UDC 332; DOI 10.18551/rjoas.2022-12.02

STUDY OF CRYPTOCURRENCY'S MARKET EFFICIENCY POST-COVID-19 ANNOUNCEMENT

Putri Ida Ayu Widya Laksmi*, **Candradewi Made Reina**
Faculty of Economics and Business, University of Udayana, Indonesia
*E-mail: ia.widyalaksmiputri@gmail.com

ABSTRACT
The announcement of the coronavirus disease (COVID-19) as a pandemic by the World Health Organization (WHO) on March 11, 2020, caused revenue decline in many companies due to the implementation of lockdown policies in various countries, which limited people's activities and mobility. The COVID-19 pandemic also caused panic that made many investors put their shares on the market, resulting in company stock prices dropping in various sectors. Therefore, many investors are interested in cryptocurrency, which has experienced a price surge since the announcement of COVID-19. This study tests the weak-form of the Efficient Market Hypothesis in 32 cryptocurrency markets categorized as the large and medium market capitalization within two years after the announcement of the COVID-19 pandemic. This study is quantitative research performed to test return predictability using run-test analysis techniques. The results of this study show that 20 out of 32 cryptocurrencies used in this study are efficient, including Terra, Cardano, and Dogecoin, which are categorized as large market caps. We also found inefficiencies in the cryptocurrencies within the large market caps, such as Bitcoin, Ethereum, Binance Coin, and XRP.

KEY WORDS
Efficient market hypothesis, weak-form, cryptocurrency, run test.

COVID-19, declared a pandemic by the World Health Organization (WHO) on March 11, 2020, led to the implementation of lockdown policies in many countries. The practice of a lockdown policy that limited community activities and mobility then hampered the company's operations and decreased its income. The decline in the company's income gave investors a negative perception of the company's ability to earn profits in the future. Investors' negative perceptions also arose since there was no certainty in the period of the implementation of the lockdown policy, resulting in many investors selling their stocks and leading to a decline in stock prices in numerous companies. The stock price plunges then made investors try to find an alternative investment that appeared to be promising, such as cryptocurrency, which had experienced a surge in price since the announcement of COVID-19.

Cryptocurrency is a digital asset obtained through a series of complex mathematical calculations, secured using cryptographic techniques, based on blockchain technology, and without any intermediary parties in transactions (Furneaux, 2018, pp. 3-8). Although originally designed as a payment method, many people presently consider cryptocurrency an alternative investment. Many studies also state that cryptocurrency can be used for portfolio diversification [Bouri, *et al*. (2017); Brauneis & Mestel (2019); Kajtazi & Moro (2019); Inci & Lagasse (2019); Ma, *et al*. (2020), hedging (Matkovskyy, *et al*., 2021), as well as a safe haven asset (Bouri, *et al*., 2017); Mariana et al. (2021); Melki & Nefzi (2022). In addition, the high level of volatility of cryptocurrency also attracts investors' attention to gain profits. The large number of participants in a market will make the market efficient. Therefore, many researchers are testing the cryptocurrency market's efficiency to prove whether the cryptocurrency market allows participants to make a profit.

Sarkodie, *et al*. (2022) state that the market prices of Bitcoin, Ethereum, Bitcoin Cash, and Litecoin increased as the number of confirmed cases and deaths due to COVID-19 increased. Based on data from the Coinmarketcap.com website, the price of Bitcoin reached USD 29,001.72 at the end of 2020 and USD 46,306.45 at the end of 2021. The data also reports that the price of Ethereum reached USD 737.80 at the end of 2020 and USD 3,682.63 at the end of 2021. In addition, The Economic Times website stated that Bitcoin had experienced a rise in the price of up to 500% since COVID-19 to May 2021, as well as other cryptocurrencies such as Ethereum, Ripple, Dogecoin, and many more. Hou, *et al*. (2021) state that investors and the public's psychological state significantly influence the price of Bitcoin in the long run due to cashless transactions, lower risk of virus transmission, decentralization, and ease of payments.

The rapid change in cryptocurrency prices happens because there are many market participants involved. Based on a survey from the University of Chicago, around 13% of Americans bought or sold cryptocurrencies between July 2020 to July 2021 (Iacurci, 2021). Based on the Buku Kajian Stabilitas Keuangan published by Bank Indonesia, the number of cryptocurrency investors in Indonesia is estimated to have reached 6.5 million in June 2021 (Bank Indonesia, 2021, pp. 34-35) and to reach 11 million in December 2021 based on data from the Ministry of Trade of the Republic Indonesia (Azka, 2022). In addition, based on the Crypto Market Sizing report published by Crypto.com, there was an increase in the global population of crypto ownership by 178% in 2021, with nearly 300 million users (Crypto, 2022).

The Efficient Market Hypothesis by Fama (1970) states that stock prices are always in a state of equilibrium because all information will be quickly absorbed in prices so that investors or traders do not have the opportunity to obtain abnormal returns from information circulating. Fama (1970) divided market efficiency into three forms based on the type of information circulating: weak, semi-strong, and strong. The test for weak-form market efficiency is often performed on Bitcoin or Ethereum, but only some studies test the weak-form market efficiency of the ever-growing Altcoins.

Previous studies on efficiency in the cryptocurrency market still give mixed results, namely that the cryptocurrency market is a weak-form of inefficient [Hu, *et al*. (2019); Palamalai, *et al*. (2021); Dowling (2022)], that the cryptocurrency market is weak-form efficient [Apopo & Phiri (2021); Aslan & Sensoy (2020)], and that the cryptocurrency market will become more efficient in the future [Wei (2018); Caporale, *et al*. (2018); Al-Yahyaee, *et al*. (2020); Nan & Kaizoji (2019); Tran & Leirvik (2020); Mnif, *et al*. (2020)]. In addition, studies are often performed on Bitcoin [Urquhart (2016); Vidal-Tomás et al. (2019); Jiang, *et al*. (2018); Zargar & Kumar (2019)] and are still limited to Altcoins. Therefore, testing the weak-form market efficiency of Bitcoin and Altcoin is deemed necessary to be carried out again, considering the mixed results of previous studies and the number of Altcoins that continues to grow. Therefore, this study examines whether the cryptocurrency market is weak-form efficient.

This study aims to test the weak-form market efficiency of the cryptocurrency market due to the phenomenon of significant price changes and an increase in the number of market participants in the cryptocurrency market after the emergence of the COVID-19 pandemic, which raises the question of whether investors can obtain abnormal returns from this significant price increase. Thus, it was deemed necessary to conduct tests on other types of cryptocurrency since previous studies still gave varying results and mainly focused on Bitcoin.

METHODS OF RESEARCH

The data used in this study is cryptocurrency historical price (daily price) obtained from the Yahoo! Finance website. This study used 32 cryptocurrency markets categorized as large and medium market capitalization as of April 29, 2022. The data sample consisted of 730 daily observations for each cryptocurrency from March 11, 2020, to March 11, 2022. Table 1 is descriptive statistics for log return (rt) time series data, defined below:

$$r_t = ln\left[\frac{P_t}{(P_{t-1})}\right] \quad (1)$$

Table 1 – Descriptive statistics of the log return time series for 32 cryptocurrencies between March 11, 2020, to March 11, 2022

Cryptocurrency Name	Code	N	Mean	SD	Max	Min
Bitcoin	BTC	730	0.0022	0.0418	0.1718	-0.4647
Ethereum	ETH	730	0.0035	0.0543	0.2307	-0.5507
Binance Coin	BNB	730	0.0043	0.0629	0.5292	-0.5431
XRP	XRP	730	0.0018	0.0703	0.4448	-0.5505
Terra	LUNA	730	0.0083	0.0842	0.6414	-0.4876
Cardano	ADA	730	0.0041	0.0634	0.2794	-0.5036
Dogecoin	DOGE	730	0.0054	0.1007	1.5163	-0.5151
Polygon	MATIC	730	0.0059	0.0849	0.4578	-0.7140
Litecoin	LTC	730	0.0011	0.0574	0.2484	-0.4491
TRON	TRX	730	0.0019	0.0591	0.3342	-0.5231
Cosmos	ATOM	730	0.0030	0.0762	0.2809	-0.5902
Bitcoin Cash	BCH	730	0.0001	0.0612	0.4208	-0.5613
Stellar	XLM	730	0.0018	0.0648	0.5592	-0.4100
Monero	XMR	730	0.0016	0.0575	0.3450	-0.5342
Ethereum Classic	ETC	730	0.0019	0.0654	0.3525	-0.5064
Filecoin	FIL	730	0.0021	0.0981	0.7692	-0.4729
Hedera	HBAR	730	0.0020	0.0706	0.4585	-0.5882
VeChain	VET	730	0.0032	0.0752	0.2989	-0.6172
Theta Network	THETA	730	0.0046	0.0765	0.2576	-0.6039
Tezos	XTZ	730	0.0002	0.0704	0.3059	-0.6073
Fantom	FTM	730	0.0073	0.1044	0.4150	-0.7059
EOS	EOS	730	-0.0006	0.0658	0.4396	-0.5042
Zcash	ZEC	730	0.0018	0.0669	0.2528	-0.5394
IOTA	MIOTA	730	0.0018	0.0703	0.3192	-0.5436
Waves	WAVES	730	0.0040	0.0729	0.4478	-0.4871
Bitcoin SV	BSV	730	-0.0012	0.0630	0.4552	-0.5603
Stacks	STX	730	0.0031	0.0816	0.7994	-0.7124
Kusama	KSM	730	0.0055	0.0830	0.4642	-0.5387
Neo	NEO	730	0.0010	0.0648	0.2531	-0.4656
Harmony	ONE	730	0.0048	0.0976	0.6437	-0.7285
Zilliqa	ZIL	730	0.0027	0.0755	0.3237	-0.5659
Dash	DASH	730	0.0004	0.0651	0.4513	-0.4655

If a market is weak-form efficient, market participantss cannot predict future prices because prices move randomly (random walk). To analyze whether the cryptocurrency market is weak-form efficient, we perform the run test of Wald & Wolfowitz (1940), which could capture the randomness of the data. We use the run test (Wald & Wolfowitz , 1940) since it is a non-parametric statistical test, where the analyzed data does not have to meet certain assumptions or parameters, such as the assumption of normality of the data. The null hypothesis of the run test is that the order in the sample data is randomly generated.

RESULTS AND DISCUSSION

Table 2 is the result of the run test, where the null hypothesis is rejected when the p-value is less than the significance level of 0.05 or 5%, and vice versa. Based on the results of the run test, random walk patterns were not found in as many as 12 types of cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), XRP (XRP), Bitcoin Cash (BCH), Ethereum Classic (ETC), Hedera (HBAR), VeChain (VET), EOS (EOS, IOTA (MIOTA), Bitcoin SV (BSV), and Zilliqa (ZIL).

No random walk pattern was found, indicating that those 12 cryptocurrencies are weak-form inefficient, making their price predictable. Therefore market participants have the opportunity to earn abnormal returns. In addition, predictable prices also enable market participants to use technical analysis to develop strategies in order to gain abnormal returns. Jalali & Heidari (2020) states that the price of Bitcoin can be predicted accurately and investors can acquire maximum profit by choosing the right time frame.

Jogiyanto (2017) states that there are several causes for a market to be inefficient, namely because there are a small number of market participants, the price of obtaining information is high, unequal access among market participants, the information can be predicted by partly of market participants, as well as the investors involved are naïve and unsophisticated investors who have limited ability to interpret the information received and consequently make wrong decisions.

Referring to Jogiyanto (2017), the weak form inefficiency in the cryptocurrency above might occur due to unequal access to information, and the market consists of many naive investors that often make decisions based on sentiment or follow other investors. Those refer to the result of Lewis (2018), which states that changes in cryptocurrency prices occur due to encouragement from sellers and buyers who make decisions based on factors such as sentiment, technical success or failure, support from community leaders, and many more; result of Haryanto et al., (2020) which states that herding increases in periods when there is an increase or decrease in the price of Bitcoin; result of Gurdgiev & O'Loughlin (2020) which states that investor sentiment can predict the direction of cryptocurrency prices and indicates a direct effect on herding and anchoring bias; as well as a result of Rubbaniy et al. (2021) which states that there is evidence of herding in investing in the cryptocurrency market during COVID-19. In addition, Zargar & Kumar (2019) states that inefficiency in cryptocurrency occurs due to endogenous factors from developing and immature markets, as well as the absence of fundamental traders in the cryptocurrency market with the intention that prices are determined purely based on speculation. Those statements explain the inefficiency in the cryptocurrency market despite the increasing number of market participants.

Table 2 – Run test results of the log return time series for 32 cryptocurrencies between March 11, 2020, to March 11, 2022

Cryptocurrency Name	Code	N	N1	N2	Runs	Z-statistics	P-value
Bitcoin	BTC	730	392	338	399	2.6067	0.0091
Ethereum	ETH	730	401	329	393	2.2853	0.0223
Binance Coin	BNB	730	400	330	404	3.0919	0.0020
XRP	XRP	730	379	351	400	2.5621	0.0104
Terra	LUNA	730	378	352	387	1.5919	0.1114
Cardano	ADA	730	380	350	389	1.7523	0.0797
Dogecoin	DOGE	730	359	366	381	1.3034	0.1924
Polygon	MATIC	730	377	353	389	1.7348	0.0828
Litecoin	LTC	730	385	345	382	1.2702	0.2040
TRON	TRX	730	398	331	382	1.4637	0.1433
Cosmos	ATOM	730	374	356	387	1.5730	0.1157
Bitcoin Cash	BCH	730	380	350	415	3.6815	0.0002
Stellar	XLM	730	374	356	390	1.7953	0.0726
Monero	XMR	730	407	323	385	1.7891	0.0736
Ethereum Classic	ETC	730	381	349	399	2.5012	0.0124
Filecoin	FIL	730	349	381	376	0.7942	0.4271
Hedera	HBAR	730	384	345	405	3.0139	0.0026
VeChain	VET	730	386	344	397	2.3937	0.0167
Theta Network	THETA	730	384	346	387	1.6333	0.1024
Tezos	XTZ	730	377	353	373	0.5483	0.5835
Fantom	FTM	730	382	348	385	1.4693	0.1418
EOS	EOS	730	370	360	399	2.4500	0.0143
Zcash	ZEC	730	391	339	367	0.2123	0.8318
IOTA	MIOTA	730	383	347	403	2.8133	0.0049
Waves	WAVES	730	403	327	347	-1.1266	0.2599
Bitcoin SV	BSV	730	350	380	395	2.1975	0.0280
Stacks	STX	730	377	353	373	0.5483	0.5835
Kusama	KSM	730	369	361	379	0.9663	0.3339
Neo	NEO	730	382	348	371	0.4300	0.6672
Harmony	ONE	730	369	360	387	1.5980	0.1100
Zilliqa	ZIL	730	381	349	395	2.2043	0.0275
Dash	DASH	730	388	342	387	1.6696	0.0950

Meanwhile, based on the results of the run test, random walk patterns were found in as many as 20 types of cryptocurrencies consisting of three types of cryptocurrencies categorized as large market capitalizations, namely Terra, Cardano, and Dogecoin, as well as 17 other types of cryptocurrencies categorized as medium market capitalization, namely Terra Classic (LUNA), Cardano (ADA), Dogecoin (DOGE), Polygon (MATIC), Litecoin (LTC), TRON (TRX), Cosmos (ATOM), Stellar (XLM), Monero (XMR), Filecoin (FIL), Theta Network (THETA), Tezos (XTZ), Fantom (FTM), Zcash (ZEC), Waves (WAVES), Stacks (STX), Kusama (KSM), Neo (NEO), Harmony (ONE), and Dash (DASH). The finding of a random walk pattern indicates that the cryptocurrency market is weak-form efficient. Therefore, market participants cannot use technical analysis to obtain abnormal returns.

CONCLUSION

Most types of the cryptocurrency market are weak-form efficient, such as Terra, Cardano, Dogecoin, Polygon, Litecoin, TRON, Cosmos, Stellar, Monero, Filecoin, Theta Network, Tezos, Fantom, Zacash, Waves, Stack, Kusama, Neo, Harmony, and Dash. Therefore, market participants do not have the opportunity to gain abnormal returns from changes in cryptocurrency prices. In addition, market participants cannot use technical analysis to develop strategies to obtain abnormal returns.

The types of cryptocurrencies that do not follow a random walk and hence are inefficient in weak forms are Bitcoin, Ethereum, Binance Coin, XRP, Bitcoin Cash, Ethereum Classic, Hedera, VeChain, EOS, IOTA, Bitcoin SV, and Zilliqa. No random walk pattern is found, making the price of related cryptocurrencies predictable, and thus market participants have the opportunity to gain abnormal returns. In addition, predictable prices also allow market participants to use technical analysis to develop strategies in order to obtain abnormal returns.

Individuals and institutions considering investing in cryptocurrency should develop strategies based on deep technical analysis of the cryptocurrency market of various time frames, particularly those considered weak-form inefficient. Investors should also consider global events affecting cryptocurrencies' price movement. Regulators should consider all cryptocurrency aspects thoroughly in making cryptocurrency trading regulations to boost investors' confidence in the cryptocurrency market.

Future studies may involve cryptocurrencies categorized as small market capitalization, conducting tests on market efficiency in semi-strong forms or strong forms on the cryptocurrency market, or comparing the market efficiency level of the period during the implementation of the lockdown policy and the period after it was revoked.

REFERENCES

1. 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. North American Journal of Economics and Finance, 52. https://doi.org/10.1016/j.najef.2020.101168.
2. Apopo, N., & Phiri, A. (2021). On the (in)efficiency of cryptocurrencies: have they taken daily or weekly random walks? Heliyon, 7(4). https://doi.org/10.1016/j.heliyon.2021.e06685.
3. Aslan, A., & Sensoy, A. (2020). Intraday efficiency-frequency nexus in the cryptocurrency markets. Finance Research Letters, 35. https://doi.org/10.1016/j.frl.2019.09.013.
4. Azka, Rinaldi M. 2022. Jumlah Investor Crypto Kalahkan Pasar Modal, Aplikasi Trading Gencar Promo. Bisnis.com. [cited 2022 Apr. 8]. Available from: https://market.bisnis.com/read/20220308/94/1508076/jumlah-investor-crypto-kalahkan-pasar-modal-aplikasi-trading-gencar-promo.
5. Bank Indonesia. 2021. Bersinergi Mendorong Intermediasi, Mengakselerasi Pemulihan Ekonomi. Kajian Stabilitas Keuangan Nomor 37, September 2021.
6. Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and

safe haven properties of Bitcoin: Is it really more than a diversifier? Finance Research Letters, 20. https://doi.org/10.1016/j.frl.2016.09.025

7. Brauneis, A., & Mestel, R. (2019). Cryptocurrency-portfolios in a mean-variance framework. Finance Research Letters, 28, 259–264. https://doi.org/10.1016/j.frl.2018.05.008.
8. Caporale, G. M., Gil-Alana, L., & Plastun, A. (2018). Persistence in the cryptocurrency market. Research in International Business and Finance, 46. https://doi.org/10.1016/j.ribaf.2018.01.002.
9. Crypto. 2022. Research: Global Crypto Owners Near 300 Million, Predicted to Hit 1 Billion by the End of 2022. [cited 2022 Apr. 8]. Available from: https://blog.crypto.com/global-crypto-owners-near-300-million-predicted-to-hit-1-billion-by-the-end-of-2022/
   Dowling, M. (2022). Fertile LAND: Pricing non-fungible tokens. Finance Research Letters, 44. https://doi.org/10.1016/j.frl.2021.102096.
10. Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, 25(2). https://doi.org/10.2307/2325486.
11. Furneaux, N. (2018). Investigating Cryptocurrencies. John Wiley & Sons Inc.
12. Gurdgiev, C., & O'Loughlin, D. (2020). Herding and anchoring in cryptocurrency markets: Investor reaction to fear and uncertainty. Journal of Behavioral and Experimental Finance, 25. https://doi.org/10.1016/j.jbef.2020.100271.
13. Hartono, Jogiyanto. 2017. Teori Portofolio dan Analisis Investasi. Edisi Kesebelas. Yogyakarta: BPFE-YOGYAKARTA.
14. Haryanto, S., Subroto, A., & Ulpah, M. (2020). Disposition effect and herding behavior in the cryptocurrency market. Journal of Industrial and Business Economics, 47(1). https://doi.org/10.1007/s40812-019-00130-0.
15. Hou, J. P., Liu, J., & Jie, Y. J. (2021). Examining the Psychological State Analysis Relationship Between Bitcoin Prices and COVID-19. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.647691.
16. Hu, Y., Valera, H. G. A., & Oxley, L. (2019). Market efficiency of the top market-cap cryptocurrencies: Further evidence from a panel framework. Finance Research Letters, 31. https://doi.org/10.1016/j.frl.2019.04.012.
17. Iacurci, Greg. 2021. 13% of Americans traded crypto in the past year, survey finds. CNBC. [cited 2022 Apr. 8]. Available from: https://www.cnbc.com/2021/07/23/13percent-of-americans-traded-crypto-in-the-past-year-survey-finds.html.
18. Inci, A. C., & Lagasse, R. (2019). Cryptocurrencies: applications and investment opportunities. Journal of Capital Markets Studies, 3(2). https://doi.org/10.1108/jcms-05-2019-0032.
19. Jiang, Y., Nie, H., & Ruan, W. (2018). Time-varying long-term memory in Bitcoin market. Finance Research Letters, 25. https://doi.org/10.1016/j.frl.2017.12.009.
20. Kajtazi, A., & Moro, A. (2019). The role of bitcoin in well diversified portfolios: A comparative global study. International Review of Financial Analysis, 61. https://doi.org/10.1016/j.irfa.2018.10.003.
21. Lewis, A. (2018). The Basics of Bitcoins and Blockchains. Mango Media Inc.
22. Ma, Y., Ahmad, F., Liu, M., & Wang, Z. (2020). Portfolio optimization in the era of digital financialization using cryptocurrencies. Technological Forecasting and Social Change, 161. https://doi.org/10.1016/j.techfore.2020.120265.
23. Mariana, C. D., Ekaputra, I. A., & Husodo, Z. A. (2021). Are Bitcoin and Ethereum safe-havens for stocks during the COVID-19 pandemic? Finance Research Letters, 38. https://doi.org/10.1016/j.frl.2020.101798.
24. Matkovskyy, R., Jalan, A., Dowling, M., & Bouraoui, T. (2021). From bottom ten to top ten: The role of cryptocurrencies in enhancing portfolio return of poorly performing stocks. Finance Research Letters, 38. https://doi.org/10.1016/j.frl.2019.101405.
25. Melki, A., & Nefzi, N. (2022). Tracking safe haven properties of cryptocurrencies during the COVID-19 pandemic: A smooth transition approach. Finance Research Letters, 46. https://doi.org/10.1016/j.frl.2021.102243.

26. Mnif, E., Jarboui, A., & Mouakhar, K. (2020). How the cryptocurrency market has performed during COVID 19? A multifractal analysis. Finance Research Letters, 36. https://doi.org/10.1016/j.frl.2020.101647.
27. Nan, Z., & Kaizoji, T. (2019). Market efficiency of the bitcoin exchange rate: Weak and semi-strong form tests with the spot, futures and forward foreign exchange rates. International Review of Financial Analysis, 64. https://doi.org/10.1016/j.irfa.2019.06.003.
28. Palamalai, S., Kumar, K. K., & Maity, B. (2021). Testing the random walk hypothesis for leading cryptocurrencies. Borsa Istanbul Review, 21(3), 256–268. https://doi.org/10.1016/j.bir.2020.10.006.
29. Rubbaniy, G., Polyzos, S., Rizvi, S. K. A., & Tessema, A. (2021). COVID-19, Lockdowns and herding towards a cryptocurrency market-specific implied volatility index. Economics Letters, 207. https://doi.org/10.1016/j.econlet.2021.110017.
30. Sarkodie, S. A., Ahmed, M. Y., & Owusu, P. A. (2022). COVID-19 pandemic improves market signals of cryptocurrencies–evidence from Bitcoin, Bitcoin Cash, Ethereum, and Litecoin. Finance Research Letters, 44. https://doi.org/10.1016/j.frl.2021.102049.
31. Tran, V. Le, & Leirvik, T. (2020). Efficiency in the markets of crypto-currencies. Finance Research Letters, 35. https://doi.org/10.1016/j.frl.2019.101382.
32. Urquhart, A. (2016). The inefficiency of Bitcoin. Economics Letters, 148. https://doi.org/10.1016/j.econlet.2016.09.019.
33. Vidal-Tomás, D., Ibáñez, A. M., & Farinós, J. E. (2019). Weak efficiency of the cryptocurrency market: a market portfolio approach. Applied Economics Letters, 26(19). https://doi.org/10.1080/13504851.2019.1591583.
34. Wald, A., & Wolfowitz, J. (1940). On a Test Whether Two Samples are from the Same Population. The Annals of Mathematical Statistics, 11(2), 147–162. https://doi.org/10.1214/aoms/1177731909.
35. Wei, W. C. (2018). Liquidity and market efficiency in cryptocurrencies. Economics Letters, 168. https://doi.org/10.1016/j.econlet.2018.04.003
36. Zargar, F. N., & Kumar, D. (2019). Informational inefficiency of Bitcoin: A study based on high-frequency data. Research in International Business and Finance, 47. https://doi.org/10.1016/j.ribaf.2018.08.008.