Hype as a Factor on the Global Market: The Case of Bitcoin

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Abstract

The impact of Bitcoin-related Google queries, Facebook likes, reposts and comments on Bitcoin price is analyzed with the help of ARDL and GARCH models. Our results have led us to the following conclusions. Firstly, a sharp increase in Bitcoin's popularity or hype, which manifested itself through a rise in the number of Bitcoin-related Google queries, has resulted in an increase in Bitcoin price. This effect corresponds to the description of the 'collective hysteria' that spread in the online community and was triggered by the increasing volatility of the Bitcoin market. Secondly, we found that Bitcoin's popularity among ordinary Internet users has a positive impact in low-volatile and highly volatile rising markets but a negative one in a highly volatile falling market. Thirdly, Bitcoin's popularity among informed Internet users has a negative impact on Bitcoin price in a period of low volatility. Fourthly, uninformed users' trust in Bitcoin has a positive influence on Bitcoin price in low-volatile and highly volatile falling markets. Finally, the main factors that shape the Bitcoin market are trust and popularity.

Keywords: Bitcoin; social media; popularity; hype

G15; G14; G41

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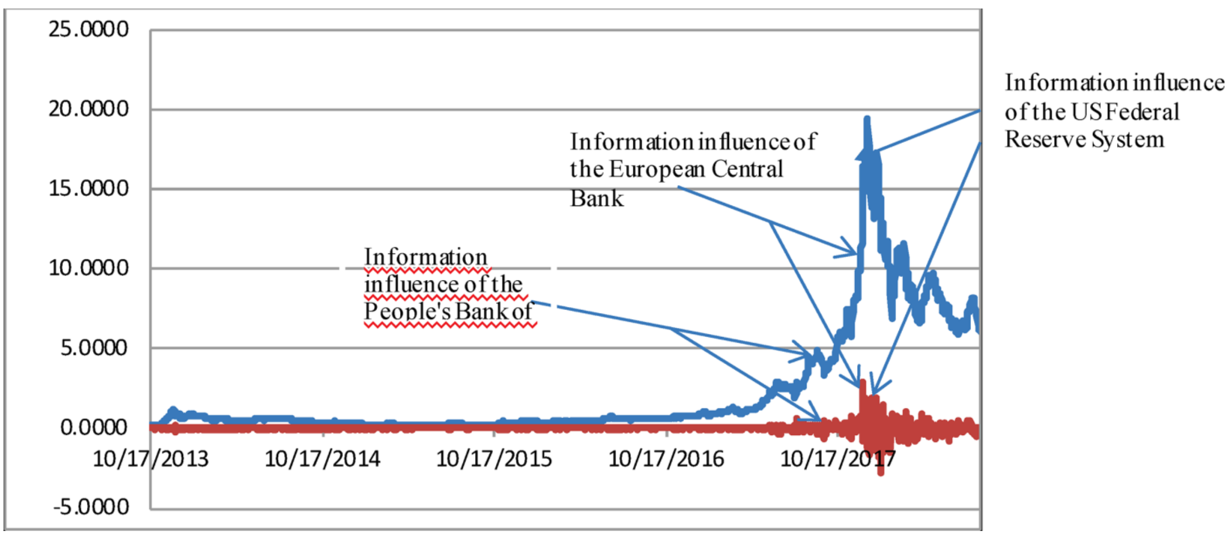
Introduction

Bitcoin was the first established cryptocurrency, which was introduced in 2008. Bitcoin has reached a market capitalization of over 650 billion USD and accounts for over 30% of the crypto market. Bitcoin's capitalization more than twice exceeds that of Etherium, the second-largest cryptocurrency.[1] Therefore, the behavior of bitcoin determines the behavior of the entire cryptocurrency market.

The public attitude to Bitcoin can be described as contradictory: on the one hand, it is seen as an honest financial instrument, 'free of politics and human error', worthy of trust and investment (Strydom 2013). On the other hand, Bitcoin is often viewed as nothing more than a speculative bubble.[2] Both sides of this conflict explain the development of the Bitcoin market by pointing out the impact of crypto investors' knowledge and expectations of Bitcoin's future value, which provoked our interest in the role of factors like popularity and trust in crypto markets.

The perceived media behavior of the key world financial regulators in relation to Bitcoin dynamics (see Figure 1) led us to suppose that the US Federal Reserve System, the Bank of China and the European Central Bank have been trying to influence public trust in Bitcoin and its popularity, which is what particularly incited our interest.

Figure 1. Dynamics of Bitcoin price and the role of financial regulators' information influence. Note: (1) blue-coloured graph represents Bitcoin price in USD; red-coloured graph, daily change in Bitcoin price, USD; (2) Information Influence of the People's Bank of China: The People's Bank of China banned all ICO (Initial Coin Offering) operations on 11.09.2017. *Wall Street Journal*. Access mode: https://www.wsj.com/articles/china-to-shut-bitcoin-exchanges-sources-1505100862. Last accessed date: 15.04.2018; (3) Information influence of the European Central Bank: Vitor Constancio,\vice-president European Central Bank 22.09. 2017 "Bitcoin is a sort of tulip"; Access mode: https://www.reuters.com/article/us-ecb-bitcoin-stability/ecbs-constancio-compares-bitcoin-to-dutch-tulip-mania-idUSKCN1BX26C. Last accessed date: 15.04.2018; (4) Information influence of the Federal Reserve System: Janet Yellen, the former Chair of the Federal Reserve System, at the press-conference held on 13.12.2017 referred to Bitcoin as 'not a stable source of value' and as a 'highly speculative asset'.
AQ9 Transcript of Chair Yellen's Press Conference. Access mode: https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20171213.pdf. Last accessed date: 9.03.2018.



The regulators' behavior can be explained by the theory of behavioral finance and crowd psychology. In accordance with the theory of behavioral finance (see, for example, De Bondt and Thaler 1985), external shocks, which, in our view, can include the measures taken by regulatory authorities, affect the behavior of market participants by making it more irrational. The Internet greatly contributes to the dissemination of information—information is shared through interconnected online communities (Dong and Bollen 2015; Chou et al. 2016; Langley and Leyshon 2017), making mass hysteria spread faster and farther (Le Bon 18 96; Kunieda 2014).

Following the theory of behavioral finance and crowd psychology, we suppose that information may be the means by which regulators can influence crypto markets. The question we are thus seeking to address in this article is as follows: are Bitcoin's popularity and users' trust in it significant for Bitcoin's capitalization and do they remain significant when the Bitcoin market experiences a sharp growth or a drop? This question seems to be a justified research problem.

There is a vast research literature on popularity and trust among Internet users. To measure popularity, different studies use the volume of Wikipedia queries (Garcia et al. 2014), Google queries (Kristoufek 2013) and mentions in Twitter or retweets (Li and Wang 2017). Brand trust can be characterized by the number of likes (Halaszovich and Nel 2017) and the number of reposts (Phua and Ahn 2016; Ciaian, Rajcaniova, and Kancs 2018) in social media.

It was found that in a relatively stable Bitcoin market (until 2016), among the factors that affected Bitcoin price were public interest in Bitcoin and its popularity, as reflected in the number of Wikipedia queries (Ciaian et al., 2016a), Google queries (Kristoufek 2015; Bouoiyour and Selmi 2015), tweets and retweets (Li and Wang 2017) and Facebook reposts (Garcia et al. 2014). Social media reflect and influence investors' mood swings (Lopez-Cabarcos et al. 2019). In its turn, investors' mood affects volatility and market profitability (Güler 2021), including that of the Bitcoin market. In a number of cases, the declining investor happiness index leads to the growing volatility of the market (Bouri et al., 2021a).

It should be noted, however, that these studies do not go into much detail in their discussion of the 'mood effect' (Chou et al. 2016) and 'hysterical contagion' (Le Bon 1896; Allen and Levine 1968; Gehlen 1977), which can change participants' behavior and distort the effect of the factors in question (Lee, Hosanagar, and Tan 2015; Gambino and Kim 2016).

The work that is most relevant to our research is the study by Figa-Talamanca and Patacca (2019), who examine the relationship between the number of Google queries as a measure of investor attention and the volatility and profitability of the Bitcoin market.

Our contribution to the existing research is fourfold: (a) we analyzed the low volatility and highly volatile phases of the Bitcoin market; (b) we found the impact of trust in Bitcoin and its popularity among informed and uninformed Internet users on Bitcoin price in a non-stable market; (c) we proved the effect of 'collective hysteria' or hype; and (d) we demonstrated the prevalent role of social media in shaping trust in Bitcoin and the popularity of this cryptocurrency.

This study focuses on the situation in the Bitcoin market from 18 October 2013 to 15 August 2018. This period was chosen for the following reasons. We intended to investigate the impact of trust and popularity as well as hysteria and hype surrounding Bitcoin on the market. Since 2019, the situation in various markets has been heavily affected by the COVID-19 pandemic (Gandhi, Jaffer, and Shabani 2022), which means that the behavior of market participants was largely shaped by hype and hysteria around the novel coronavirus (see, for example, Nepp et al. 2022). In this paper, we are going to demonstrate that the attention paid to the asset itself and the hype surrounding it can act as an independent factor in its own right.

This article is structured the following way: the second section focuses on the impact of popularity and trust on the value of various assets. In this section, we also discuss the influence of collective consciousness. In the following sections, we formulate hypotheses for our research, describe the data and methodology we rely on, present and discuss our results.

Do popularity and trust affect the value of assets in global markets?

The impact of popularity and trust on economic development and markets

The theoretical framework for our study was provided by Herbert's decision-making theory (Herbert, 1976), which explores human cognitive limitations in rational decision-making, and his concept of bounded rationality (Agosto 2002).

Trust is often interpreted as willingness not to engage in opportunistic behaviors (Guiso, Sapienza, and Zingales 2008; Dell 2010). An increase in trust has a positive impact on the number of stock market operations (Guiso, Sapienza, and Zingales 2003) and investment activity (Guiso, Sapienza, and Zingales 2009; Aggarwal and Goodell 2009).

Investors tend to buy 'attention-grabbing stocks' (Barber and Odean 2008). Information demand improves the prediction power of modeling stock returns (Chronopoulos, Papadimitriou, and Vlastakis 2018) and the volatility (Vlastakis and Markellos 2012) of the stock market. Stock value is influenced by the price of information bought by investors (Veldkamp 2006) and stocks' ability to capture investors' attention (Han, Li, et al. 2018). Investor attention to assets affects the volatility of foreign exchange markets (Peltomäki, Graham, and Hasselgren 2018) and stock indices (Ruan and Zhang 2016; Peltomäki and Vähämaa 2015; Smales 2016).

The term 'trust' can be also applied to study online space, although researchers may use parameters that are not quite typical. For example, reliance on Wikipedia as a source of information can be assessed by looking at the frequency of its use (Menchen-Trevino and Hargittai 2011). Trust manifests itself through user satisfaction with this or that online resource and with the perceived fairness or unfairness of the price for using this resource (Zhu and Chen 2012). Another term which is often used instead of 'trust' is that of credibility of sources (Wathen and Burkell 2002) and credibility of information (Flanagin and Metzger 2003). Brand trust can be assessed through the number of likes (Halaszovich and Nel 2017) and reposts (Phua and Ahn 2016; Ciaian, Rajcaniova, and Kancs 2018). On the other hand, it is hard to say whether the characteristics of websites and online space can replace interpersonal trust, which is at the core of successful online business projects (Thelwall 2018).

Popularity can be measured through the number of queries in social networks (Fan, Geddes, and Flory 2013). Bitcoin's popularity, the level of expertise of Internet users in this sphere and their trust in Bitcoin also shape the Bitcoin market and the cryptocurrencies market in general. The volume of Google and Wikipedia queries shows a rise in user interest in Bitcoin (Kristoufek 2013), Bitcoin trade volume (Matta, Lunesu, and Marchesi 2015), and Bitcoin price (Zhang et al. 2018).

The majority of studies on the impact of trust, popularity and level of users' expertise on financial markets and the Bitcoin market use the data on tranquil markets with a relatively stable upward trend and low volatility. These studies, therefore, do not take into account Bitcoin's price surge and its fall. Therefore, there is an evident lack of empirical research on the impact of popularity and trust in an unstable Bitcoin market with high volatility, which is the question that this paper seeks to address.

The impact of the 'mood effect' and 'mass hysteria' on value through the factors of trust and popularity

The early works on crowd psychology were written by Mackay (1841) and Le Bon (1896), who compared crowds to social formations consisting of 'primitive beings'. In such formations, ideas spread like a 'disease' with group members developing a common emotion (for example, fear) (Gehlen 1977). Hysteria is inherently irrational and comparable to fear (Freud and Breuer 1895). Some authors compare the effects of spreading information with those of spreading infection and thus support Le Bon's idea of 'hysterical contagion' (Scales, Zelenev, and Brownstein 2013).

Group decisions and moods can also be guided by popular leaders. The impact of popularity can be positive (urban self-government) or negative (Hitler's theory of persuasion) (Borch 2013). Popularity may also shape public opinion (Waddell 2018; Hassan Zadeh and Sharda 2014).

The development of the Internet and broadband internet connections turned small online groups into vast online communities (Liang and Nordin 2013). Theories of collective behavior can be applicable to virtual communities (Chou et al. 2016). In terms of the Internet, a crowd consists of members of social media (Lee, Hosanagar, and Tan 2015; Dong and Bollen 2015).

In the case of speculative bubbles, market participants can change their behavior under the influence of 'hysterical contagion' (Kunieda 2014). One of the main reasons behind the appearance of bubbles is 'collective hysteria' (Owhadi 2004) and the 'mood effect' (Bak, Paczuski, and Shubik 1997). Some economists have approached the Bitcoin market as another kind of speculative bubble and as a case of mass hysteria (Kearns 2013; Bouri, Shahzad, and Roubaud 2019; Chaim and Laurini 2019).

While there is substantial research literature on the impact of behavior on different markets, there is a lack of empirical studies on the effects of crowd behavior on cryptocurrency markets and Bitcoin in particular. Our research is aimed at addressing this research gap, which is why we are considering the impact of popularity and trust among Internet users.

Research methodology

Hypotheses

Following Halaszovich and Nel (2017), Phua and Ahn (2016) and Ciaian, Rajcaniova, and Kancs (2018), we regard likes and reposts as trust-related factors (Ahn, Phua, and Shan 2017). The number of reposts corresponds to the level of trust among informed users since it is normally the users who are knowledgeable about bitcoins who share news about cryptocurrencies (Adams, Phung, and Venkatesh 2014).

We have managed to find only one article discussing the impact that an increase in the volume of Facebook reposts and mentions on Twitter has on Bitcoin. Garcia et al. (2014) came to the conclusion that a drastic increase in information searches caused by external events has a negative impact on Bitcoin price. This study, however, says little about the impact of trust among Internet users on the Bitcoin market and uses data for the period until 2014, when the market had a low level of volatility. To cover this research gap, we are going to formulate the following hypothesis:

H1: An increase in the number of uninformed and well-informed Internet users has a positive impact on the dynamics of Bitcoin price.

As we have shown in the previous section, another important factor affecting global markets is popularity. A suitable proxy for popularity among ordinary (uninformed) users can be the number of Google queries (Kristoufek 2013), which has demonstrated a positive correlation between the price level of Bitcoin and the volume of search queries. Later, Garcia et al. (2014) specified that Bitcoin price dynamics positively affect search queries but certain external events can reverse this impact and make it negative.

It should be noted that these studies rely on the data characteristics of a relatively tranquil market (until 2016); therefore, they do not consider the phase of high volatility (from 2017 to present).

We are going to formulate the following hypothesis for high volatility markets:

H2: An increase in the volume of Bitcoin-related Google queries as an indicator of Bitcoin's popularity among uninformed Internet users has a positive impact on the dynamics of Bitcoin price in the tranquil phase of the market as well as in the high volatility phase.

Nevertheless, the influence of popularity on the Bitcoin market can change if we consider informed users. For example, Bhattacharya et al. (2009) show that the expertise of crypto investors in the conditions of a falling market can have a negative influence on Bitcoin price. Waddell (2018) specifies that if the sentiment of the crowd becomes negative, popularity and comments in online communities will have a negative impact on news credibility and issue importance.

We take it as a point of departure that comments are written by well-informed Internet users (Han, Wu, et al. 2018; Adams, Phung, and Venkatesh 2014; Walton and Johnston 2018). Sieving through the research on this topic, we found that only one study demonstrated the impact of comments on the Bitcoin market using the data on its tranquil phase (until 2016) (Garcia et al. 2014). Thus, there is a perceived lack of evidence for the impact of Bitcoin's popularity. To address this research gap, we have formulated the following hypothesis:

> *H3: Bitcoin's popularity among informed users can have a negative effect on Bitcoin price in a highly volatile market.*

The instability of the Bitcoin market and its increasing volatility since 2017 (see Figure 1) sent shockwaves through the online community, affecting its collective consciousness and triggering 'collective hysteria'. This factor had a distorting effect on the impact of Bitcoin's popularity and people's trust in it. Such effects can be observed, for example, in other financial markets. An increase in volatility provokes hysteria in the stock market (Boyer, Kumagai, and Yuan 2006) and in the foreign exchange market (Bae, Karolyi, and Stulz 2003). When market participants suffer financial losses, this creates the so-called 'contagion' or rapid spread of declining prices, declining liquidity, increased volatility and so on (Kyle and Xiong 2001). Collective hysteria in online communities can increase the impact of forums and social media on restaurants' popularity (Anderson and Magruder 2012). However, there is currently a lack of studies on manifestations of mass hysteria in the Bitcoin market. In our understanding of hysteria, we follow the definition from the Cambridge Dictionary—'extreme fear, excitement, anger, etc., that cannot be controlled'. The notion of 'hype' refers to the situations when something is repeatedly advertised or discussed in the media in order to attract everyone's interest.[3]

Based on the above, we have formulated the following hypothesis:

> *H4: The impact of Bitcoin's popularity on Bitcoin price increases considerably under conditions of high volatility and fluctuations in public sentiment, which means that hype can be regarded as a manifestation of 'hysterical contagion'.*

Econometric model and data

Model description

To test our hypotheses, we first need to select the type of econometric model that will take into account the nature of our research problem and the specific characteristics of the market in question. To study the Bitcoin market and cryptocurrency market in general, different models are used such as OLS (Aysan et al. 2019; Polasik et al. 2015), GARCH (Chronopoulos, Papadimitriou, and Vlastakis 2018; Kristjanpoller and Minutolo 2018), VAR (Bouri et al. 2018; Bação et al. 2018), ARDL (Ciaian et al., 2016a), and neural networks (~~Jang and Lee,~~ Jang and Lee 2018).

It should be noted that ARDL models were used primarily for forecasting and finding how the aforementioned determinants affect the value and volatility (profitability) of the asset, which, among other things, is dependent on previous cost values. Therefore, in this study we have chosen ARDL models to reveal the impact of trust and popularity on Bitcoin price.

In this paper, we are going to study the value of Bitcoin, which is a dependent variable ($Bprc_t$). We have divided independent variables into vectors characterizing groups of specific determinants of the Bitcoin market. The main vector is the vector of the variables in question ($TRPP_t$—Trust and Popularity). There is also the vector of controlled variables ($CRCM_t$—Cryptocurrency market) and a group of parameters characterizing commodity markets and financial markets ($ECNM_t$—Economic market). The generalized model looks as follows:

$$Bprc_t = TRPP_t + CRCM_t + ECNM_t \tag{1}$$

where:

index t is the time (day).

$Bprc_t$—the dependent variable—represents the change in Bitcoin price within one day in USD.

Data

For dependent variable $Bprc_t$ we used daily Bitcoin prices in USD from 18 October 2013 to 15 August 2018. The data were obtained from the website Blockchain.[4] In this period can we intended to investigate the impact of trust and popularity as well as hysteria and hype surrounding Bitcoin on the market without influence the COVID-19 pandemic (Gandhi, Jaffer, and Shabani 2022; Nepp et al. 2022). In this paper, we are going to demonstrate that the attention paid to the asset itself and the hype surrounding it can act as an independent factor in its own right.

Vector $TRPP_t$ contains the variables in question and characterizes users' trust in Bitcoin and its popularity. It includes the relative number of Bitcoin-related Google queries per day ($Gtrn_t$) from the website https://trends.google.com and the number of likes, reposts and comments in Facebook communities devoted to Bitcoin ($Flks_t$, $Fshr_t$, and $Fcmn_t$, respectively), for which we used Facebook API and Phyton. The role of Google queries was discussed in the studies of the factors driving Bitcoin price and its volatility (Polasik et al. 2015; Kristoufek 2013). The number of likes (Halaszovich and Nel 2017) and the number of reposts (Phua and Ahn 2016) were used as indicators for the level of online brand trust.

Vector $CRCM_t$ characterizing the Bitcoin market includes the number of transactions on the market ($Trns_t$), the hash rate or Bitcoin mining difficulty ($Hshr_t$), and the total number of bitcoins in circulation ($Totl_t$). These parameters were studied as determinants of Bitcoin price (Li and Wang 2017; Aalborg, Molnár, and de Vries 2019). The data for vector $CRCM_t$ were obtained from the following website: https://www.blockchain.com.

Vector $ECNM_t$ includes the variables characterizing commodity and financial markets, such as the Financial Stress Index ($Fsin_t$), Brent oil price per barrel in USD ($Oilb_t$), and the gold price per troy ounce in USD ($Gold_t$). The data for '$Oilb_t$' were obtained from the website of the Federal Reserve Bank of St. Louis (FRED), for variable $Gol\,\mathrm{d}_t$—the website of the World Gold Council.[5] The Financial Stress Index ($Fsin_t$) summarizes information about stock indices. In his study of Bitcoin, Kristoufek (2015) used an analogue of $Fsin_t$. Control variable $Fsin_t$ is a set of indicators of global financial markets and is determined by the Office of Financial Research, USA.[6] The impact of oil price and gold price was considered in the studies of Bitcoin price and volatility (Ciaian, Rajcaniova, and Kancs 2016b).

Descriptive statistics for the variables are presented in Appendix A, online supplementary material.

Econometric model

As Figure 1 illustrates, in the given period the market went through different phases with different levels of volatility. We conducted the Gregory-Hansen Test (see Appendix B, online supplementary material), as we assumed that there was a problem of structural breaks and distortions stemming from the effects in question. We determined the points of discontinuity, which allowed us to divide the sample into three clusters: a stable market (with a relatively low volatility) from 18 October 2013 to 24 March 2017; a highly volatile rising market from 25 March 2017 to 17 December 2017; and a highly volatile falling market from 18 December 2017 to 15 August 2018.

To tackle the problem of non-stationarity, we conducted the Augmented Dickey-Fuller test (Dickey and Fuller 1979) (see Appendix C, online supplementary material). Results making it necessary to use first differences in the final model to avoid biased estimates.

For our basic model, we used the ARDL model. However, we did not use ECM interpretation to study the long-term impact of the given parameters for the following reasons: (a) we were considering short-term clusters of time series; (b) our aim was to reveal the effect of 'collective hysteria' (or hype), which usually does not last long. Based on the Akaike information criterion, taking into account values R^2 and applying graphical analysis with the help of bivariate cross-correlograms, we determined the individual number of lags for each parameter of the ARDL model (Akaike 1974). Taking into consideration the contents of the vector in model Eq.1 and the need to study the variables' differences by following the results of the Dickey-Fuller Test, we obtained the following basic model:

$$\Delta Bprc_t = \beta_0 + \sum_{i=1}^{p} \alpha_i \Delta Bprc_{t-i} + \sum_{i=0}^{q1} \gamma_i \Delta Totl_{t-i} + \sum_{i=0}^{q2} \delta_i \Delta Trns_{t-i} + \sum_{i=0}^{q3} \theta_i \Delta Hshr_{t-i} + \sum_{i=0}^{q4} \mu_i \Delta Gtrn_{t-i} + \sum_{i=0}^{q5} \pi_i \Delta Flks_{t-i} + \sum_{i=0}^{q6} \rho_i \Delta Fshr_{t-i} + \sum_{i=0}^{q7} \tau_i \Delta Fcmn_{t-i} + \beta_1 \Delta Fsin_t + \beta_2 \Delta \mathrm{O}ilb_t + \beta_3 \Delta Gold_t + \varepsilon_t \quad (2)$$

Robustness checks

For more robust results, we can show the impact of the given factors on Bitcoin price with the help of

GARCH models, taking into account the autoregression of conditional heteroscedasticity, on the same clusters and with the same lags.

The stability of the models in time was checked with the help of a cumulative sum control chart (CUSUM Test). Comparison of the test results leads us to conclusions about the problems and opportunities presented by these models.

To reveal the cause-effect relationships of the variables, we applied the Granger causality test for each of the three periods. In the test, we used four additional models with left-side the variables needed to test hypotheses—$\Delta\, Gtrn_t$, $\Delta\, Flks_t$, $\Delta\, Fshr_t$, and $\Delta\, Fcmn_t$. We included in the model the individual number of lags of each variable that we chose for the basic model.

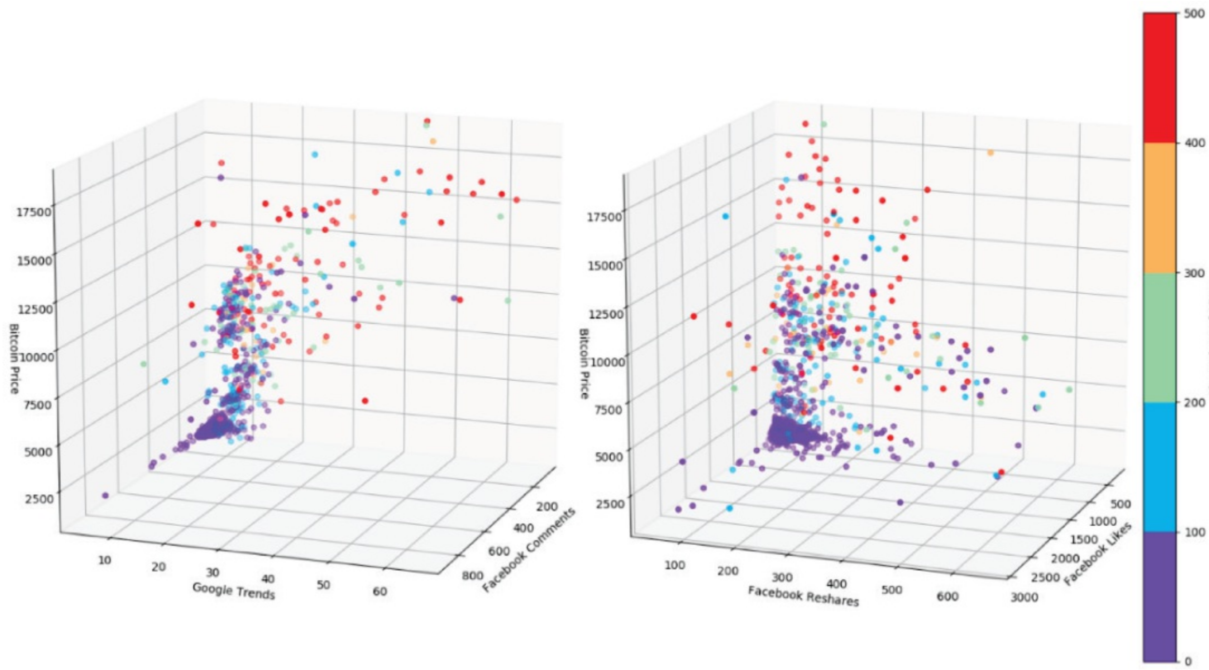
Robust results are thus provided by the GARCH model compared with the ARDL model once the problems of structural breaks and stationarity are addressed.

Results

General results

Figure 2 illustrates Bitcoin price, variables $Flks_t$ and $Fshr_t$ (characterizing trust), and variables $\Delta\, Gtrn_t$ and $\Delta\, Fcmn_t$ (characterizing popularity).

Figure 2. Visualization of Bitcoin price with Google trends, Facebook comments, characterizing popularity (left) and Facebook reshares, Facebook likes, characterizing trust (right). Note: colorbar shows absolute values of Bitcoin price first differences.



We conducted the CUSUM Test of the ARDL model constructed by using the data for the whole period (18 October 2013–15 August 2018): the test showed the instability of the model for the whole period (see Appendix E, online supplementary material). However, the parameters of the model are suitable to describe Bitcoin price formation during the period of high market volatility. This supposition is confirmed by the stable results of the CUSUM Test for models of the clusters of aggressively growing and sharply falling markets.

Let us first look at the ARDL model results (see Appendix D, online supplementary material) and check their robustness by using the GARCH method (see Appendix F, online supplementary material).

For the low-volatile market phase (until 24.03.2017), no considerable differences were found: the results of the GARCH model agree with those of the ARDL model. Differences are found in the significance of the factors on different lags or in different levels of significance. Thus, in general, we can regard these results as solid.

Before discussing these results in the light of our hypotheses, let us first consider the results of control variable analysis vectors—$CRCM_t$ and $ECNM_t$.

In our study, Bitcoin was not influenced by the variables characterizing the gold market, oil market or the composite index of financial markets. Our results contradict those of previous studies, which revealed the impact of gold (Bouri et al. 2018), stock indices (Zhang et al. 2018), and oil (Ciaian et al., 2016a). The evidence we found confirmed the conclusions made by Plakandaras, Bouri, and Gupta (2021) and Bouri et al. (2021b), who demonstrated that Bitcoin, which is independent of stock markets, is a safe haven for investment portfolios.

Such results can be explained, firstly, by the fact that we are considering a highly volatile market and, secondly, that we analyzed changes in Bitcoin price as a dependent variable. However, since the study of variables characterizing commodity and financial markets was outside the scope of this research, we are not going to discuss these results in greater detail.

Our study has shown the positive effect of mining difficulty (Hash Rate) on short lags for a rising and falling market. On long lags, the effect was negative. Following the institutional theory, it would make sense to compare the difficulty of Bitcoin mining with the market's transaction costs (Young 2013), which are traditionally considered by organizational economics as the distance between the supply and demand. Thus, our results fit well into the logic of institutional and organizational economics: an increase in the difficulty of mining as transaction costs of the Bitcoin market should lead to greater price fluctuations, which is exactly what we observe for short time lags. But here another question arises as to why we observe the negative effects for long lags? These results can be explained by the market participants' use of a shorting strategy (may) in an effort to keep their losses from mounting or to lock in their profits. Such situation is described, for example, by Bouri, Shahzad, and Roubaud (2019), who analyzed explosivity in crypto markets.

The number of transactions had a positive influence on the tranquil and rising markets. Overall, our results correspond to those of Li and Wang (2017), who found a positive impact of mining difficulty and the number of transactions on Bitcoin price.

The main aim of our study was to find the impact of trust and popularity. We found that Bitcoin price is affected more by trust and popularity than by the ‘classical’ factors of the Bitcoin market, commodity markets and financial markets. Our results agree with those of Al-Khazali, Bouri, and Roubaud (2018) and correspond to the theory of behavioral finance, especially concerning the impact of behavioral factors on investors' rational decision-making (see, for example, De Bondt and Thaler 1985), and to the conclusions made by Bouri et al. (2021a), Tavani (2020) and Güler (2021) about the influence of investors' mood on crypto markets.

Let us now take a closer look at the results and systematize them in accordance with our hypotheses.

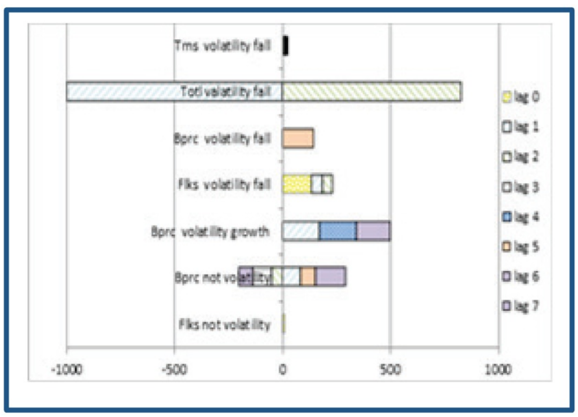
Trust is the first secret of the success. (Ralph Waldo Emerson)

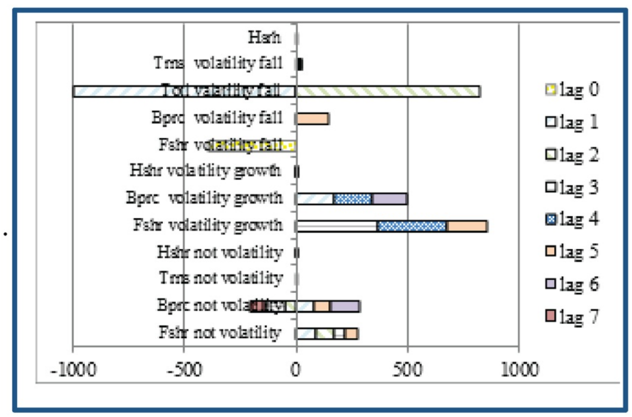
According to Hypothesis 1, an increase in the number of likes and reposts contributes to users’ trust in Bitcoin and has a positive impact on Bitcoin price. Following Halaszovich and Nel (2017), Phua and Ahn (2016) and Ciaian, Rajcaniova, and Kancs (2018), we considered likes and reposts as a sign of trust among

Internet users.

The impact of reposts ($Fshr_t$), characterizing trust among informed Internet users (see Figure 3), is found in low-volatile markets and highly volatile rising and falling markets. In low-volatile and highly volatile rising markets, this impact is positive, while it turns negative in a highly volatile falling market. The strongest influence of informed users' trust in Bitcoin price was found in a volatile rising market (4 lags) and in a volatile falling market (0 lag). At the same time, the trust of informed Internet users affects the value of Bitcoin most strongly in a volatile rising market (4 lags) and in a volatile falling market (0 lag). The results of the Granger causality test (see Appendix G, online supplementary material) showed that the number of reposts and Bitcoin price had a mutual effect in a rising market and a falling highly volatile market

Figure 3. The impact of uninformed users' trust—Flks_t (left) and informed users' trust Fshr_t (right) on Bitcoin price. Note: (1) This figure does not show variables $Trns_t$ (for a low-volatility market) and $Hshr_t$, which demonstrated significance, but with insignificant coefficients; (2) The variables shown in Figure 3 are multiplied by 10^3.





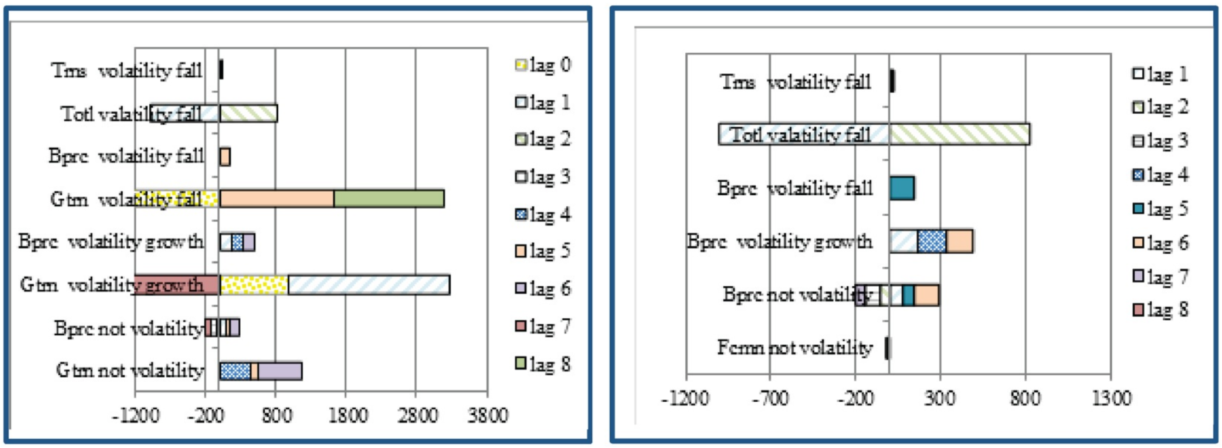
Our results for a tranquil and rising market indirectly support the conclusions made by Garcia et al. (2014), although the negative effect of trust in falling market conditions contradicts his results. Thus, our results that showed the positive impact of trust in a tranquil and rising market confirm Hypothesis 1, while the results for a falling market contradict it.

You can`t buy what is popular and do well. (Warren Buffett)

According to Hypothesis 2, the impact of Google queries as an indicator of Bitcoin's popularity among uninformed Internet users was expected to have a positive impact on Bitcoin price both in a relatively stable market phase and in a more volatile market phase.

As our results demonstrate (see Figure 4), the popularity of Bitcoin among uninformed Internet users has a positive impact on Bitcoin price if the market is relatively stable or rising with high volatility. In a falling market, this effect becomes negative.

Figure 4. The impact of Bitcoin's popularity among uninformed users Gtrn_t (left) and among informed users Fcmn_t (right) on Bitcoin price. Note: (1) The figure does not show variables $Trns_t$ (for a low-volatility market) and $Hshr_t$, which demonstrated significance but have insignificant coefficients; (2) The variables shown in Figure 4 were multiplied by 10^3; variable $Gtrn_t$, by 10^2.



The comparison of the impact of Bitcoin's popularity among uninformed Internet users with that of the control variables highlights the effect of Google queries. We see that the trust of ordinary Internet users is the most significant variable. The impact of Google queries considerably exceeds that of the 'strongest' control variable— the number of bitcoins in circulation.

The Granger causality test (see Appendix G, online supplementary material) shows that Bitcoin's popularity among uninformed users not only affects Bitcoin price but also itself experiences a significant countereffect. The strength of the countereffect, however, is considerably below that of the direct impact of Google queries on Bitcoin price.

Thus, our results for a relatively stable market or a rising market with high volatility support the conclusions made by Kristoufek (2013) and confirm Hypothesis 2. At the same time, the results for a falling market refute this hypothesis.

Following Hypothesis 3, it was expected that a change in Bitcoin's popularity among informed users will have a negative impact on Bitcoin price. Following Walton and Johnston (2018), we used Facebook comments to measure Bitcoin's popularity among informed Internet users.

Our results (see Figure 4) demonstrate that Bitcoin's popularity among informed users has a significant negative effect only in low-volatile market conditions. If the market is volatile, rising or falling, no effect of Google queries was found. The depth of impact in the low-volatile period is 2 lags. An increase in time (lag) leads to an increase in significance.

Bitcoin’s popularity among informed Internet users has a strong influence on Bitcoin’s price in comparison with the control variables characterizing other markets—oil and gold markets, the Financial Stress Index, the number of Bitcoin transactions and the number of bitcoins in circulation. The effect of Facebook comments on Bitcoin price was comparable with the number of reposts, which characterize the level of trust among informed Internet users. The impact of Bitcoin’s popularity among informed users was stronger than that of likes, which characterize trust among uninformed users, but weaker than the impact of Google queries, which correspond to Bitcoin’s popularity among uninformed users.

Analyzing the results of the Granger causality test (see Appendix G, online supplementary material), we found that informed users’ trust has a one-sided effect on Bitcoin price if there is no counter-effect in a low-volatile market and a volatile rising market. Changes in Bitcoin price did not significantly affect the number of comments in a low-volatile market and highly volatile falling market. For a volatile falling market, the countereffect had little significance.

Thus, our results show that Facebook comments, which correspond to Bitcoin’s popularity among informed users, have a negative impact on Bitcoin price in a relatively stable and low volatility market. This fact confirms Hypothesis 3 and the conclusions made by Garcia et al. (2014) and Waddell (2018) about the negative influence of informed users on the Bitcoin market. Our results confirm the conclusions made by Figa-Talamanca and Patacca (2019), who pointed out the impact of Google SVI, characterizing investor attention, on Bitcoin’s volatility and profitability.

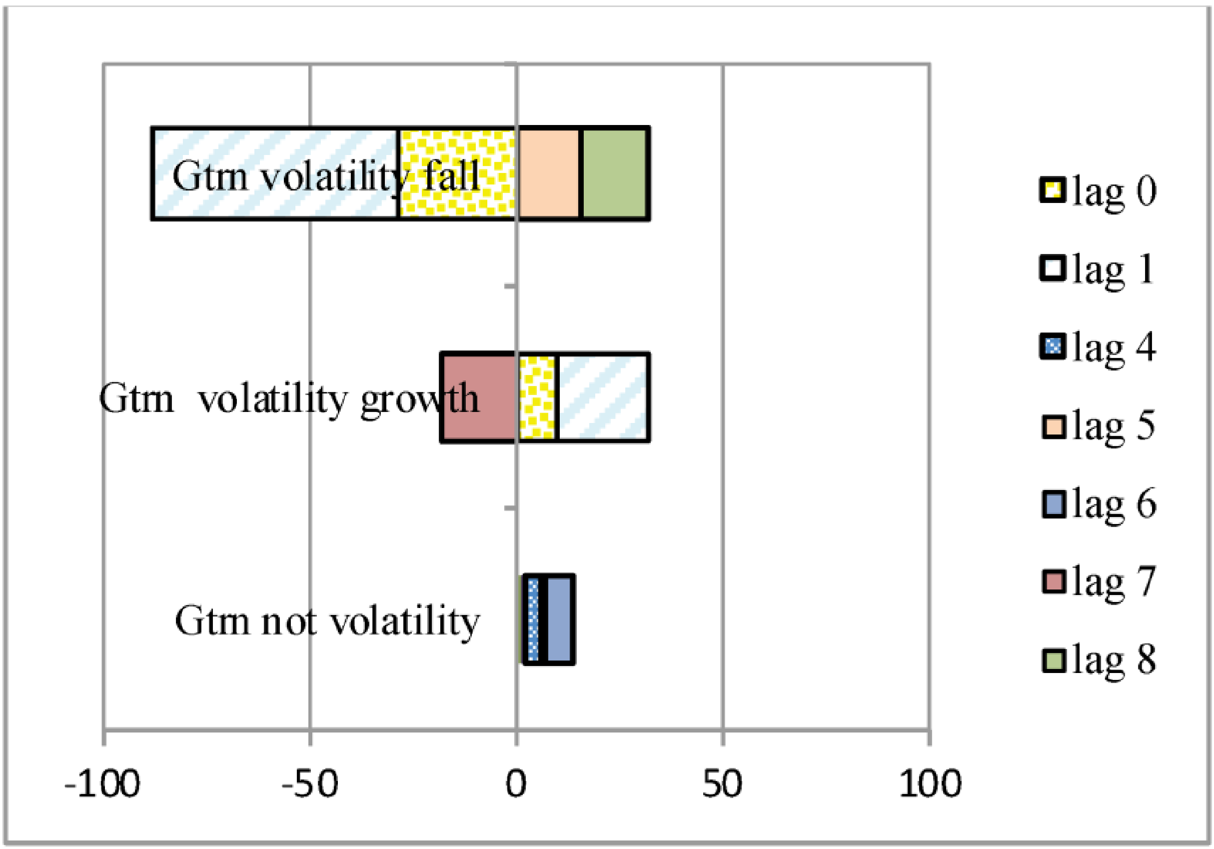
We have also indirectly confirmed the conclusions of Gandal et al. (2018) about the impact of bots' activity on popularity, which affects the price of assets. At the same time, in a volatile market, either rising or falling, Bitcoin’s popularity among informed users has no apparent influence on Bitcoin price.

Irrational hysteria. (Freud and Breuer *1895)*

According to Hypothesis 4, the impact of Bitcoin’s popularity on its price increases substantially if there are events triggering mass emotional reactions.

Applying the Gregory-Hansen test (see Appendix B, online supplementary material), we found bursts of emotion among those interested in Bitcoin in a highly volatile market. As Figure 5 demonstrates, the significance of Bitcoin’s popularity among uninformed users rises sharply if the market is volatile. The significance of the most significant lag of Google queries in a rising volatile market increases more than 3 times, and more than 9 times in a falling volatile market.

Figure 5. The impact of hype (a sharp increase in the effect of Bitcoin's popularity among uninformed users (Gtrn_t)) on Bitcoin price.



The significance of Bitcoin's popularity among uninformed users compared with that of controlled variables confirms our conclusions. If the coefficient of the most significant lag of Google queries exceeded the significance of the most significant lag of Bitcoin price, the strongest of our control variables, more than 46 times, then in a rising volatile market this figure was already more than 87 times.

Our results support Hypothesis 4 and agree with the conclusions made by Kunieda (2014) and Owhadi (2004) about the behavior of market participants subject to mass hysteria triggered by shock.

To analyze the significance of Bitcoin's popularity among informed users we relied on Facebook comments data. As our study has shown (Figure 5), Facebook comments in conditions of mass hysteria became insignificant, both for a rising volatile market and for a falling market. In this case, however, there is no conflict between the results and Hypothesis 4. According to Freud's crowd behavior theory (Freud and Breuer 1895), in situations of mass panic, people act emotionally rather than rationally and tend to ignore professional opinion and advice. Freud's idea about the irrationality of collective hysteria explains the insignificance of Bitcoin's popularity among informed users in our model.

Thus, our results do not confirm Hypothesis 4 concerning the impact of Bitcoin's popularity among informed users. Our results are indirectly supported by the works of Freud and Breuer (1895) and Le Bon (1896).

Conclusion

Bitcoin, one of the most commonly known cryptocurrencies, has demonstrated both explosive growth and a sharp plunge. Public attitude to Bitcoin can be described as contradictory: on the one hand, it is seen as a trustworthy currency, free from politics and human error. On the other hand, Bitcoin is also often presented as having all the hallmarks of a dangerous speculative bubble. Both sides point to the specific characteristics associated with Bitcoin's popularity and Internet users' trust in it. The key world financial regulators—the US Federal Reserve System, the Bank of China and the European Central Bank—are trying to influence the Bitcoin market through its popularity and users' trust.

The question remains open as to how and to what extent these factors affect Bitcoin price in various market conditions. In this article, we were trying to fill in the aforementioned research gap and focused on studying the impact of Bitcoin's popularity and trust in Bitcoin among informed and uninformed users on its price.

We have demonstrated that in a volatile market, users tend to go into a state of 'financial frenzy', that is, their behavior is largely shaped by the so-called 'collective hysteria'.

The results of our research have led us to the following conclusions: firstly, the Bitcoin's popularity and trust in this cryptocurrency are the most significant determinants for the Bitcoin market. Their impact is much stronger than that of other factors related to the Bitcoin market and commodity and financial markets. Secondly, the trust of uninformed users has a positive effect on Bitcoin price in low-volatile and highly volatile falling markets. Thirdly, the trust of informed users in low-volatile and highly volatile rising markets has a positive effect on Bitcoin price and a negative effect in a falling market. Fourthly, Bitcoin's popularity among ordinary Internet users has a positive impact on its price in a low-volatile and highly volatile rising market and a negative impact in a falling market. Next, Bitcoin's popularity among informed users negatively affects its price if the market has low volatility. Finally, the impact of Bitcoin's popularity among ordinary users on its price grows considerably if the market is volatile, which reveals the influence of hype on Bitcoin price.

We believe that the results of this study could be interesting and useful for players on the Bitcoin market, investors since they provide us with a better understanding of the impacts of trust and popularity, hype and hysteria on the dynamics of the crypto market. On the other hand, our findings may prove useful to regulators of financial markets as they shed light on the factors that affect Bitcoin.

In the course of our research, there emerged a range of problems that might call for further studies. In our research on likes and reposts as characteristics of trust and comments as a characteristic of popularity, we did not take into account content-related characteristics and did not conduct content analysis. We would also recommend more in-depth research on the connection between Internet characteristics, trust and popularity.

In view of our findings, another question worth exploring could be the ability of the crypto market to be efficient (Fama 1970). This task could be solved by applying the sliding window approach (see, for example, Ferreira 2018) or the fractional integration model (Usman and Nduka 2022).

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2) In the figure, callout No. 1 needs to be supplemented by People`s Bank of China.