THE EFFECT OF BEHAVİOURAL FACTORS ON THE DYNAMİCS OF BİTCOİN MARKET EFFİCİENCY

Mateusz Skwarek
Poznan University of Economics and Business
Mateusz.Skwarek@ue.poznan.pl

Abstract:

Bitcoin has attracted great attention from academics and investors. However, there is a lack of knowledge about the drivers of Bitcoin market efficiency. This paper aims to study the effect of behavioural factors on the dynamics of Bitcoin market efficiency. Therefore, a novel approach to the dynamics of market efficiency is proposed. This approach is based on the Hurst exponents estimated by Multifractal Detrended Fluctuation Analysis. The investigated behavioural factors are investor uncertainty proxied by economic policy uncertainty indexes and investor attention based on the Google Trends data. The relationship between these variables and the dynamics of market efficiency is estimated using the Autoregressive Distributed Lag model. The findings indicate that investor sentiment is positively associated with the dynamics of Bitcoin market efficiency. Besides, it is noticed that the level of market illiquidity negatively affects the dynamics of Bitcoin market efficiency. The research may be useful for investors and regulators.

***Keywords*:** Adaptive market hypothesis, Bitcoin, Behavioural finance, Hurst exponent, Market efficiency.

Funding: The study was supported by funds granted by the Minister of Science of the Republic of Poland under the „Regional Initiative for Excellence" Programme for the implementation of the project "The Poznań University of Economics and Business for Economy 5.0: Regional Initiative – Global Effects (RIGE)".

INTRODUCTION

The adaptive market hypothesis (AMH) of Bitcoin has attracted the attention of many academics (e. g. Al-Yahyaee et al., 2020; Khuntia & Pattanayak, 2020; Noda, 2021; Mokni et al., 2024). AMH states that market efficiency fluctuates over time and dynamic economic conditions may contribute to that (Lo, 2004). The markets are informationally efficient when the asset prices incorporate all available information (Fama, 1970). The AMH assumes that market efficiency may be cyclical and combine with behavioural factors. However, the evidence in this area in the cryptocurrency market is limited.

This paper aims to study the effect of behavioural factors on the dynamics of Bitcoin market efficiency. Studies confirm that cryptocurrency market efficiency may be related to market liquidity (e.g. Wei, 2018; Takaishi & Adachi, 2020), capitalization (Brauneis & Mestel, 2018) and volatility (Al-Yahyaee et al., 2020). However, it is not clear whether behavioural factors affect Bitcoin market efficiency. The results of studies on the effect of investor sentiment on cryptocurrency market efficiency are mixed (e. g. Chu, Zhang, & Chan, 2019; Mokni et al., 2024).

Previous studies suggest that investor attention and the economic policy uncertainty in different countries (EPU) may be associated with the behaviour of Bitcoin returns (Kristoufek, 2013; Demir et al., 2018; Shaikh, 2020). Additionally, investors may be subject to heuristics by evaluating the credibility of the Initial coin offerings (ICO) based on the reputation of the ICO's country of origin (Shrestha et al., 2021). Thus, Bitcoin market inefficiency may strengthen with increased investor attention and economic policy uncertainty in the largest Bitcoin mining countries/regions.

To study behavioural factors related to the monthly changes in Bitcoin market efficiency, a novel approach to the dynamics of market efficiency is proposed. This approach is based on Hurst exponents estimated using the MF-DFA algorithm (Multifractal Detrended Fluctuation Analysis). The results indicate that the dynamics of Bitcoin market efficiency is related to Bitcoin trading volume and liquidity. The importance of market liquidity for Bitcoin market efficiency is confirmed by others (e.g. Brauneis & Mestel, 2018; Wei, 2018; Al-Yahyaee et al., 2020; Mokni et al., 2024). The trading volume may proxy investor sentiment (Anusakumar et al., 2017). It may be concluded that investor sentiment is the most important behavioural factor for the dynamics of Bitcoin market efficiency among studied others. The relationship between Bitcoin volume and Bitcoin market efficiency may be explained by the sunk cost effect (Arkes, & Blumer, 1985), cognitive dissonance (Festinger, 1962) and prospect theory (Kahnemann. & Tversky, 1979).

METHODOLOGY

The research data covers the period from December 2013 to June 2023. The reasons for selecting this period are the accessibility of the data and the relatively low popularity of Bitcoin on Google trends in the previous years. The dataset consists of the following parts:
- Bitcoin prices in USD for Bitstamp exchange (http://api.bitcoincharts.com/v1/csv/),
- Bitcoin volume and market capitalisation downloaded from https://data.bitcoinity.org,
- Global economic policy uncertainty index (GEPU), and other EPU indexes for the largest Bitcoin mining territory - Canada, China, Europe, Germany, Ireland, Russia, USA (https://policyuncertainty.com/),
- Global Google Search Volume (GSV) index for the word 'bitcoin' during the study period (https://trends.google.pl/),
- VIX index obtained from https://www.cboe.com/tradable_products/vix/vix_historical_data/.

To provide a sufficiently long time series for the studied relationship, the Hurst exponent is employed as a measure of market efficiency. This measure may indicate the relationship between the variability of the studied time series and the different lengths of the subperiods over which this is examined. Due to the varying number of hourly closing prices in the following months, the MF-DFA algorithm is used to estimate the Hurst exponent (Kantelhardt et al., 2002). In particular, the squared fluctuation function is applied, which makes MF-DFA similar to the detrended fluctuation analysis. The advantage of the MF-DFA is including the behaviour of the remaining part of the time series after dividing it into equal subintervals. The minimum and maximum lengths of the subperiods are set to 10 datapoints and 1/4 length of the series of hourly logarithmic returns for the given month.

The Hurst exponents close to 0.5 denote a random walk of time series (efficient market). When the Hurst exponent is more or less than 0.5, the market is inefficient. However, the values above and below 0.5 indicate inefficiency driven by different processes – long or short memory of returns. Therefore, they may not be subtracted to indicate the size of the change in market efficiency. To manage this issue, a novel approach to the dynamics of market efficiency is proposed. Motivated by others (e.g. Kristoufek & Vosvrda, 2013; Bariviera, 2017), the dynamics of market efficiency is calculated as differences between the absolute value of Hurst exponents reduced by 0.5. This is shown below:

$$d\_ef_t = -(|H - 0{,}5|_t - |H - 0{,}5|_{t-1}), \qquad (1)$$

where d_ef_t means the change in market efficiency over a period of 't' in reference to the previous time 't-1', H_t is the Hurst exponent during a period of 't'. Increase / decrease in the value of this measure means increae / decrease in market efficiency.

In the study, the independent variables are GSV index as a proxy for investor attention to Bitcoin, EPU indexes and controls (market illiquidity, capitalisation, index VIX and trading volume). The variables are at a monthly frequency and in the form of logarithmic first differences to meet the condition of stationarity (Augmented Dickey-Fuller test, Kwiatkowski–Phillips–Schmidt–Shin test). All studied time series are winsorized to eliminate outliers.

To study the effect of behavioural factors on the dynamics of Bitcoin market efficiency, the ARDL model (Autoregressive Distributed Lag model) is estimated using OLS. The reason for this is the autoregressive nature of the studied variables. The detailed specification of the model is selected based on the method 'from specific to general' (Gruszczyński, Kuszewski, & Podgórska, 2009, pp. 231). During the study, the combined effect of all variables and their partial influence are considered. The general form of the model is presented below:

$$d\_ef_t = a_0 + a_1 d\_ef_{t-1} + a_2 d\_ef_{t-2} + \sum_{k=0}^{k} \gamma_k \Delta EPU_{i,t-k} + \beta_1 \Delta GSV_t + \beta_2 \Delta ILLIQ_t + \beta_3 \Delta ILLIQ_{t-1} + \beta_4 \Delta Vol_t + \beta_5 \Delta MC_t + \beta_6 \Delta VIX_t + \varepsilon, \qquad (2)$$

where d_ef_t denotes the change in market efficiency over a period of 't' in reference to 't-1', a_0 is a constant, GSV_t is a GSV index for the word 'bitcoin' during a period of 't', $EPU_{i,t-k}$ means EPU index in a country / region 'I' during a period 't' and lagged 'k' months, $ILLIQ_{i,t}$ is an Amihud (2002) illiquidity measure for a month 't', Vol_t, MC_t, VIX_t are, respectively: Bitcoin volume and market capitalization, and average value of VIX index during a month 't', 'ε' is a random term.

The correctness of the ADL model is confirmed using different tests: the Durbin-Watson test, VIFs (Variance Inflation Factors), RESET tests for regressors and fitted values, Shapiro-Wilk and Breuscha-Pagan tests, the Chow test for halving date. Due to the higher autocorrelation coefficient in the second and third lag, Newey-West errors are applied. For the robustness check, the ARMA (7,1) model is estimated by the Maximum Likelihood function. This model is more restrictive assuming autocorrelations near zero for all lags (Ljung–Box test).

FINDINGS

Table 1 shows the effect of behavioural factors on the dynamics of Bitcoin market efficiency. Due to the distributed influence of variables over time, the combined effect of all lags for the given variable is calculated - Long-run Multiplier (Gruszczyński, Kuszewski, & Podgórska, 2009, pp. 229-232). The Long-run Multipliers for the variables are presented in Table 2.

Table 1. The effect of behavioural factors on the dynamics of Bitcoin market efficiency

Variable	Coefficient (Standard error)
d_ef_(t-1)	-0.59132*** (0.07726)
d_ef_(t-2)	-0.41345*** (0.07425)
∆ILLIQ_t	-0.01080*** (0.00372)
∆ILLIQ_(t-1)	-0.00512 (0.00330)
∆MC_t	0.00851 (0.01353)
∆Vol_t	0.01104 (0.00703)
∆GSV_t	-0.00459 (0.01023)
∆GEPU_t	0.02325 (0.01811)
∆GEPU_(t-1)	0.02033 (0.01751)
∆VIX_t	-0.00839 (0.01565)
Constant	-0.00049 (0.00197)
Observations	112
R^2	0.38684
Adjusted R^2	0.32613
Residual Std. Error	0.02579 (df = 101)
F Statistic	6.37212*** (df = 10; 101)
Durbin-Watson Statistic (p-value)	2.20396 (0.228)

*Note: ***, **, * mean statistically significant at the level of 1%, 5%, 10%. The robust standard errors for heteroscedasticity and autocorrelation are applied (Newey-West). In the process of estimation of robust standard errors, the number of lags equal to 3 is assumed based on the ACF plot of residuals.*

Table 2. Long-run Multipliers

Variable	Coefficient	F Statistic (p-value)
ΔILLIQ	-0.0079	5.404*** (0.006)
ΔMC	0.0042	0.396 (0.531)
ΔVol	0.0055	2.470 (0.119)
ΔVIX	-0.0042	0.287 (0.593)
ΔGSV	-0.0023	0.201 (0.655)
ΔGEPU	0.0217	1.255 (0.289)

*Note: ***, **, * mean statistically significant at the level of 1%, 5%, 10%. The estimation of parameters is based on the model of the combined effect of behavioural factors on the dynamics of Bitcoin market efficiency.*

Table 2 shows that only market illiquidity is statistically significant at 1%. The negative sign of the coefficient means that an increase in market illiquidity is associated with a decrease in the Bitcoin market efficiency. This is consistent with others (e.g. Brauneis & Mestel, 2018; Wei, 2018; Al-Yahyaee et al., 2020; Mokni et al., 2024). In Table 2, it can be noticed that Bitcoin trading volume is statistically significant at 12%. For 4 out of 9 estimated models of the partial influence of behavioural factors on the dynamics of Bitcoin market efficiency, this is a statistically significant association at 10% (unreported). Thus, we find weak evidence that Bitcoin trading volume positively affects the dynamics of Bitcoin market efficiency. Similar findings are in Łęt et al. (2023).

The effect of Bitcoin volume can be interpreted in the context of behavioural factors, e. g. investor sentiment (e. g. Anusakumar et al., 2017). When the investor's sentiment strengthens it can be expected that the number of transactions increase (and the other way around). In this case, some investors may realise profits quickly. They may feel good with lower but a certain profit. However, others may behave as 'noise traders'. This may reflect the lack of consensus between investors on whether Bitcoin has fundamental value. During negative sentiment, investor behaviour may be more motivated by gambling and the sunk cost effect (Arkes, & Blumer, 1985) than in the previous case. In this situation, cognitive dissonance (Festinger, 1962) between the information concerning the incurred cost by traders who have invested in Bitcoin and market sentiment may strengthen and lead to an overestimation of the probability of profit. This may also occur because potential losses may hurt investors more than equivalent gains (Kahnemann, & Tversky, 1979) and traders may want to get invested money back.

The estimated models indicate that EPU indexes do not effect on the dynamics of Bitcoin market efficiency (unreported). The reason behind that may be that there is no consensus between investors about the save-haven property of Bitcoin. This is supported by Choi and Shin (2022). Besides, the effect of investor attention on the dynamics of Bitcoin market efficiency is not confirmed. This may result from the low accuracy of indexes provided by Google – low popularity is marked as the same values, e.g. 1%. The lack of a statistically significant effect of the VIX index on the dynamics of Bitcoin market efficiency may be due to the narrow information capacity of this measure, which does not reflect Bitcoin specificity. Similar findings are in Mokni et al. (2024). Finally, the effect of Bitcoin market capitalisation on the dynamics of Bitcoin market efficiency is not confirmed. This may be explained by the fact that others used cross-sectional data with a frequency different from this study (Brauneis & Mestel, 2018). The results are robust to a model specification because the estimated ARMA (7,1) model indicates similar conclusions to the ADL model.

CONCLUSIONS

The results indicate that investor sentiment towards Bitcoin positively influences the dynamics of Bitcoin market efficiency. This may be explained by the sunk cost effect, cognitive dissonance, and prospect theory. The market illiquidity in the Bitcoin market is negatively associated with the dynamics of Bitcoin market efficiency. Similar findings are in Brauneis and Mestel (2018), Wei (2018), Al-Yahyaee et al. (2020), and Mokni et al. (2024). Contrary to Mokni et al. (2024), the effect of the global financial stress indicator is not confirmed in the case of Global EPU. However, the approach to the dynamics of market efficiency and used data frequency are different from them. The results are limited to only one measure of market efficiency and selected data frequency. Besides, this study considers only linear relationships between investigated variables.

The effect of illiquidity on the dynamics of Bitcoin market efficiency is the greatest among the studied factors. This may reflect the difficulties in price negotiations during high volatility presented in the Bitcoin market. Thus, Bitcoin investors should pay attention to the level of market illiquidity that may signal Bitcoin market inefficiency. Besides, the results suggest that the sunk cost effect, cognitive dissonance and prospect theory may drive investor irrationality in the long term. Thirdly, this paper adds to the literature on the AMH by the first study of the link between some behavioural factors and the dynamics of market efficiency. The effect of investor sentiment is consistent with the AMH. Changes in economic conditions may lead to negative sentiment, and in effect, investor behaviour may be irrational. Therefore, it may be expected that the dynamics of Bitcoin market efficiency fluctuate. For policymakers, it is recommended to support the education of investors about the behavioural mistakes related to investor sentiment.

REFERENCES

Al-Yahyaee, K. H., Mensi, W., Ko, H.-U., Yoon, S.-M., & Kang, S. H. (2020). Why cryptocurrency markets are inefficient: The impact of liquidity and volatility. *The North American Journal of Economics and Finance*, 52(C). https://doi.org/10.1016/j.najef.2020.101168

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31-56. https://doi.org/10.1016/S1386-4181(01)00024-6

Anusakumar, S. V., Ali, R., & Wooi, H. C. (2017). The Effect of Investor Sentiment on Stock Returns: Insight from Emerging Asian Markets. *Asian Academy of Management Journal of Accounting and Finance*, 13(1), 159-178. https://doi.org/10.21315/aamjaf2017.13.1.7

Arkes, H., & Blumer, C. (1985). The psychology of sunk cost. *Organizational Behavior and Human Decision Processes,* 35(1), 124-140. https://doi.org/10.1016/0749-5978(85)90049-4

Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: A dynamic approach. *Economics Letters*, 161, 1–4. https://doi.org/10.1016/j.econlet.2017.09.013

Brauneis, A., & Mestel, R. (2018). Price discovery of cryptocurrencies: Bitcoin and beyond. *Economics Letters*, 165, 58-61. https://doi.org/10.1016/j.econlet.2018.02.001

Choi, S., & Shin, J. (2022). Bitcoin: An inflation hedge but not a safe haven. *Finance Research Letters*, 46, 102379. https://doi.org/10.1016/j.frl.2021.102379

Chu, J., Zhang, Y., & Chan, S. (2019). The adaptive market hypothesis in the high frequency cryptocurrency market. *International Review of Financial Analysis*, 64, 221-231. https://doi.org/10.1016/j.irfa.2019.05.008

Demir, E., Gozgor, G., Lau, M. C. K., & Vigne, S. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2018.01.005

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383–417. https://doi.org/10.2307/2325486

Festinger, L. (1962). Cognitive Dissonance. *Scientific American*, 207(4), 93–106. Retrieved from http://www.jstor.org/stable/24936719

Gruszczyński, M., Kuszewski, T., & Podgórska, M. (2009). *Ekonometria i badania operacyjne*. Warszawa: Wydawnictwo Naukowe PWN.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47(2), 263–291. https://doi.org/10.2307/1914185

Kantelhardt, J. W., Zschiegner, S. A., Koscielny-Bunde, E., Havlin, S., Bunde, A., & Stanley, H. E. (2002). Multifractal detrended fluctuation analysis of nonstationary time series. *Phys. Stat. Mech. Appl.*, 316, 87–114. https://doi.org/10.1016/S0378-4371(02)01383-3

Khuntia, S., & Pattanayak, J. (2020). Adaptive Long Memory in Volatility of Intra-day Bitcoin Returns and the Impact of Trading Volume. *Finance Research Letters*, 32, 101077. https://doi.org/10.1016/j.frl.2018.12.025

Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific Reports*, 3, 3415. https://doi.org/10.1038/srep03415

Kristoufek, L., & M. Vosvrda (2013). Measuring capital market efficiency: Global and local correlations structure. *Physica A*, 392, 184–193. https://doi.org/10.1016/j.physa.2012.08.003

Lo, A. W. (2004). The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective. *The Journal of Portfolio Management*, 30(5), 15–29. Retrieved from https://www.researchgate.net/publication/228183756_The_Adaptive_Markets_Hypothesis_Market_Efficiency_from_an_Evolutionary_Perspective

Łęt, B., Sobański, K., Świder, W., & Włosik, K. (2023). Investor sentiment and efficiency of the cryptocurrency market: The case of the Crypto Fear & Greed Index. In: M. H. Bilgin, H. Danis, E. Demir, L. Wincenciak, & S. T. (Ed.), *Eurasian Business and Economics Perspectives: Proceedings of the 38th Eurasia Business and Economics Society Conference* (Vol. 25, pp. 271–287). https://doi.org/10.1007/978-3-031-36286-6_16

Mokni, K., El Montasser, G., Ajmi, A. N., & Bouri, E. (2024). On the efficiency and its drivers in the cryptocurrency market: the case of Bitcoin and Ethereum. *Financial Innovation*, 10, 39.https://doi.org/10.1186/s40854-023-00566-3

Noda, A. (2021). On the evolution of cryptocurrency market efficiency. *Applied Economics Letters*, 28, 6, 433-439. https://doi.org/10.1080/13504851.2020.1758617

Shaikh, I. (2020). Policy uncertainty and Bitcoin returns. *Borsa Istanbul Review*, 20(3), 257-268. https://doi.org/10.1016/j.bir.2020.02.003

Shrestha, P., Arslan-Ayaydin, Ö., Thewissen, J., & Torsin, W. (2021). Institutions, regulations and initial coin offerings: An international perspective. *International Review of Economics & Finance*, 72, 102-120. https://doi.org/10.1016/j.iref.2020.10.014

Takaishi, T., & Adachi, T. (2020). Market Efficiency, Liquidity, and Multifractality of Bitcoin: A Dynamic Study. *Asia-Pacific Financial Markets*, 27, 145–154. https://doi.org/10.1007/s10690-019-09286-0

Wei, W. C. (2018). Liquidity and market efficiency in cryptocurrencies. *Economics Letters*, 168, 21-24. https://doi.org/10.1016/j.econlet.2018.04.003