

Islamic View Towards Bitcoin

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Abstract

This paper proposes to analyze the agent behavior by means of big data extracted from the search engine « Google trends » and Twitter API to visualize the emotions and the manner of thinking about « Bitcoin » in the Islamic context. Two kinds of sentiment measures are constructed. The first is based on search query of the word « Bitcoin » with religious connotation in all over the world from 14/04/2017 to 14/04/2018 in weekly frequency. The second is built on twitter data from 03/04/2018 to 13/04/2018, by using a Bayesian machine learning device exploiting deep natural language processing modules to assign emotions and sentiment orientations. In the next step, the Granger causality analysis is used to investigate the hypothesis that this sentiment causes the volatility and the returns of « Bitcoin ». The results show that, at a first-level that twitter users of the word « Islamic Bitcoin » improve positive sentiment. Secondly, the Twitter sentiment measure has a significant effect on lagged Bitcoin returns and volatility. Furthermore, this sentimental variable Granger causes Bitcoin returns and volatility.

This study contributes to the literature by studying the influence of the doctrinal view towards Bitcoin on his prices dynamics. Knowing that Bitcoin is a new financial asset and there is a large debate on his compliance with shariah

Keywords-component; *Bitcoin, microblogging, sentiment analysis, text mining, Islamic finance.*

I. INTRODUCTION

The development of information technology over the past two decades has changed the ways of generating, processing and transmitting information and thus profoundly influenced the asset prices in capital markets. A huge volume of searches, news, comments and recommendations are generated daily on social media, from which behavioral economics researchers extract proxies reflecting investor sentiment.

In particular, Bitcoin gained increasing media attention in social networks. Bitcoin is a form of cryptocurrency introduced by Nakamoto (2008). It is a payment system based on blockchain.

Muslim people occupy an important space from the world. They present over than 23,4% from all the world in 2011. Some of them which are looking for satisfying their religious needs are focusing on the sharia compatible degree of the Bitcoin [1]. Many studies have focused on studying the Muslim psychology [2] and the Islamic market [3][4] [5].

In order to measure investor sentiment, empiricists use sentiment analysis approach which is a process of detecting the contextual polarity of the text. It determines whether a given text is positive, negative or neutral. In this analysis, the opinions about «Bitcoin» combined to «Islam » are collected from the users of different social media and classified by their polarity.

Furthermore, behavioural Science uses search query data to analyze the degree of users' attention towards these terms. In fact, it constitutes a mean of sentiment analysis.

In this paper, we propose a semantic approach to discover user attitude and business insights from social media and web users. For this purpose, we will first give brief literature in section1. Then, in the second section, we will try to visualize the attention of internet users of the word «Bitcoin» in the context of religions and beliefs by means of « Google trends ». In the third section, we will focus on the Twitter user's emotion and polarity who interact around the subject « Bitcoin » in Islamic doctrine. A measure of sentiment will be associated with this category of Twitter users. This sentiment will be used to test our hypothesis of the existence effect caused by this sentiment. This methodology will be explained in section 4.

The results will be discussed in section 5. Finally, we will conclude by some remarks.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Actually, many studies using Google Trends have demonstrated several examples of how the search volume for keywords coincides with as many patterns showing how these kinds of correlation hold for many local phenomena. For instance, it seems that media providers and policymakers are interested in looking at Google Trends in order to determine the hot topics for their editorial content. As an example, we can take a look on the case of a popular political site which could benefit by looking at the current hot queries and, consequently, writing down a post on the site containing focused keywords so that Google can quickly index the post. These examples are just some of the many strategies adopted by SEO practitioners (Yun et al.). The high penetration rate of the Internet [6] is not sufficient to be representative of the entire population. In our case, we are interested especially on the effect on financial markets, traders and policy maker's decisions. Furthermore, we

consider the fact that active users issue more queries than less active ones, with the consequence of blinding the weight carried by each user in creating the aggregated queries. Accordingly, many other researchers focused on the validity of search queries as potential indicators of public opinion [7]. More optimistically, others have argued for predictive models based on search query data (Varian and Hal, 2015) and social media sentiments data (Ruths et al., 2014) and (Asur, 2010).

As for [7] the views expressed in polls are solicited because search users are volunteers; while survey pollsters, under the pressure of survey staff, select respondents. The discretionary nature of search behaviors loans verisimilitude to the query data, which are not altered by search engines [7].

[8] suggest that the data generated by « Google Trends » has an influence on the market movements. By analyzing changes in query volumes on Google for terms related to finance, they found patterns that can be interpreted as "early warning signs" of shares to market movements.

Milas and C. Panagiotidis Th. (2014) attempted to explain the influence degree of the information contained in social media (Twitter and Facebook) and Web search queries (Google) on financial markets. Using a multivariate system and focusing on the peripheral countries of the euro area, the GIIPS (Greece, Ireland, Italy, Portugal and Spain), they showed that the discussion of social media and search queries related to Greek debt crisis provide significant information in the short term mainly to the bond yield differential of Greek/German state, even when other financial control variables (default risk, liquidity risk, and international risk) are recognized and to a much lesser extent, Portuguese and Italian yield spreads.

D'Avanzo et al (2017) led an experimental framework allowing the integration of Google search query data and Twitter social data. They built a pipeline interrogating Twitter to track, geographically, the feelings and emotions of Twitter users about new trends. The core of the pipeline is represented by a sentiment analysis framework using a Bayesian machine learning device exploiting deep natural language processing modules to assign emotions and sentiment by Twitter data. They employed the pipeline for consumer electronics, healthcare and politics. Their results show that the proposed approach in order to measure social media sentiments, and emotions concerning the trends emerged on Google searches is plausible.

[9] introduced the concept of divergence of sentiment to the behavioral finance literature. They measured the distance between people with the positive and negative sentiment on a daily basis for 20 countries by using data from status updates on Facebook. Their results showed that the divergence of sentiment is positively related to trading volume. They further predicted and found a positive relation between the divergence of sentiment and stock price volatility. They also compared the effect of the specific country measures to a global measure of divergence of

sentiment. They found that the separate effects of specific country and global divergence measures depend on a country's level of market integration.

[10] examined the relationship between investor attention and Bitcoin fundamentals. He found that realized volatility and volume have significant effect on the Bitcoin attention.

[11] used a dual process diffusion model to assess the impact of Twitter and Google Trends on Bitcoin. They showed in their results that Bitcoin prices are partially influenced by the web and Twitter information.

Unfortunately, empirical studies focusing on the use of big data to visualize the Islamic view are very rare. As we know our work is the first empirical framework focusing on the influence of the agent's psychological component on the Bitcoin by means of big data. For this purpose, we propose the following hypothesis.

Hypothesis: The Twitter sentiment has an effect on the contemporaneous and lagged bitcoin return and volatility.

III. SEARCH QUERY SENTIMENT

In this section, we will present the search query tool generated by Google trends in order to build a measure of investor sentiment based on the search query of the word « Bitcoin » in the Islamic context.

A. Search query presentation

The service of google trends offers a curve representing an indicator of the number of a term of research given in function of time. The time scale goes back to January 1, 2004, and is up to about two days before the current date, the updates are very fast. In addition, the user also has access to news related to the curve, allowing him to draw conclusions about the impact of such an event on the user's interest. In the end, the service details the most often related to term research and a map seeing areas where the expression is the most sought at the global, national and regional levels, as well as cities. It is possible to enter up to five terms and compare their developments.

In our methodology, the proposed measure is based implicitly on the fact that people collect information on the internet using search engines. Furthermore, search-based sentiment measures are available in real time; as economic fundamentals change over time, a high frequency sentiment measure can carry out more precise empirical tests. Second, such a measure reveals attitudes rather than inquire about them [12]. While surveys lack cross-verified data on actual behavior, search behavior proves to be this objective external verification [13].

This framework exploits Google Trends, which summarizes queries through the analysis of web users search behaviors in order to find the most relevant queries related to « Bitcoin » in the context of « Religions and beliefs ». Google Trends is a tool designed for tracking the popularity of any given search term over time [14]. We start then by introducing the

word « Bitcoin » since 2004 in monthly frequencies with religious connotation as shown in Figure 1.

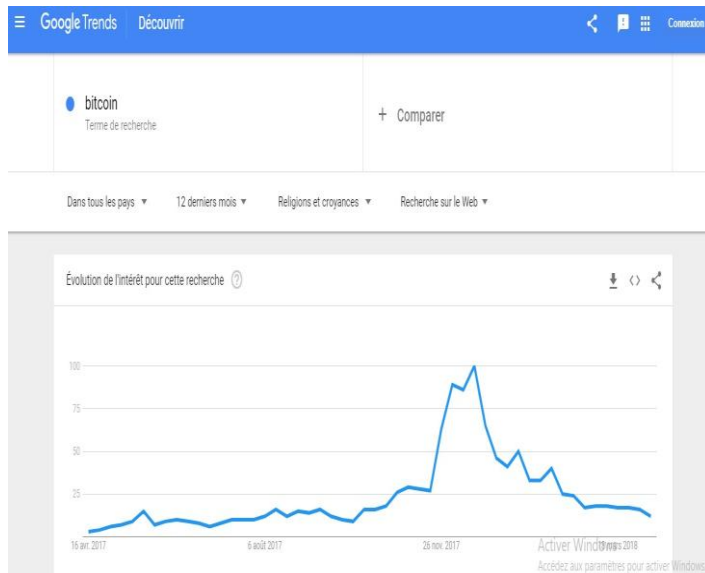


Figure 1. interest search evolution for the term “Bitcoin”, source « Google trends »

Figure 1 represents the behaviour of the search query of the word “Bitcoin” with religion and belief’s connotation from the period between 14/04/2017 and 14/04/2018. In figure 1, we can observe that the frequency of the term « Bitcoin » is very high in the period between 17/11/2017 and 23/11/2017. This period is marked by the remarkable evolution of the “Bitcoin”.



Figure 2. Geographical Search query

Figure 2 shows that the word “Bitcoin” in the mentioned context is very frequent in Slovenia, South Africa, Malaysia, United Arab Emirates, Turkey, Croatia, Singapour, Australia, and Pakistan.

B. Search query sentiment:

As we have previously reported, the investor sentiment is a much-debated topic in behavioral finance. The researchers were very interested in how to measure investor sentiment. Some empiricists use indirect measures based on market sentiment indices. We may mention for example the approach of Baker and Wurgler (2006) offering an indirect measure of investor confidence by using six "inputs".

Other empiricists use direct measurements with indices based on surveys, such as the consumer confidence index or "Consumenten Conjunctuur Onderzoek (CCO)" CBS Netherlands¹ While this approach shows a clear theoretical link of investor confidence, it has the disadvantage of taking time in the polls and creating an offset [15]. In addition, respondents are often biased by answering questionnaires ; it is proving to be a difficult task to obtain sincere and prudent responses by respondents [16].

Thus we will consider the series given by google trends as a measure of the sentiment involving the degree of attention paid by internet users for the word « Bitcoin » in the context of « religion and beliefs ».

IV. TWITTER SENTIMENT

This framework is planned on the basis of two kinds of analysis. The first aim at measuring the sentiment, while the second one is oriented at estimating the emotions expressed in posts broadcasted on social networks. Tweets are retrieved by using Twitter APIs, exploiting the default access level. By using a special account, Twitter APIs can also provide two other levels of access, the firehose and the gardenhose, returning, respectively, 100% and 10% of all public tweets. The retrieved data of the tweet, contain other features, such as date, source, type, profile, location, number of favorited friends, followers, URL, hashtag, and so forth. Relevant tweets were searched and extracted from Twitter programmatically by using twitteR package, written in R programming language. This comprehensive tweet search was conducted between 03/04/2018 to 13/04/2018. Consequently, the collection of related tweets was retrieved and saved in csv files. The data in this file contained the tweet information along with user information posting the tweet. Posting dates were also substantial for the analyses. However, not all the tweets had the posting date information. The analyses in this study performed using the tweets with no missing values.

¹ www.cbs.nl

During data cleaning, the retweets were also omitted as the aim of this study is to specify the sentiments or opinions of individuals and the retweets were not considered to reflect a new personal opinion. Therefore, we removed retweets from our analyses.

The language of each tweet is automatically detected and, if it is different from English, an online translation service is invoked, so as to translate in the best possible way the currently examined tweet using only English. In fact, according to [17], [18] and [19] in some cases a translation procedure can be useful for detecting sentiment in language other than English. At this point of the development of the entire framework, this allows us to refine as much as possible the modules as a function of only one language. All tweets so obtained are, then, pre-processed as in the following: stop words are filtered out, links and hashtag are removed, and words of length less than three characters were discarded before processing the text because they often hide off-topic posts or even spam. The tweets containing mainly abnormal sequences of characters were discarded [20]. The processing step just described, culminates in the intervention of the two modules of sentiment and emotion analysis. In particular, the sentiment detection module estimates the predominant orientation, i.e. positive or negative, of each tweet. Simultaneously, the emotion detection module identifies the emotions expressed by the current tweet, giving as a result the predominant feeling among one of the following: anger, disgust, fear, joy, sadness, and surprise [21]. The choice of these six emotions comes from the psychological evidence of human non-verbally expressed emotions proposed by Ekman (1992). Therefore, we introduce some details about both the sentiment and emotion detection modules that, at this stage of overall development of the framework, cover the most important experimental role. Furthermore, some aspects of the visualization module are also introduced.

A. Sentiment detection module

Sentiment detection module exploits different sentiment detection tools, constituting a submodule, which can be plugged or unplugged, at will. In particular, at present the sentiment detection module exploits naive Bayes detection algorithm as sentiment analysis tool. The dataset contains 941 terms, each of which is associated to a sentiment which can be “positive” naive Bayes detection algorithm has been trained on Wiebe’s subjectivity lexicon [22]; overall, or “negative”. The learning module analyzes a given text and for each polarity returns its absolute log likelihood expressing that sentiment; results are then evaluated, resulting in the most likely polarity

B. Emotion detection module

As well known, Tweets can express also emotions and, as such, this module estimates the most appropriate one for each tweet among the six basic emotions: anger, disgust,

fear, joy, sadness, surprise proposed by Ekman (1992). The emotion detection module can exploit different emotion detection tools, embedded as sub-modules, which can be plugged or unplugged at will. In particular, two sub-modules, a naive Bayes learning algorithm and a voter algorithm have been at present plugged in the emotion detection module. Each of them is briefly summarized below:

- The simple voter algorithm uses the above-mentioned lexicon by counting the number of occurrences of the anger, disgust, fear, joy, sadness and surprise words contained in the text. The majority of counts give the prevalent emotion associated to the text message. If the text does not contain a prevalent number of words expressing a given emotion, the text message is labeled as carrying “no emotion”.

The outcome of each sub-module is the percentage of retrieved tweets classified as expressing an emotion among the aforementioned six or classified as “no emotion”. Finally, the results coming from all the submodules on the retrieved tweets are averaged, obtaining an “emotion” distribution, obtaining: Disgust, Fear, Joy, Sadness, Surprise and Anger, whereas the overall sum must be equal to 1. As is the case for the sentiment module, results obtained from all the retrieved tweets are averaged, and the averaged distribution is the outcome of the module.

C. Visualization module

An overall result is therefore presented to the user in a graphical manner, in order to help us in her decisional process (Dhar, 2003). Data visualization offers to decision-makers a way to make sense of large dataset, allowing the discovering of patterns for decision support (White and Colin, 2011). The user can decide also to plot and compare the analysis results regarding different queries in order to get an idea on the general feelings that arise from twitter social network regarding specific themes or features of interest. This feature can be helpful also for the comparison of sentiments and emotions arising from tweets retrieved by using different queries. This approach simplifies the decisional process and allows overcoming the information overload by quickly having an idea about the general sentiment or emotions raised by news goods or aspects.

D. Experiments

We have implemented and tested the prototype employing « Islamic » combined by « Bitcoin ». The tweets retrieved in this context are represented in table 1. In fact, as we have said, the framework proposed represents for us an experimental laboratory where we can test hypotheses and models on different social phenomena, using social behavioral data. We analyzed the word frequencies for English tweets about “Islamic Bitcoin » using word clouds. Their visualisation figures of emotions, polarity in figure 3.

TABLE I. BITCOIN TWEETS IN ISLAMIC CONTEXT

text	favorited	truncated	screenName	retweet Count	isRet weet	Retwee ted
1	RT @APompliano: An important Islamic scholar has deemed Bitcoin to be compliant with Sharia law. This means 1.6 BILLION Muslims are now pe...	13/04/2018 20:28:57	Twitter for iPhone	probabl ysaif	218	TRUE
2	RT @APompliano: An important Islamic scholar has deemed Bitcoin to be compliant with Sharia law. This means 1.6 BILLION Muslims are now pe...	13/04/2018 20:28:45	Twitter for iPhone	TheRea IVherus	218	TRUE
3	RT @crypToBanger: @jack "Islamic Scholar Declares Bitcoin Sharia Law Compliant, Potentially Opening Market To 1.6 Billion Muslims"	13/04/2018 20:28:35	Twitter for Android	adi014 9	21	TRUE
4	RT @APompliano: An important Islamic scholar has deemed Bitcoin to be compliant with Sharia law. This means 1.6 BILLION Muslims are now pe...	20:27:38 13/04/2018	Twitter for Android	ColinC allahan 46	218	TRUE
5	RT @APompliano: An important Islamic scholar has deemed Bitcoin to be compliant with Sharia law.	20:27:25 13/04/2018	Twitter for iPhone	Pupsric s	218	TRUE
	This means 1.6 BILLION Muslims are now pe...		iPhone			
6	#cryptocurrency #Bitcoin #halal (declared permissible) under Sharia Law - 1.6 Billion Muslims can now enter crypto... https://t.co/BQ0SKdS6sy	20:27:12 13/04/2018	Twitter Web Client	LarryA llhands	0	FALSE

The wordcloud is presented figure 4. These figures address the thinking style of Twitter users.

In fact, twitter users have a global positive view towards "Islamic + Bitcoin". Their emotion of "Joy" towards the two cited words is dominant.

When running the VAR-models it is important to include the right lag length of the dependent variable as well as the independent variables. The lag length for the VAR (p) can be determined using selection criteria model.

The lag length for the VAR (p) model can be determined using model selection criteria. The basic idea is to fit VAR (p) models with orders $p=0, 1, \dots, p_{max}$ and choose the appropriate value of p which minimizes the model selection criteria (Lütkepohl, 1991).

In our work we use the SC criteria and additional criteria of Hannan-Quinn information HQ formally stated:

$$HQ = 2k + -2L_{max} \log \log n$$

Where: L_{max} represents the log likelihood probability data into a model, k is the number of parameters, n: is the number of observations.

Using these models, we can identify if the tested variable is persistent, and if its value in the past still weighing on today's values; and therefore the integration time offsets is necessary and obvious. According to the FPE "Final prediction error", the number of significant lags to use is 5 lags, while LR, Hannan-Quinn information criteria HQIC and SBIC and AIC "Akaike information criterion", suggest eleven lags. In this work we use five lags in order to simplify the calculations.

*** The "Granger" causality test**

Granger causality test, proposed in 1969, is a statistical hypothesis test to determine whether a time series is useful in forecasting another. Normally, regressions reflect the "simple" correlations, but Clive Granger argued that the economy causality could be tested by measuring the ability to predict future values of time series with past values of another series time. Since the question of the "real causality" is deeply philosophical and guess that something before another can be used as proof of causation, econometricians argue that the test of Granger believes "predictive causality".

Hence, if we control the information contained in past Y, we can say then that X "Granger cause" Y (Datta et al., 2006).

Formally, the possible Granger causal links between stock and bond outcome (returns and volatility noted by R) and sentiment (s) is formulated as follow:

$$R_t = \sum_{i=1}^m \beta_i R_{t-i} + \sum_{i=1}^m \gamma_i S_{t-i} + \eta_t + \epsilon_t$$

C. Empirical Results:

In this section we try to give the results of testing our hypotheses. Therefore, we use the regression with Newey-West standard errors in order to avoid any autocorrelation and heteroscedasticity of the errors. Table 2 provides the results of this regression. In this table we clearly show that most of the coefficients of twitter, and google trends measures statistically significant in their relation with the return of Bitcoin. These results conduct us to confirm our first hypothesis. The second part of this table shows that

sentimental proxies are statistically significant. This result confirms our second hypothesis.

TABLE II NEWEY-WEST STANDARD ERRORS REGRESSION RESULTS

	Twitter sentiment
Bitcoin Return	0.3282316
Bitcoin Volatility	0.0329292

When we apply the VAR model, we find that the Twitter sentiment has a delayed effect on the return and the volatility of Bitcoin. Table 3 details the results of the VAR model.

TABLE III VAR MODEL RESULTS

Bitcoin		Twitter sentiment
Bitcoin Return	Lag 1	0.0479795
	Lag 2	-0.0010292
	Lag 3	-0.0957978
	Lag 4	-0.1831325***
	Lag 5	0.0619689
Bitcoin Volatility	Lag 1	1.850196
	Lag 2	1.583181
	Lag 3	-0.7420697
	Lag 4	1.212408
	Lag 5	-2.880991***

For our last hypothesis, Table 4 expresses the results of Granger causality test with five lags. In this table 4 most of the p values are under 5% which show that our sentimental proxies Granger causes the Bitcoin return and volatility.

TABLE IV GRANGER CAUSALITY RESULTS FOR BITCOIN

Granger causality test	Chi2	Freedom degree	P value
Twitter → bitcoin return	7.1305	5	0.211
Twitter → bitcoin volatility	12.488	5	0.029**
Twitter → bitcoin return and volatility	23.511	10	0.009*

CONCLUSION:

The compliance of Bitcoin to Shariah has created great debate between Muslim people. This work visualizes the attention and the emotions towards Bitcoin with regard to its conformity with Sharia law. For this purpose, a measure of sentiment is constructed based on Twitter and Google Trends data. Then the top methods are proposed to investigate whether these sensations and emotions have an impact on the market sentiment and the price fluctuations.

Bayesian machine learning device exploiting deep natural language processing modules has been used to assign emotions and sentiment orientations. The contemporaneous effect deduced by Newey-west regression, the delayed influences tested by VAR model, and Granger causality analysis are used to investigate the hypothesis that the constructed measure of sentiment has an impact on the volatility and the returns of Islamic assets.

These metrics prove that this sentimental index has a significant effect on the Bitcoin variables. Both positive and negative sentiment are expressed by Twitter users'. Bitcoin is not totally accepted by Muslim people who seek to satisfy their religious needs. We let future research to develop new Islamic cryptocurrencies satisfying Sharia requirements.

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