PRESENCE OF PRICE CLUSTERING AND PSYCHOLOGICAL BARRIERS IN BITCOIN MARKET

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Abstract

In the last year, the market of Bitcoin experienced one of the most turbulent times of its existence. In the last year, there were bull markets, bear markets, and sideways markets. This paper deals with the most apparent virtual currency, Bitcoin and the evidence of price clustering and the presence of psychological barriers of investors. The primary objective of this paper is to find out if the last digit and last two digits of the maximum (or minimum) price of Bitcoin tend to cluster around digit nine (or zero). Paper uses price clustering to determine if the theory of behavioural finance also implies conditions of the Bitcoin market, namely if investors in Bitcoin tend to see the resistance line when the maximum price ends with digit nine and if the minimum price with last digit 0 signals the support line. Results of the 2191 observations showed robust results in terms of support line, however not so unambiguously in the case of resistance line. The paper suggests that Bitcoin is changing its reputation as a solely speculative asset and transforming into a long-term investment strategy.

Keywords: price clustering, bitcoin, psychological barriers, behavioural finance, financial markets

JEL Classification: G41, G10

Introduction and theoretical background

Market practitioners and journalists frequently mention the existence of psychological obstacles in stock markets. Many investors feel that round numbers act as barriers and that prices will struggle to overcome them. Furthermore, technical analysis assumes that traders will continue in the given trend of buying or selling once the price breaks up or break down through a "psychologically important" level, implying that crossing one of these barriers may push prices up (down) more than is otherwise warranted. Frequently used terminology like "support level" and "resistance level," implying that price rises and declines may be limited until a significant barrier is breached. The presence and effects of such phenomenon were researched well in the past, mainly on stock markets and indices (Donaldson and Kim, 1993; Garzarelli et al., 2014). Later, also applied to modern financial instruments such as exchange-traded funds (ETFs) (Fonesca et al., 2021), or in a more complex way, when analysing discrepancy among territorial market structures, indices, and financial behaviour in different regions (Lobão and Pereira, 2017; Lobão and Couto, 2019). The origin of price clustering theory was significantly developed by Ball et al. (1985) as they argue that when trading, counterparties face costs associated with continued negotiations. To mitigate the costs of further negotiations, the counterparties will settle on round prices. To the extent that enough market participants behave in such a way, observed prices will cluster on round prices. From the most recent literature contributing to the topic, Baig et al. (2019) developed the theory of the relation between economic freedom and price clustering, as they claim the lack of economic freedom and policy uncertainty will contribute to the magnitude of the negotiation costs since uncertainty makes it difficult to know true, or actual equilibrium prices. Concerning the findings from cryptocurrency markets presented in Binance (2021) and Chainanalysis (2021), the adoption of cryptocurrencies is also done in countries with lower levels of economic freedom and relatively high levels of economic freedom. Baig et al. (2019b) found evidence that Bitcoin shows signs of unusual price clustering and is also related to investor sentiment, claiming a causal and positive relation between investor sentiment and the clustering of equity prices and suggesting that the microstructure patterns of price clustering in Bitcoin are to some extent similar to the equity markets.

The use of round numbers as a foundation is significant because it has high explanatory power for several characteristics usually associated with financial markets. The anchoring effect, a well-known behavioural bias initially described by Tversky and Kahneman (1974), is the primary reason for psychological barriers in financial markets. Individuals tend to fixate ('anchor') on a prominent number while completing an estimation in an unclear scenario, even if that number is unimportant to the calculation. The existence of psychological barriers runs counter to the efficient market hypothesis since it implies that stock markets are predictable, leading to extraordinary risk-adjusted returns. Subsequently, it is possible to define behavioural financial economics as the study of behavioural economics, including how market decisions are made and the mechanisms that drive public choice (Zeiler and Teitelbaum, 2018). As a result, empirical proof for psychological barriers is essential to practitioners seeking successful tactics and the literature on market efficiency and market oddities. When applying the theory of psychological barriers to cryptocurrency, this paper deals with the claim of Ajzen (2020) as perceived behavioural control might be referred to consumers' subjective probability of inhibiting or facilitating their evaluations of a controlling factor (i.e., money, Bitcoin price in this study) in each situation or period.

When it comes to psychological barriers at financial markets, the two most common terms are usually mentioned: resistance line and support line. Garzarelli et al. (2014) and Menkhoff (2010) argued that the technical analysis definition of support and resistance is rather qualitative than quantitative. So-called "support line" is a price level, a local minimum of the price, where the price will bounce on other occasions afterwards, whereas resistance is a price level, a local maximum of the price, where the price will bounce on other occasions afterwards. When a high number of investors see a support or resistance level, it is anticipated that the likelihood of the price bouncing off the support or resistance level to be greater than the probability of the price crossing the support or resistance level. This paper focuses on the presence of mentioned psychological barriers such as support and resistance lines in the virtual (crypto) currency market and its most dominant representative – Bitcoin.

The cryptocurrency market or Bitcoin itself is described as a vision to establish a new financial system (Nakamoto, 2008). Behind the basic technology setup for Bitcoin (or any other virtual currency) is the idea that the classical financial system is greedy in many ways, and even though there is more and more wealth in the world, a large part of the population has no chance of achieving it. This gap between poverty and wealth is still growing. Establishing a new decentralised ecosystem of currency should help re-establish an environment where there will be far better and fairer supervision of projects, transactions, or individual participants of evidence. Despite its novel status, research about trading Bitcoin was conducted. Blau (2018), Cheah and Fry (2015) investigated the speculative behaviour of investors in the Bitcoin market. Glaser et al. (2014) argued that there are strong indications, especially if considering uninformed users approaching digital currencies, who are not primarily interested in an alternative transaction system but seek to participate in an alternative investment asset. According to a recent study by Baur and Dimpfl (2021), Bitcoin displays value characteristics over long periods. According to a study by Binance Research (2021), virtual currency owners have almost unanimous trust in the asset (97%). More than half (52%) do not consider investing in the virtual (crypto) currency as a hobby but as a means of income; 15% of virtual currency owners consider them their primary source of income. Another result of conducted survey has shown the top three reasons to invest in virtual currencies (e.g., Bitcoin) are: own cryptocurrencies as part of a long-term investment strategy (55%), disbelief in the current financial system (38%), short-term business opportunities (31%). In line with a conducted survey of Binance Research (2021), it is possible to argue that more than half of cryptocurrency owners are using cryptocurrency as an asset for long-term holdings.

During and after the COVID-19 pandemic, consumers may need to immediately accept and use cryptocurrency as money for financial transactions at home to reduce physical interactions with others (Cheema et al., 2020). According to mentioned finding, Kim (2021) claimed that consumers' intention to accept and use Bitcoin should be studied, focusing more on the psychological aspect of money rather than its perceived technological aspects. The cryptocurrency markets are experiencing breakthroughs by implementing crypto assets into conventional financial instruments, such as ETFs. As stated by Hull (2021) and Chainanalysis (2021), there is evidence of large institutional investors investing and diversifying their funds into cryptocurrency assets (e.g., Tesla, Inc., Microsoft, Inc.) In connection with the claim about the entry of large institutional investors into the world of virtual currencies, the approval of the first hybrid ETF index, based on investing in Bitcoin's cryptocurrency futures. As La Monica (2021) stated, recently launched ETF ProShares is the first ETF fund to invest in Bitcoin futures, and in addition to ProShares, several investment firms have asked the US Securities and Exchange Commission (SEC) to launch Bitcoin ETFs.

Material and methods

This paper aims to examine if there is evidence of such phenomena as psychological barriers in the most significant cryptocurrency market nowadays – Bitcoin. This paper analyses psychological barriers by observing the last digit and last two digits of maximum (minimum) prices of Bitcoin in 240 minutes intervals. To examine the existence of any psychological barriers at the resistance or support price level, it is necessary to look for evidence of price clustering. Therefore, the first hypothesis of this paper is:

H1: The existence of price clustering in the last digit of Bitcoin price is present.

The mentioned hypothesis could be rejected if it is not possible to reject the null hypothesis; thus, the last digit of Bitcoin price would be equally distributed in intervals from 0 to 9. To support *H1*, there are formulated sub hypotheses 1.1 - 1.4:

H1.1: Existence of price clustering of the last digit in a maximum price of Bitcoin.

H1.2.: Existence of price clustering of the last digit in the minimum price of Bitcoin.

H1.3: Existence of price clustering of last two digits in maximum price of Bitcoin.

H1.4: Existence of price clustering of last two digits in minimum price of Bitcoin.

If there is evidence of price clustering in last digit and last two digits, thus it would be possible to test the second hypothesis:

H2: Existence of psychological barriers in prices of Bitcoin is present.

The second hypothesis deals with the presence of clustering maximum (minimum) prices in terms of being used as a resistance (support) line for investors, as defined in behavioural finance theory(Statman and Caldwell, 1987; Garzarelli et al., 2014). Thus, the maximum prices will cluster around values close to 8, 9 or 98, 99, and minimum prices should have been a tendency to cluster around lower values like 0, 1 or 01, 11. Similarly, as the first hypothesis also second is formulated in sub hypotheses 2.1 – 2.4:

H2.1: Presence of resistance line regarding the last digit of Bitcoin price.

H2.2: Presence of resistance line in terms of last two digits of Bitcoin price.

H2.3: Presence of support line regarding the last digit of Bitcoin price.

H2.4: Presence of support line in terms of last two digits of Bitcoin price.

Data used to analyse price clustering, and psychological barriers were obtained from the world's longest-running cryptocurrency exchange, Bitstamp, through trading platform TradingView. The whole dataset covers the period from November 1st, 2020, 00:00 UTC to November 1st, 2021, 00:00 UTC. To better capture price volatility and investor reaction, every trading day is divided into six time periods, which gives a total of 2191 records at 240 minutes intervals. In each price series in the examined period are observed variables: the opening price, maximum price, minimum price and closing price of Bitcoin.

Methods used to test whether the price is clustering around the last digit (or last two digits) in the opening, maximum and minimum price was Chi-Square statistics:

$$\chi^2 = \sum_{i=1}^{n} \frac{(x_i - m_i)^2}{m_i} \sim \chi^{2^{k-1}}$$

where stands for the sum of observed price digit, is represented by frequency table expected value. When accessing the result of regarding its significance and p-value, the test for distribution right-tailed is used with degrees of freedom used. In this case, when examining the last digit, the number of categories k will be 10; when examining the last two digits, the number of categories *k* will be 100. As another proof of price clustering evidence and psychological barriers presence, the Kolmogorov-Smirnov test is used, as the further proof of the statistical significance, similarly to Garzarelli et al. (2014):

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} Ix_i \leq x$$

$$D_n = sup_x|F_n x - F(x)| * \sqrt{n} \sim e^{-(D_n{}^2)}$$

where stands for empirical distribution function for *n* independent equally distributed random variables. *I* represents indicator function gaining value 1 if ≤ , and if otherwise, it is equal to 0. Afterwards, Kolmogorov-Smirnov statistics stand as mentioned, where symbol sup stands for supremum.

Results and discussion

Descriptive statistics of data

Table 1 contains the descriptive statistics of Bitcoin prices in the 4-hour range at exchange Bitstamp over one year. Regarding descriptive statistics and minimum and maximum values in Table 1, it is possible to state that in the selected period, Bitcoin experienced relatively significant movements in its price. It is a welcoming sign for further analysis of price clustering and psychological barriers of investors, as all three phases – bull market, bear market, and sideways market – will be incorporated in the analysis. As shown in Table 1, the values for asymmetry, skewness between -0.8 and 0.8, and kurtosis between -2 and +2, in this case, values can be considered acceptable to prove normal univariate distribution (George and Mallery, 2010).

Table 1 Descriptive statistics of the sample. Bitcoin prices in the 4-hour range at exchange Bitstamp between November 1st,2020 and November 1st, 2021. All prices are denominated in US dollars

	N	Min	Max	Mean	St. Dev.	Skewness	Kurtosis
Opening	2191	13396.35	66893.03	41403.17	13382.69	-.331	-.796
Max.	2191	13458.96	67016.50	41943.3	13500.50	-.351	-.779
Min.	2191	13220.31	66140.00	40802.09	13.240.61	-.309	-.816
Closing	2191	13402.31	66882.12	41423.91	13375.42	-.331	-.795

Source: Authors processing. Data: Trading View (2021)

Testing for price clustering

Table 2 displays the frequency of individual digits (0 – 9) in the last place of price. From the first sight, it is visible that if the last digit is 0, then there is confirmation of price clustering around this digit. As mentioned earlier, the price level represented by a local minimum is a support line, where investors are anticipating the pullback or reverse of the trend the price is pointing. In this sample of the four-hour window during the trading day, the price ending with 0 is clustering significantly at the minimum price; it was 447 times. On the contrary, when speaking about resistance, a price level of a local maximum of the price, it is possible to see clustering at digit 9 in terms of maximum price during a four-hour trading window, particularly 262 times what is more than 213.2 expected. To confirm mentioned evidence there is performed Chi-squared test and Kolmogorov- Smirnov test (K-S test).

Table 2 Frequency table of the last digit

Last Digit	Open	Max	Min	Close	Expected
0	257	351	447	241	213.2
1	223	206	193	227	213.2
2	209	183	197	227	213.2
3	215	171	191	174	213.2
4	207	192	166	228	213.2
5	205	197	230	218	213.2
6	198	196	186	189	213.2
7	208	188	174	190	213.2
8	188	186	154	209	213.2
9	222	262	194	229	213.2
SUM	2132	2132	2132	2132	2132

Source: Authors processing. Data: Trading View (2021)

After completing the Chi-squared test () and K-S test computation, the significance of obtained statistics must be affirmed. In Table 3, the p-value is associated with a distribution with 10 degrees of freedom. The significance level is set to alpha α= 0.05. If the p-value is less than 0.05, the null hypothesis of independence can be rejected. In terms of the maximum and minimum price of Bitcoin, it is possible to see both the test and K-S test rejecting the null hypothesis. Prices ending with 0 are usually clustered at the minimum price, which might lead to the assumption that there is a presence of a support line. Therefore, it is possible to claim the existence of price clustering.

Similarly, it is possible to claim that maximum prices are usually clustered when the last digit is 9. After confirming hypotheses H1.1 and H1.2, the same procedure for prices with the last two digits is performed to test if there is a presence of price clustering. Results are displayed in Table 4.

Table 3 Chi-squared test and Kolmogorov-Smirnov test for price clustering for the last digit

	Open	Max.	Min	Close
Chi-squared	14.5947	124.2852	302.4653	20.2795

p-value	0.1027	0.0000	0.0000	0.0163
K-S test	1.1608	2.9844	5.0635	1.1999
p-value	0.2599	0.001	0.0000	0.2370

Source: Authors processing. Data: Trading View (2021)

Table 4 Chi-squared test and Kolmogorov-Smirnov test for price clustering for the last two digits

	Open	Max.	Min	Close
Chi-squared	153.3633	495.4902	995.9922	171.3462
p-value	0.0004	0.0001	0.0000	0.0002
K-S test	0.82443	2.0120	3.1356	1.1301
p-value	0.5068	0.0175	0.0001	0.2788

Source: Authors processing. Data: Trading View (2021)

Testing for psychological barriers

Table 5 Testing for psychological barriers – resistance and support line – last digit

	Chi-squared	K-S test
Resistance	58.4873	2.0358
p-value	0.0000	0.0159
Support	175.0059	4.1149
p-value	0.0000	0.0000

Source: Authors processing. Data: Trading View (2021)

Table 6 Testing for psychological barriers – resistance and support line – last two digits

	Chi-squared	K-S test
Resistance	320.1359	1.3673
p-value	0.0000	0.1542
Support	479.5996	2.5423
p-value	0.0000	0.0016

Source: Authors processing. Data: Trading View (2021)

After testing for the evidence of price clustering, which was confirmed by and the K-S test in both situations – minimum prices ending with digits 0, 01, and 00, also maximum prices ending with 9, 99, and 98. Tables 5 and 6 illustrate results of testing for psychological barriers. In the case of the support line, it is possible to state that there is a support line in both cases when analysing the last digit or last two digits, as the *p-value* is less than 0.05 for both performed tests. However, in the case of the resistance line, the psychological barriers are not as explicit as in the support line. In table 6, it is possible to observe that the p-value of the K-S test for the resistance line is significantly higher than 0.05. Thus, the results from Table 6 are not robust, so there is not enough evidence to reject the null hypothesis to *H2.2.*

Conclusion

In this paper, the testing for price clustering of minimal and maximal prices was done in the concrete at the market of virtual currency Bitcoin. Based on results in Tables 3 and 4, it is possible to claim that the existence of price clustering in the last digit(s) of Bitcoin price is present. Thus, the statement might be that the minimum price tends to cluster around the last digit 0 or the last two digits 00 and 01. However, it might be stated that the maximum price tends to cluster around the last digit nine or the last two digits 99 and 98. All null sub hypotheses for *H1.1*, *H1.2*, *H1.3* and *H1.4* were successfully rejected. The presented results are in line with the research done by Narayan (2022), who investigated price clustering at the oil market during COVID-19 pandemics. It can be stated that COVID-19 has not changed the occurrence of price clustering in the cryptocurrency market of Bitcoin as well as other more conventional financial markets. Thus, the presented results are in line with the research of Kim (2021), as Bitcoin fulfil similar signs as stocks or money when it comes to price clustering or the psychological behaviour of possessors.

Well-functioning markets are essential for ensuring that prices reach their equilibrium points. The prevalence of price clustering in many asset markets, particularly in the Bitcoin market, indicates that there might be some frictions preventing the formulation of equilibrium pricing. According to our study, one of these frictions might be due to people's fondness for round numbers. Other conflicts are undoubtedly possible. However, the structure of price clustering might be in question.

From the presented results, a question for future research arises: *How is the structure of price clustering changing in the Bitcoin market?* To analyse changes in the price clustering structure of Bitcoin assets, it would be interesting to apply the methodology to a larger sample, especially at more actual data depicting the rise of ETFs backed by Bitcoin futures contracts and Bitcoin slump in December 2021 and January 2022. Das and Kadapakkam (2018) provided evidence that algorithm trading has adverse effects on price clustering, as the clusters are weakening and diminishing when studying their presence at conventional financial assets as backed by ETFs. Comparison of the cryptocurrency market and other stock markets using ETFs for a longer time might be interesting if there is also the relationship between bitcoin-based ETFs to weaken the occurrence of price clustering.

According to the results, it might be stated that there is the presence of psychological barriers, particularly at the level of the support line. The Chi-squared test and Kolmogorov-Smirnov test showed robust results (Table 5 and 6) when testing for support lines. However, the results for the resistance line were not robust. The chi-squared test claimed statistical significance in both situations regarding the price last digit and last two digits. On the other hand, the Kolmogorov-Smirnov test is not statistically significant for the resistance level at two digits. Therefore, it is not possible to reject the null hypothesis of *H2.2. It* cannot be unambiguously claimed there is a psychological barrier at the last two digits of the maximum price of Bitcoin – therefore no evident presence of a resistance line as described by the theory of behavioural finance.

Presented results support evidence that Bitcoin is not only a solely speculative financial asset. Based on results, that resistance line is not so significant according to behavioural finance theory; it is in line with claims that Bitcoin is growing into a long-term investment strategy asset. Missing evidence of a significant resistance line might be interpreted as investors seeing the price rising; they are not selling their assets (Bitcoins); they are holding it as a part of their long-term strategic investment in the belief that the value of Bitcoin will be rising in the future. On the other hand, evidence of support line is quite evident. That can be interpreted as price decrease at a certain level; investors tend to buy more assets because they believe in value growth in future.

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