Based on the following results of the Sentiment Analysis of Elon Musk's tweets, it appears clear that *positive*, *trust* and *anticipation* are the most frequent emotions. This result is perfectly coherent with the visionary Tesla and SpaceX CEO's personality: his hunger for innovative , out-of-the-box solutions; his continuous positive and confident approach towards insurmountable problems such as "taking the human race to Mars", conceiving re-usable rockets disrupting space industry, as well as "changing the world's concept of driving through electric autonomous driven vehicle" and many others clearly embeds those emotions.

```
##   anger anticipation disgust fear joy sadness surprise trust negative positive
## 1     2            1       1    2   1       1        1     1        2        1
## 2     0            0       0    0   0       0        0     0        0        1
## 3     1            1       2    2   0       2        0     1        2        1
## 4     0            0       0    0   0       0        0     1        0        1
## 5     0            1       0    0   1       0        0     3        0        3
## 6     0            0       0    0   0       0        0     0        0        0
```

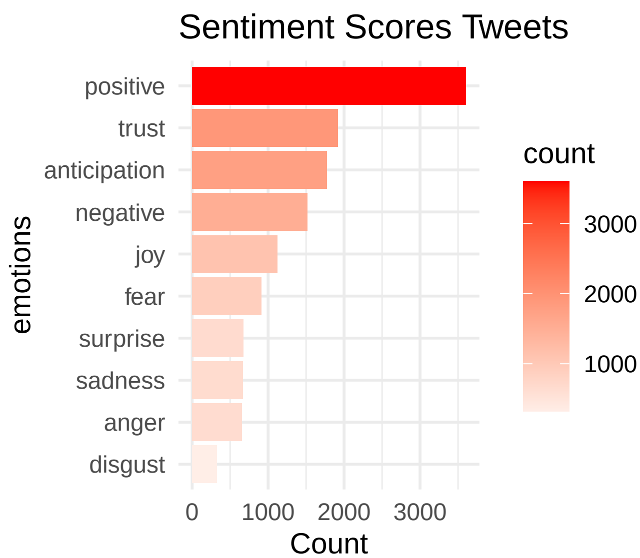


Figure 3: Sentiment scores of Elon's tweets

Another important result is outlined by the following graphs. It shows the density of sentiment: as it can be noticed it follows a normal-like distribution ($\mu = 0.18$, $ = 0.36 $), slightly positevely skewed. This result is line with the previous results, highlighting the positive polarity of the sentiments. Here follows a brief statistical summary of the density plot, followed by the plot itself.

```
##          Statistical summary sentiment
## Mean                      0.18242245
## Sd                        0.35932881
## IQR                       0.45907962
## Skewness                 -0.04752713
## Kurtosis                  0.79887814
```

Emotions at the sentence level

The following analysis detects the rate of emotion at the sentence level. This method uses a simple dictionary lookup to find emotion words and then compute the rate per sentence. The emotion score ranges between 0

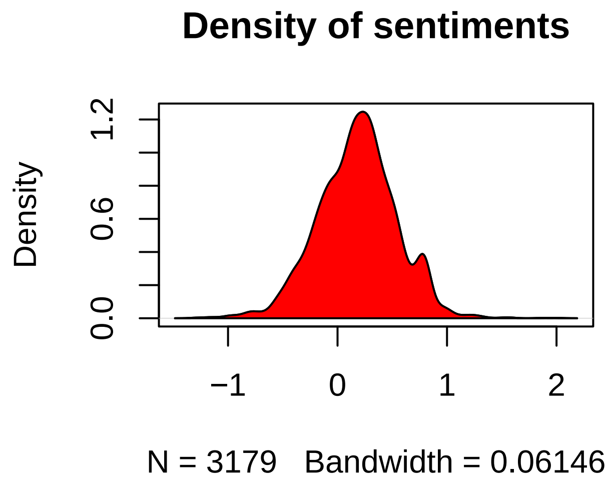


Figure 4: density of polarity scores

(no emotion used) and 1 (all words used were emotional). Once again, this result is in line with the previous ones, showing how positive emotions such as joy, trust and anticipation are predominant. Please note that the suffix *_negated* indicates the opposite of the reference emotions, which appears to be consistently absent in relation to any emotion.

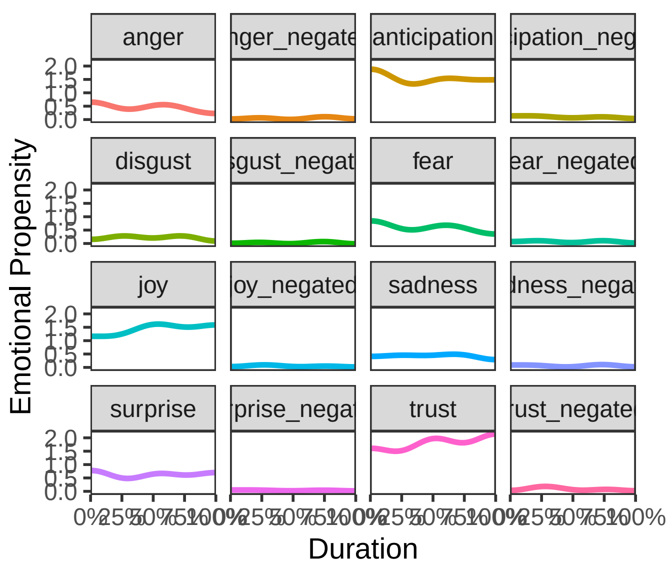


Figure 5: plot of Emotions

Subsetting sentiment from Jan 2020 without "AMP" word: Sentiment model II

Once obtained solid result for the entire dataset of tweets ranging from year 2011 to 2021, it is interesting to compare those with new results coming from a subset of the selected time frame. We believe it is an interesting way to assess our results' coherence and a further investigation into the "popular" period of Elon Musk. Furthermore we believe the most used word, i.e *AMP*, should be removed in order to assess whether the absence of this word could influence the final output. In a programatic approach, we apply the same methods, codes and considerations of the previous section on a different subset of data.

This primary result is in line with the previous ones, once again the two most used words are *tesla*, *will* and *spacex*. The frequency of each word is compared in the chart above. We proceed displaying a wordcloud, in order to have an eye-friendly visualization of the word frequency in this new subset of data.

Figure 6: Wordcloud of Elon's tweets resampled

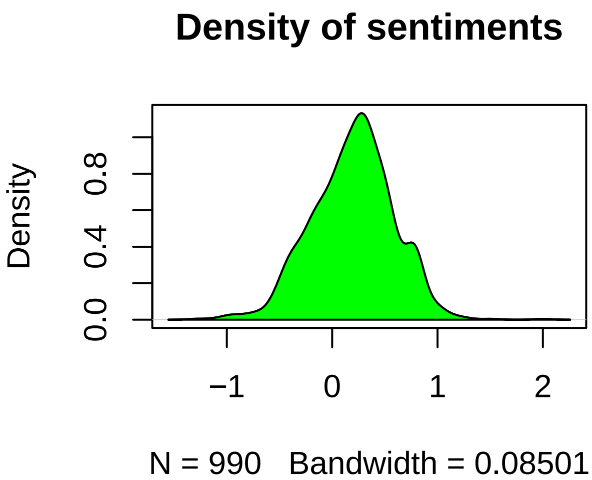
Sentiment scores and density

Consistently with the previous results, the *Muskanian* influence is still positive with the most frequent sentiments of *positive*, *anticipation* and *trust*.

The density of sentiment is slightly different from the first one: as it can be noticed it still follows a normal-like distribution ($\mu = 0.19$, \$ = 0.39 \$), slightly positevely skewed. This result is line with the previous results, stating the even more positive polarity of the sentiments in the new timeframe. A brief statistical summary of the new density plot compared to the previous one is displayed. A new density plot can be found in the chart below.

```
## New names:
## * `Statistical summary sentiment` -> `Statistical summary sentiment...1`
## * `Statistical summary sentiment` -> `Statistical summary sentiment...2`
```

```
##             Sentiment model I Sentiment model II
## Mean                0.1981359         0.18242245
## Sd                  0.3859845         0.35932881
## IQR                 0.5028519         0.45907962
## Skewness           -0.1307537        -0.04752713
## Kurtosis            0.6063917         0.79887814
```



The chart below shows an overall overlapping with the previous result. Still positive sentiment of *anticipation*, *joy* and *trust* are the most frequent. However, the sentiment of *trust* is more volatile, and there is a slight decrease in the negative sentiment of *fear*. This slight but still relevant change can be interpreted in a different context than the one of model I: the audience has become more educated and informed about the phenomenon of crypto-currencies as well as more critical towards the Tesla CEO's tweets, who sometimes has been accused more intensively of market manipulation (however without losing popularity or positive appeal). In conclusion, the Muskanian audience still listen to him and trust him, simply with more critical sense which makes the *trust* sentiment to be more volatile and the *fear* sentiment lower.

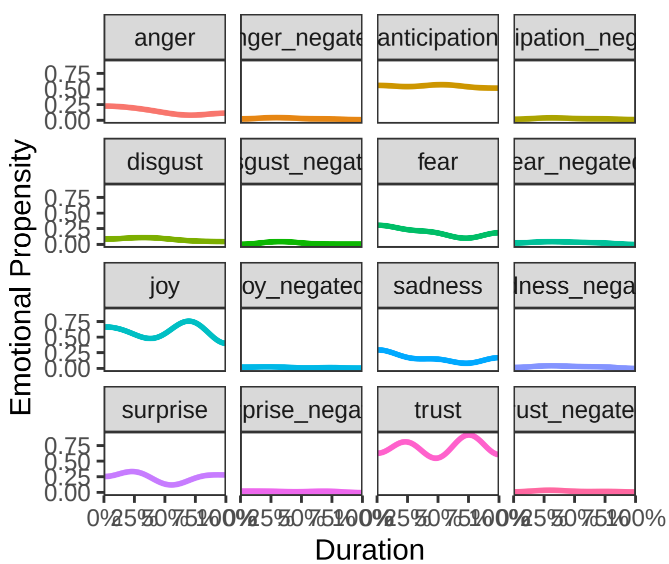


Figure 7: Emotion's Plot of Elon's tweets resampled

Testing for stationarity

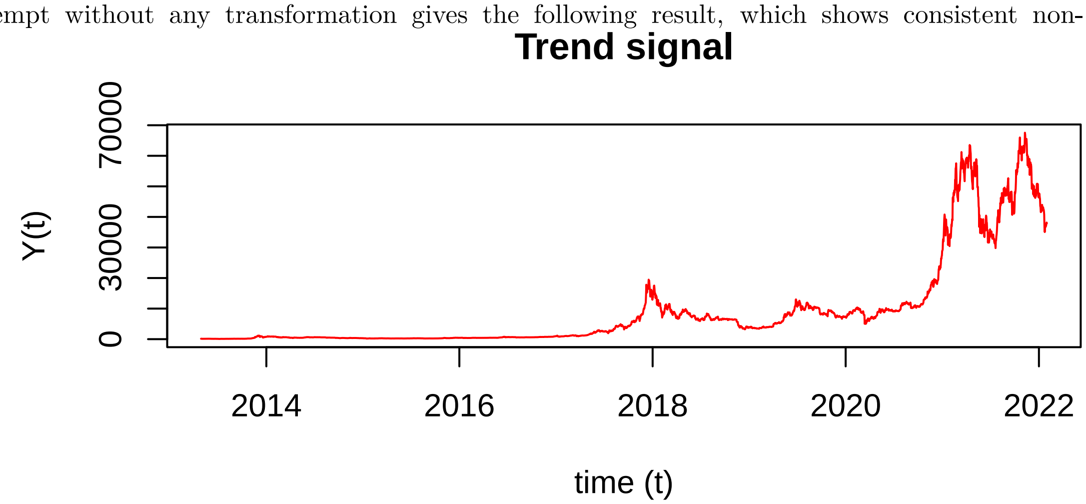
In this section we show the results obtained when testing for Bitcoin trend stationarity. We recall the hypothesis:

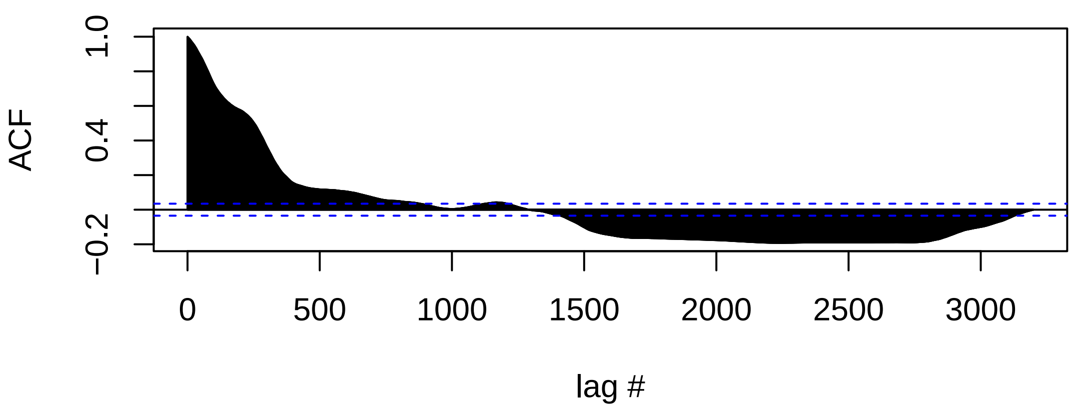
Null Hypothesis (H0 : Null hypothesis of the test is that the time series can be represented by a unit root that is not stationary. *Alternative Hypothesis (H1)*: Alternative Hypothesis of the test is that the time series is stationary. The following plot, represent our study focus.

Autocorrelation Function

The autocorrelation function (ACF) defines how data points in a time series are related, on average, to the preceding data points (Box, Jenkins, & Reinsel, 1994). In other words, it measures the self-similarity of the signal over different delay times. An autocorrelation plot shows the value of the autocorrelation function (ACF) on the vertical axis. It can range from −1 to 1. We use autocorrelation plot to assess wether the elements of a time series randomly oscilates around zero.

Our first attempt without any transformation gives the following result, which shows consistent non-





stationarity.
We proceed by applying an Augmented Dickey–Fuller (ADF) t-statistic test for unit root: in statistics and econometrics, an augmented Dickey–Fuller test (ADF) tests the null hypothesis that a unit root is present in a time series sample. The alternative hypothesis is different depending on which version of the test is

used, but is usually stationarity or trend-stationarity. It is an augmented version of the Dickey–Fuller test for a larger and more complicated set of time series models. The augmented Dickey–Fuller (ADF) statistic, used in the test, is a negative number. The more negative it is, the stronger the rejection of the hypothesis that there is a unit root at some level of confidence. Our result clearly shows a non-stationarity due to the high p-value (>0.5).

In order to go from non-stationarity to stationarity different techniques can be used. We first attempt in utilising logaritmic transformation: such transformtion can help to stabilise the variance of a time series. We apply the ADF test, still obtaining a non statistically relevant result, even though the p-value has decreased to 0.46.

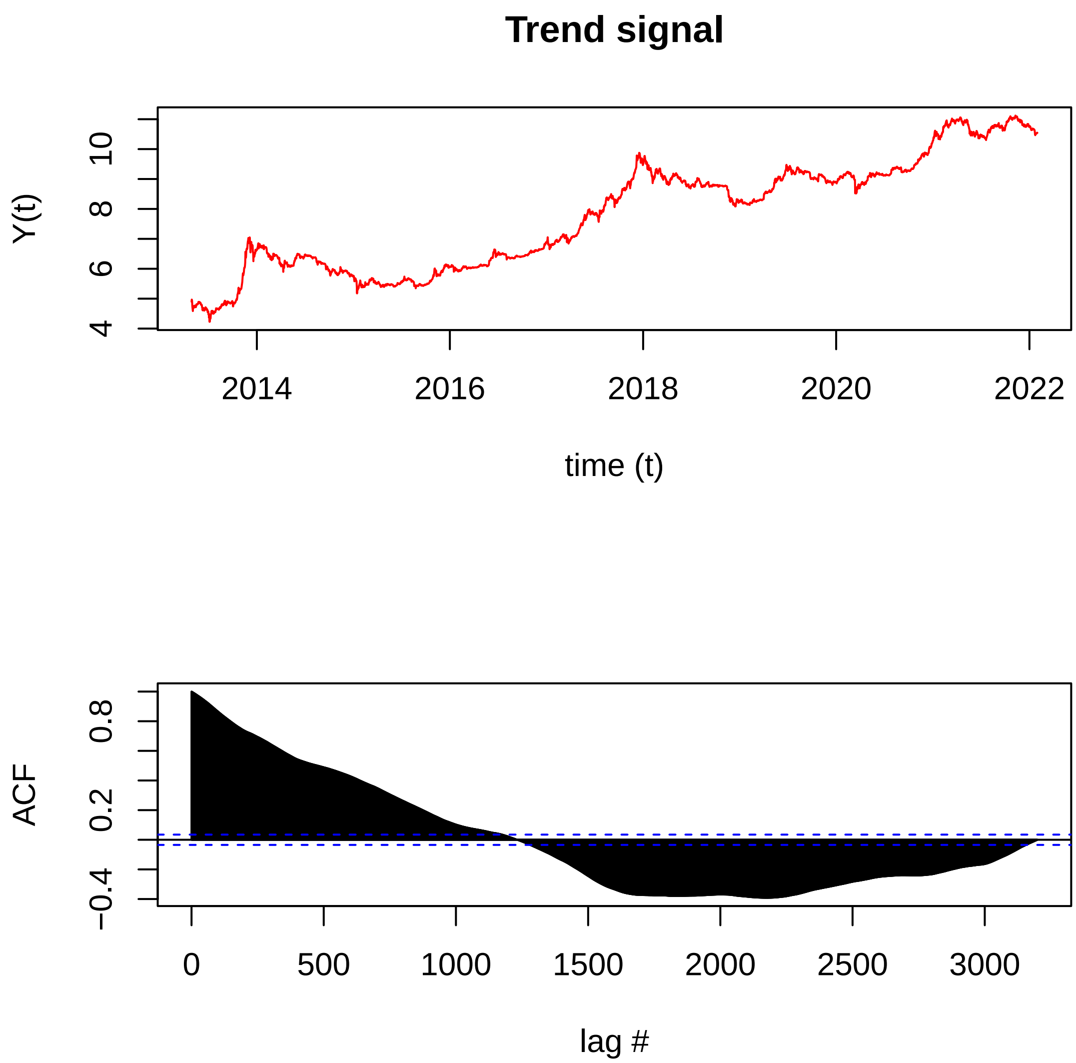


Figure 8: LogBitcoin's trend and ACF function

Differencing log values can help stabilise the mean of a time series by removing changes in the level of a time series, and therefore eliminating (or reducing) trend and seasonality. We attempt to use this transformation obtaining satisfing results. Indeed, the following plot shows how the trend has been removed and stationarity is obtained.

We conduct the ADF test to confirm our results: p-value is now 0.01 (highly significant) and we can assess that the log difference of the elements of the time series result to be non-stationary.

This means that bitcoin volatility is random, not influenced by Elon Musk's tweets. By being able to use a

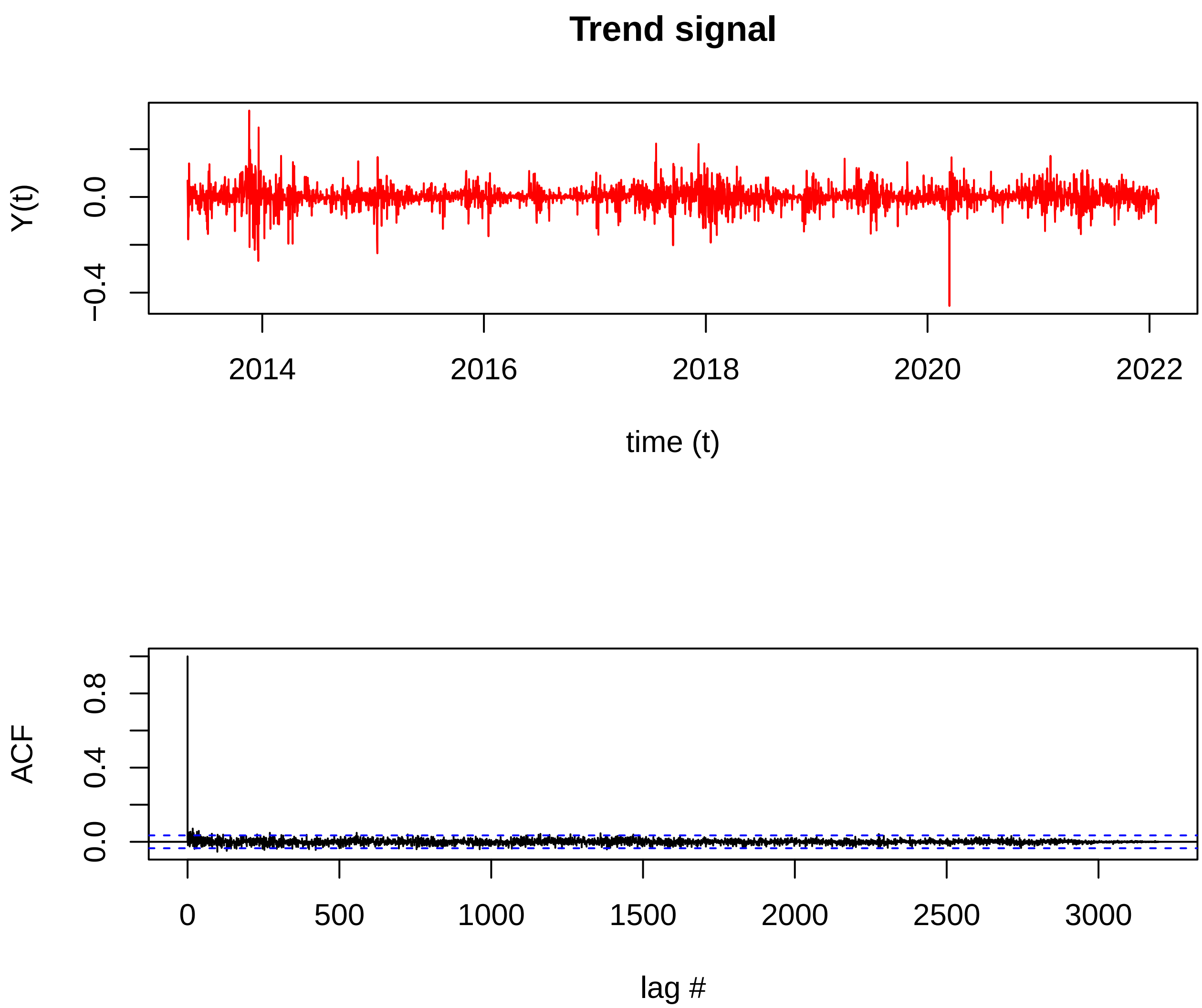
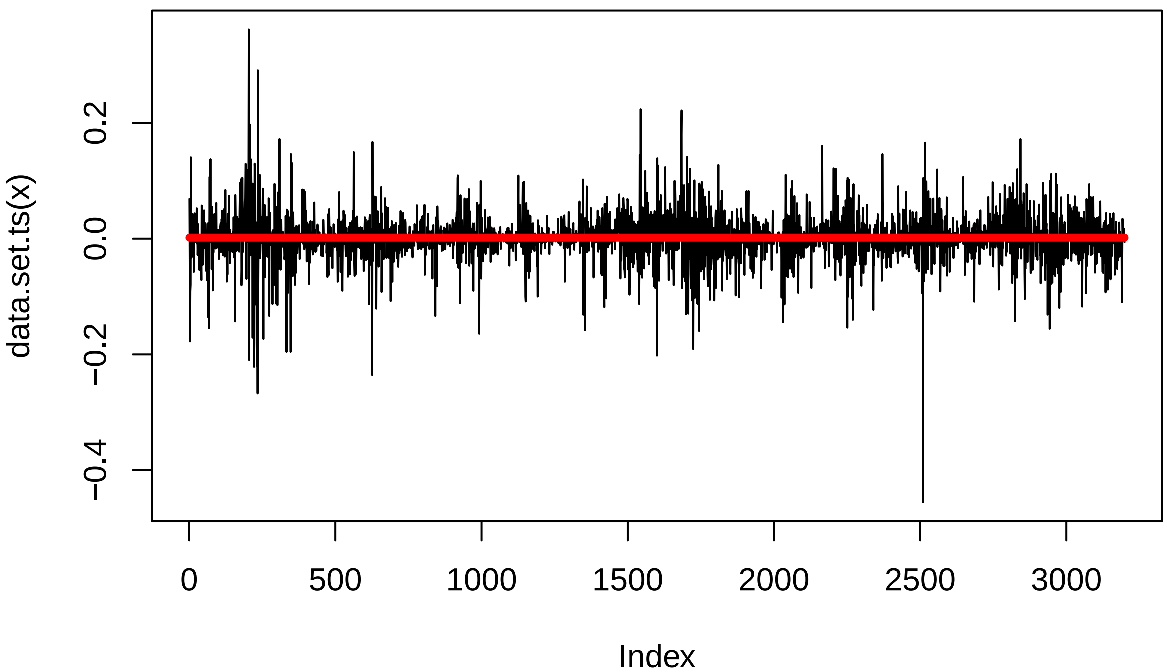


Figure 9: Differences of LogBitcoin's trend and ACF function

time-series without stationarity, it might be possible through some techniques to further investigate if, in a time-series trajectory with no trend, there are some specific changes in mean in specific timestamps. To do that we try to identify "change points" in our data. By doing taht we obtain a set of timestamps from which the variance of the time-series trajectory changed. By obtaining those timestamps and confront it with elon musks' tweet regardind crypto, it is possible to try

```
m_binseg <- cpt.mean(logdiff, penalty = "BIC", method = "BinSeg", Q = 15)

plot(m_binseg, type = "l", xlab = "Index", cpt.width = 4)
```




```
#all the changes happen from 2750 onwards approx, try to subset plot
m_binseg <- cpt.mean(logdiff[2750:3199], penalty = "None", method = "BinSeg", Q = 15)
```

In the chart below a deep investigation regarding the potential linkage between Bitcoin volatility and Musk's tweet has been conducted. In blue the *breaking points* are highlighted, which are points in time where the mean a variable undergoes a significant change. The breaking points method is broadly used in literature and comprises a variety of different methods. In purple we find highlighted when the crypto-related *tweets* were published. As we can notice, there is no correspondence or correlation of the two variables: we cannot state that Musk's tweets influence Bitcoin volatility, which is in-line with our previous result of non-stationarity.

««««< HEAD Our findings are strenghtened by the confirming the previous result and considerations for the Dogecoin cryptocurrency. We proceed in the same way as before, analzying the trend signal and moving from non-stationarity towards stationarity, as it can be seen in the results below.

The breaking points versus tweet timestamp analysis on Dogecoin currency confirms and strenghten our findings: there is no linkage between Musk's tweet and the crypto-currency volatility.

Conclusion

We have extracted a total of 4787 tweets containing 68676 words from Elon Musk's twitter profile: we investigate the impact of 26 Twitter events by Elon Musk on the trading volume and price of the cryptocurrencies

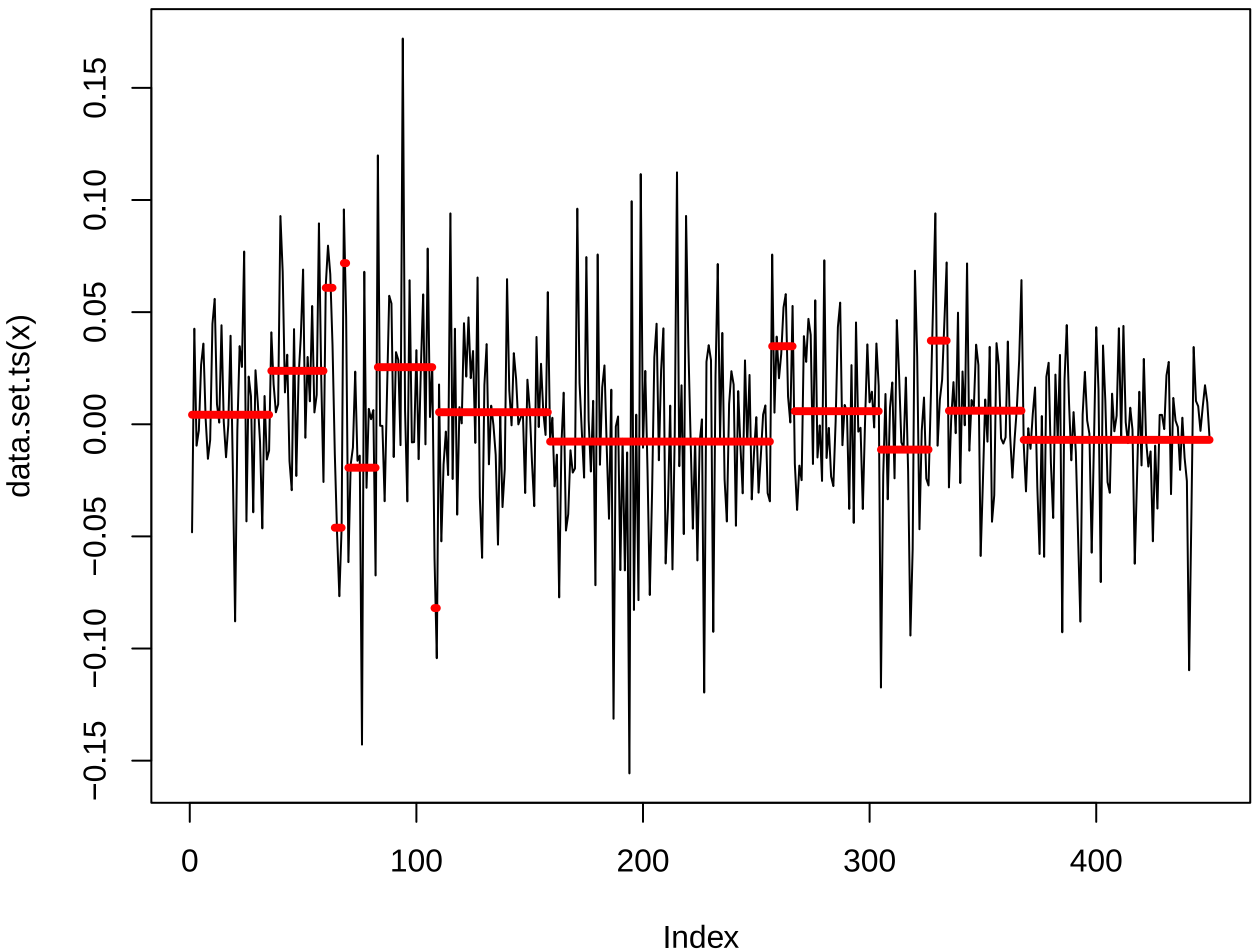


Figure 10: Changepoints in LogBitcoin Differences

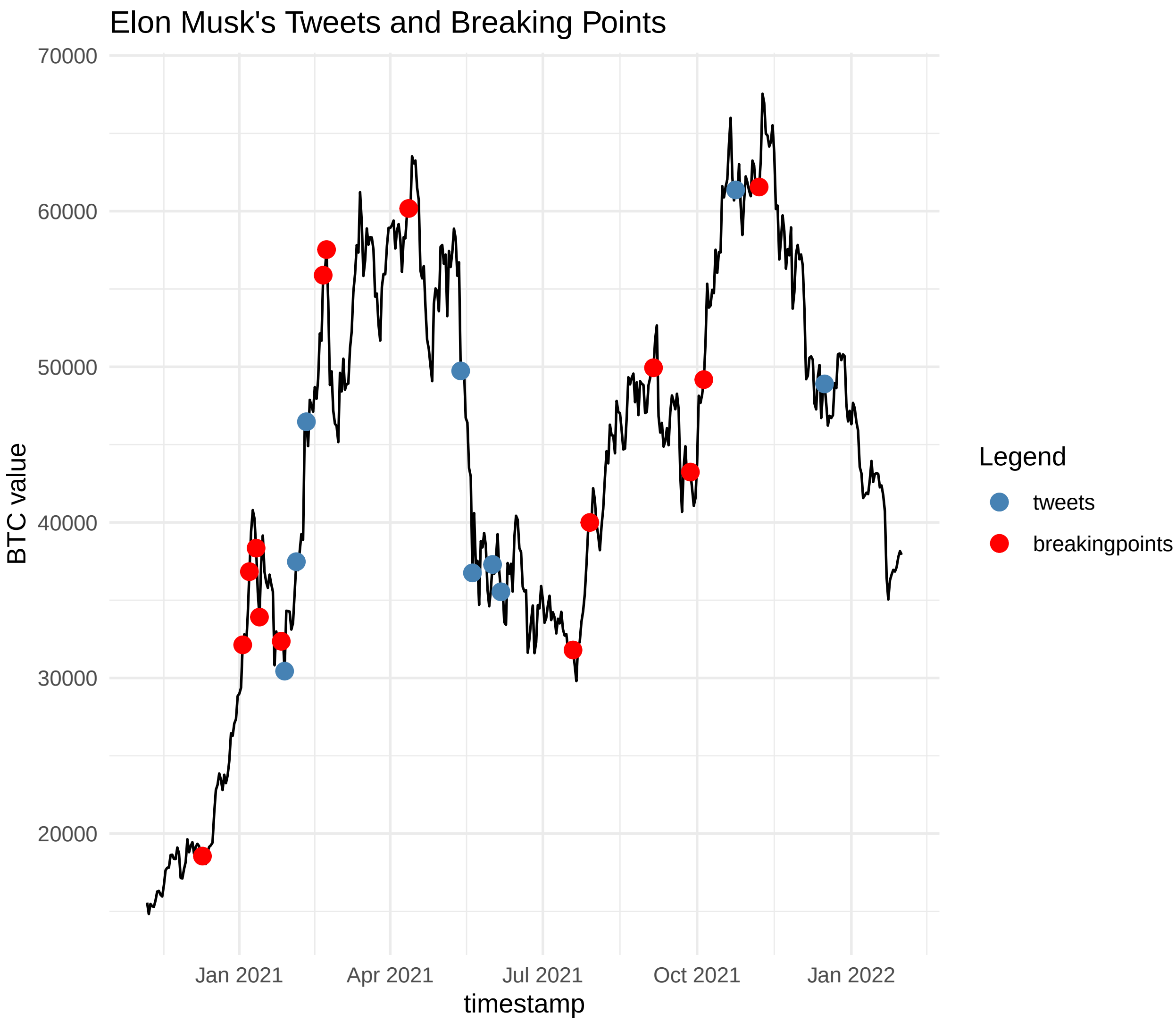


Figure 11: Elon Musk's Tweets on Cryptos and LogBTC's Changing Points Dates

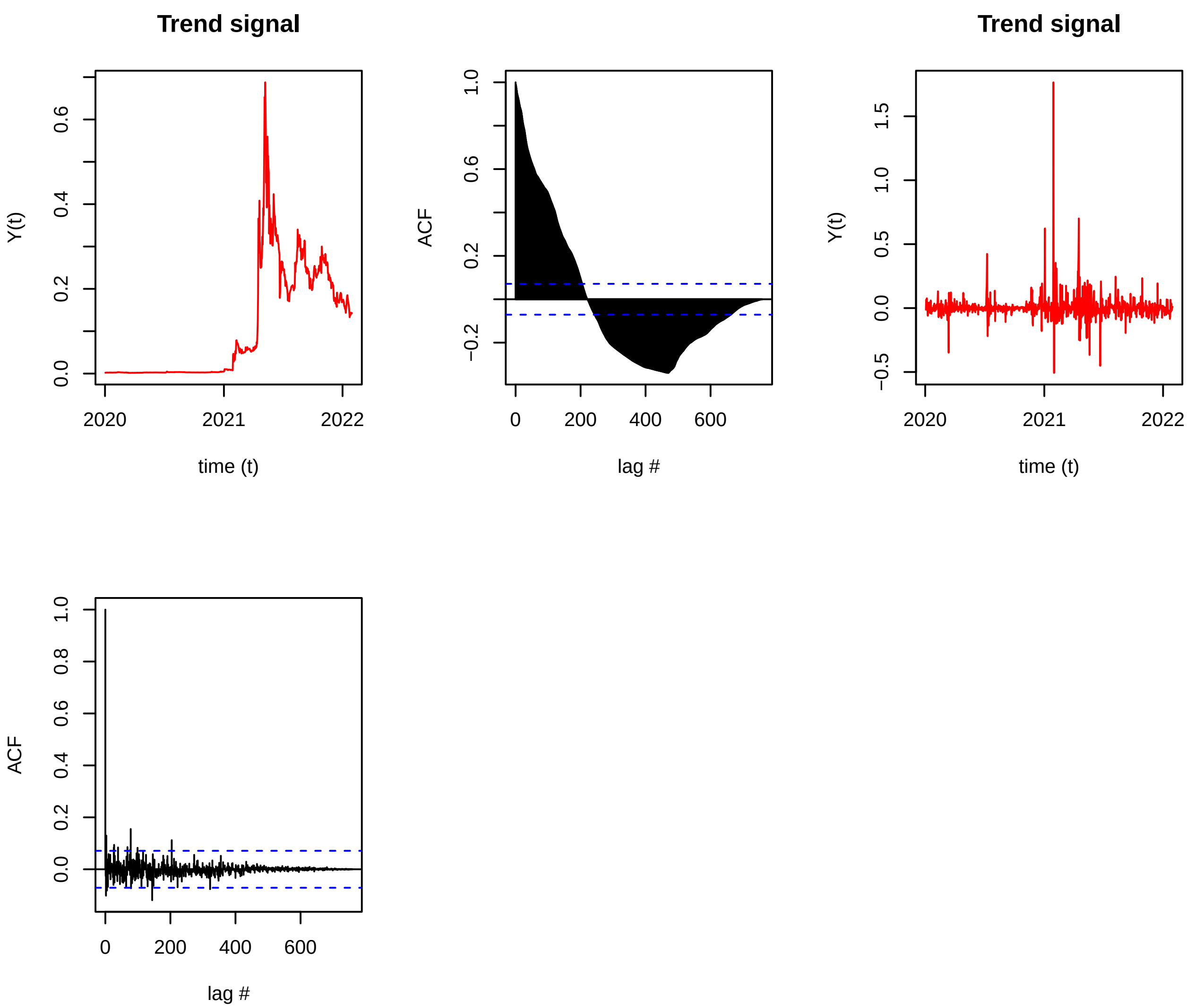


Figure 12: Doge and Diff LogDoge trend with its respective ACF

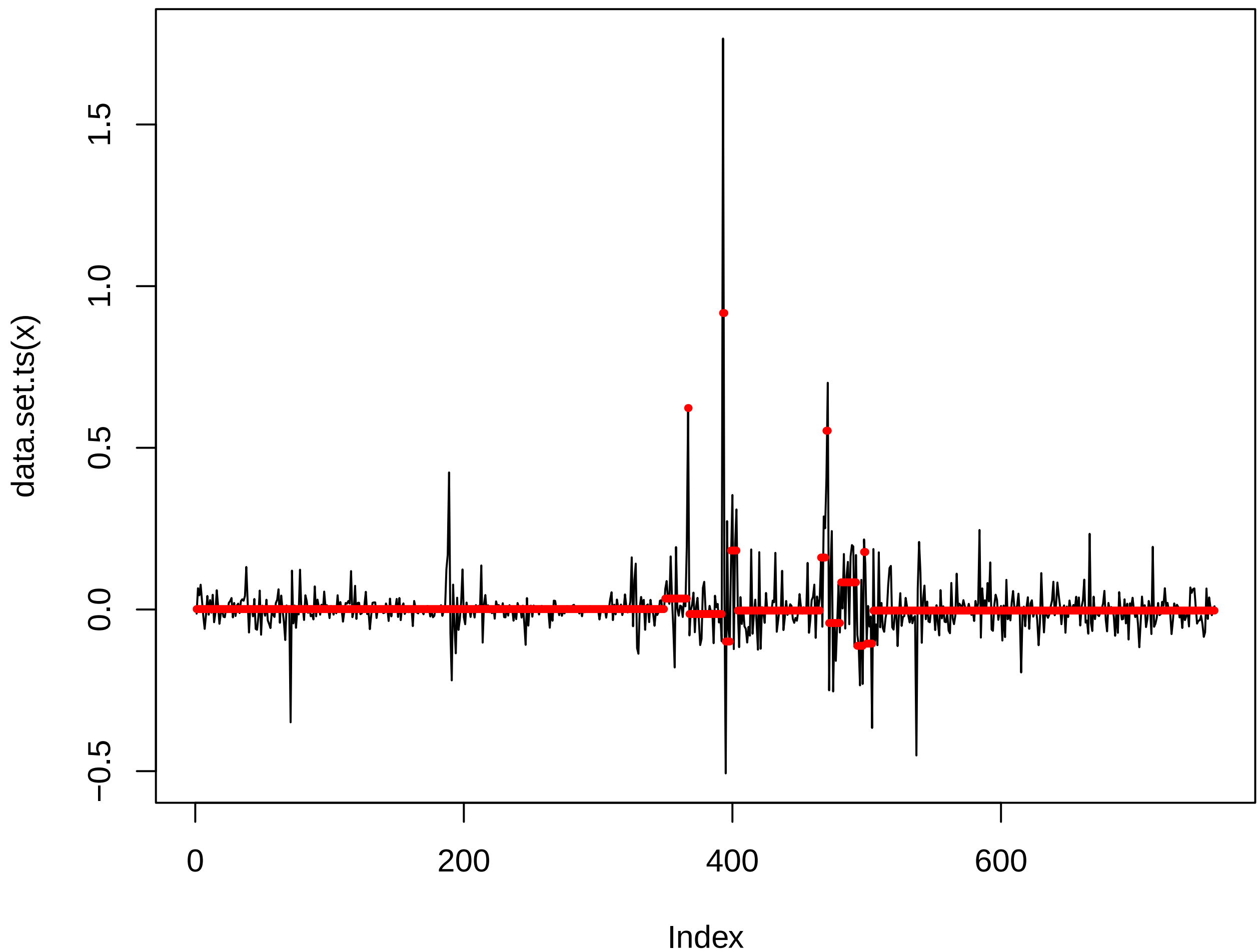


Figure 13: Change point in differences of LogDoge

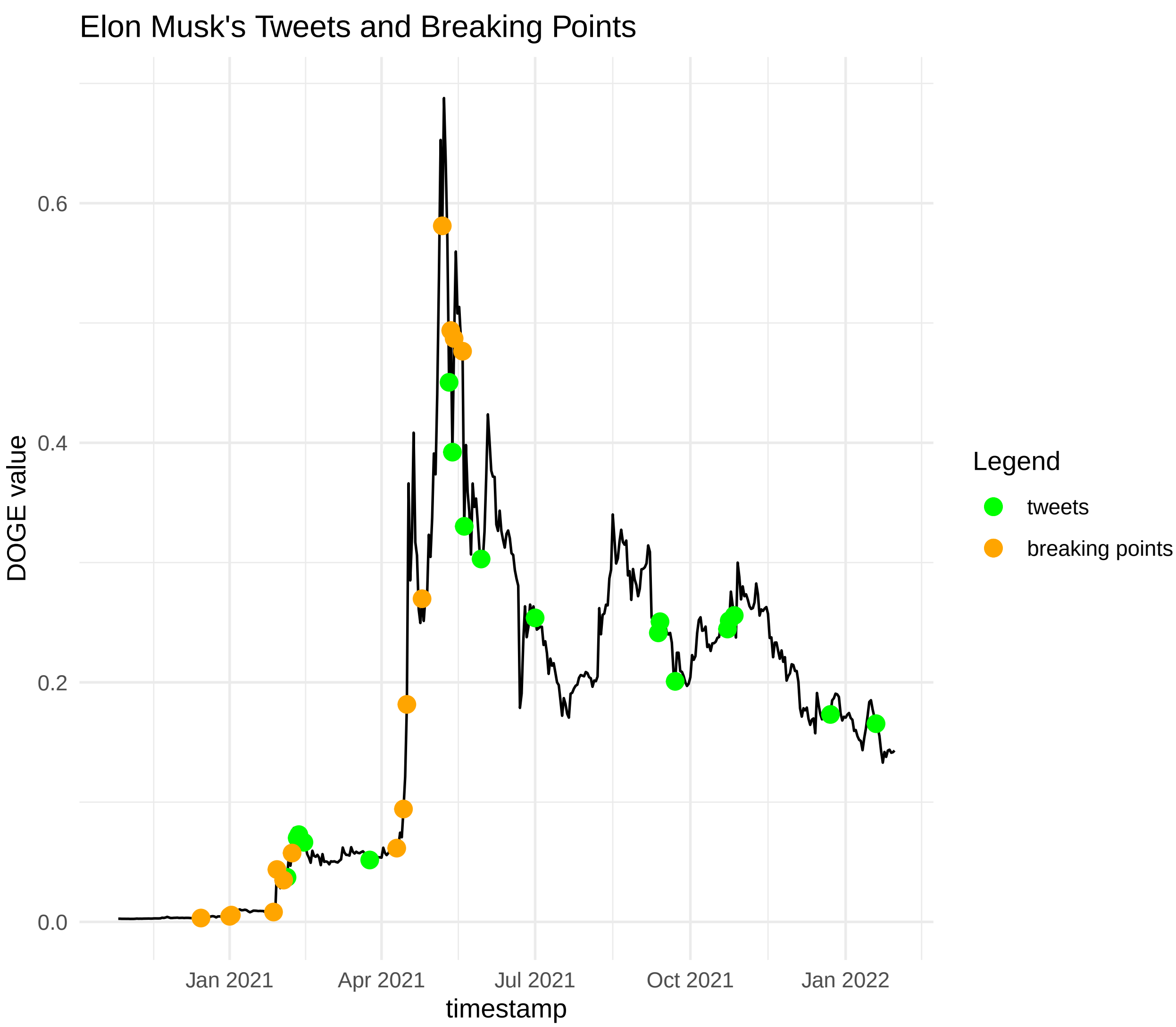


Figure 14: Elon Musk's Tweets on Dogecoin and LogDoge's Changing Points Dates

he comments on. Firstly we conducted a popularity analysis, where the influencing power of the Tesla CEO's can be seen skyrocketing throughout the years, especially after year 2016. A sentiment approach has been adopted into investigating his activity-related emotions, with an overall positive range of emotions associated to it, as well as a frequency analysis on the most used words and polarity analysis (Model I). A subset of the focus period has been investigated in a second model (Model II), namely considering tweets published from January 2020 and eliminating the most used word in the Model I (*amp*). Coherent results has been found, with a slight change in the emotions due to a late-stage of Musk's popularity, with a more self-conscious, critical and mature audience. Finally, we have investigated potential linkages between Musk's crypto-related tweets and Bitcoin volatility comparing *when* those tweets were published to critical *breaking points* in the currency value: no clear linkage has been found, assessing the randomness of the Bitcoin trend. Our result has been similar by applying the same investigation to Dogecoin.

This study contributed to the existing available knowledge on information aggregation on the internet, particularly by so-called influencers in social networks. It also serves as a foundation for assessing the impact of extremely prominent people's views on bitcoin and financial markets. The findings give market participants a better foundation for determining the importance of certain tweets. Investors may use this knowledge to design an alternative investment plan, regulators could assess the necessity for market intervention, and influencers could better understand the consequences of their actions on Twitter.

Annex

Python code to extract Elon Musks's tweets via Twitter API

```
import twint
import datetime

def delist(x):
    df = x[0]
    for i in range(1, len(x)):
        df = df.append(x[i])
    return df

def ElonPaginated():
    data = []
    start = datetime.datetime.strptime("2011-01-01", "%Y-%m-%d")
    end = datetime.datetime.strptime("2022-02-01", "%Y-%m-%d")
    date_generated = [start + datetime.timedelta(days=x) for x in range(0, (end - start).days)]
    date_generated = date_generated[::7]
    date_generated = [date_obj.strftime("%Y-%m-%d") for date_obj in date_generated]
    for i in range(0, len(date_generated) - 1):
        c = twint.Config()
        c.Username = "elonmusk"
        c.Since = date_generated[i]
        c.Until = date_generated[i + 1]
        c.Pandas = True
        twint.run.Search(c)
        Tweets_df = twint.storage.panda.Tweets_df
        if Tweets_df.empty:
            pass
        else: data.append((Tweets_df))
    return data

data = ElonPaginated()
```

```
data = delist(data)
print(data)
data.to_csv('/Users/federicopiazza/Desktop/MONTREAL/QM/elon.csv')
```

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