ISSN Print 2786-5150
ISSN Online 2786-5169

ECONOMIC AND MATHEMATICAL MODELING AND INFORMATION TECHNOLOGIES IN ECONOMICS

UDC 336.74:004.738.5]:336.76

DOI https://doi.org/10.26661/2414-0287-2023-2-58-06

ANALYSIS ANOMALIES OF THE CRYPTOCURRENCY PRICES TIME SERIES

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Key words:
cryptocurrency, bitcoin, coin market, decomposition, anomaly, time series

The article is devoted to the research of anomalies in the cryptocurrency market that affect the behavior of digital financial market agents. The relevance of the work is explained by digital transformation, which affects the conditions for the existence and development of financial sector agents, as well as the growing need for new knowledge, skills and abilities to study the behavior of such agents in various conditions. The object of the research is the time series of cryptocurrency prices based on data from CoinMarketCap, a major provider of cryptographic data. For the analysis of time series anomalies, the top 5 cryptocurrencies by capitalization were selected: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), U.S. Dollar Coin (USDC). The input data for research are daily time series of the criptocurrency prices. To identify time series anomalies, the software environment for statistical processing and data visualization R was used. Based on the results of the research, it was revealed that the Bitcoin (BTC) price time series has the smallest share of anomalies. And the time series of cryptocurrency prices that appeared later (altcoins), Ethereum (ETH) and Binance Coin (BNB) largely repeat the periods of Bitcoin (BTC) anomalies. Particular periods of anomalies were shown by time series of prices for stablecoins Tether (USDT) and U.S. Dollar Coin (USDC). They are tied to fiat currency and have a reserve fund that ensures the stability of the token rate.

АНАЛІЗ АНОМАЛІЙ ЧАСОВИХ РЯДІВ ЦІН КРИПТОВАЛЮТ

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Ключові слова:
криптовалюта, біткоїн, криптобіржа, декомпозиція, аномалія, часові ряди

Стаття присвячена дослідженню аномалій на ринку криптовалют, що впливають на поведінку агентів цифрового фінансового ринку. Актуальність роботи пояснюється цифровою трансформацією, яка впливає на умови існування та розвитку агентів фінансового сектору, а також у зростанні потреби в нових знаннях, уміннях та навичках для дослідження поведінки таких агентів в різних умовах. Об'єктом дослідження виступають часові ряди вартості криптовалют за даними CoinMarketCap – крупного постачальника криптографічних даних. Для аналізу аномалій часових рядів було обрано топ-5 криптовалют за капіталізацією: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), U.S. Dollar Coin (USDC). Вхідними даними дослідження є щоденні часові ряди цін криптовалют. Для виявлення аномалій часових рядів використано програмне середовище R, яке призначено для статистичної обробки та візуалізації даних. За результатами дослідження було виявлено, що найменшу частку аномалій містить часовий ряд ціни Bitcoin (BTC). А часові ряди цін криптовалют, що з'явилися пізніше (альткоїни), Ethereum (ETH) та Binance Coin (BNB) у значній мірі повторюють періоди аномалій Bitcoin (BTC). Особливі періоди аномалій показали часові ряди цін стейблкоїнів Tether (USDT) та U.S. Dollar Coin (USDC). Вони прив'язані до фіатної валюти та володіють резервним фондом, який забезпечує стабільність курсу токену.

Statement of the problem

The global financial market is constantly in a state of digital transformation, which is associated with an increase in the use of digital currency in the form of electronic currency or virtual currency. A type of virtual currency built on a blockchain system is a cryptocurrency. As of December 2022, the number of all cryptocurrencies in the world has reached 22000 and continues to grow [1]. The role of bitcoin and other digital currencies in global financial processes can be characterized as integrating, which is based primarily on its contribution to the formation of a network business of financial institutions.

Institutional investors are actively investing in crypto assets – organizations that pool funds into a single pool and invest with depositors' money (hedge funds, mutual funds, credit communities, banks, etc.). According to statistics, about 40% of institutional investors have crypto assets in their portfolio, most of which are stored in fundamentally strong coins. In 2021, the top three sectors in which hedge funds invest in cryptocurrencies are Store of Value (86%), Decentralized Finance (78%), and Infrastructure (74%). Cryptocurrency investment in Exchanges and Entertainment accounts for 51% and 48% of hedge fund investments, respectively. Less than 30% of cryptocurrency investment hedge funds are invested in such niche industries as Data & Clouds, Banking, Enterprise [2].

Rapid changes in the digital market draw attention directly to the behavior of market agents, the possibility of development within the new established boundaries. New challenges and updated values have actualized the demand for specific goods and services that provide a solution to complex issues of socio-economic security, have led to a fundamental change in the behavior of subjects in the financial market. Today, timely monitoring of changes in market behavior contributes to the formation of a new quality of management, rapid adaptation of business, changes in the basic principles of interaction and functioning of subjects in all areas, explanation of current trends and prediction of the formation of new trends in key indicators.

Since the cryptocurrency market is under the influence of a significant number of adverse events (regulatory pressure, macroeconomic instability, collapse and bankruptcy of cryptocurrency platforms), it is essential to quickly identify market changes in order to correct the socio-economic behavior of each agent. Therefore, tracking unexpected fluctuations in the cryptocurrency market requires identifying unusual observations (outliers, anomalies) in the time series of cryptocurrency rates.

Analysis of recent studies and publications

Anomaly detection is a problem that exists in a large number of industries and involves the identification of new or unexpected observations (or sequences) in data. Most modern anomaly detection methods are very application specific, requiring the expert to know the method as well as the situation to which it applies. Despite the origin of the data, there are three types of time series anomalies: point, contextual and collective anomalies [3–5]. For financial time series, the most common are collective anomalies, when the sequence of related data instances is anomalous with respect to the whole data set.

The article [3] considers such time series factors as temporality, dimension, non-stationarity and noise. The authors carried out a comparative analysis of modern methods for detecting deep time series anomalies using several reference data sets, and also proposed recommendations for choosing an appropriate model and learning strategy for detecting time series anomalies based on deep learning.

The research [4] compares the application of 20 anomaly detection methods for several sets of univariate time series, which belong to three categories of methods: statistical, machine and deep learning.

The article [5] discusses approaches to detecting anomalies in univariate and multivariate time series, which are related to the Internet of Things. Particular attention is paid to the use of recurrent neural networks (RNN), long short-term memory networks (LSTM) and gated recurrent units (GRU) to detect anomalies in time series.

In [6], to detect anomalies in uncontrolled time series, an Anomaly Transformer was proposed that contains an Anomaly-Attention with a two-layer structure to implement an associative mismatch. The minimax strategy is used to further enhance the difference between normal and abnormal time points.

The team of authors in [7] considers the classification of outliers in time series (point and subsequences), as well as software for detecting outliers in time series in Java, R, Pyton, C++.

The article [8] gives a classification of outlier detection methods and models: traditional (distance-based models, statistical models, classification models, angle-based models) and deep learning (deep learning for feature extraction, learning feature representations of normality, end-to-end anomaly score learning). Special attention is paid to the choice of metrics for assessing the correctness of outlier detection, the best mathematical models and methods for solving the problem of identifying outliers in test samples when management of processes in systems by state.

The study [9] is devoted to the use of statistical methods of data analysis for the detection of anomalies (survival analysis, fractal analysis of time series, decision tree method, cluster analysis and entropy method). According to the results of simulation modeling of network traffic of telecommunication networks of various protocols with 75% of legitimate traffic and 25% of attacks, it was found that the decision tree method is the best in terms of anomaly identification probability, fewer false positives and anomaly detection time. The entropy analysis method is somewhat slower and gives slightly more false positives, while the cluster analysis method detects anomalies somewhat worse.

The algorithm for detecting time series anomalies proposed in [10] consists in converting the numerical values of the time series into symbols of a predetermined alphabet and further deriving the rules of a certain language, according to which this linguistic chain is formed. The grammar that is output is a linguistic model and is a matrix of transitions between states of a discrete

ISSN Print 2786-5150
ISSN Online 2786-5169

Markov process. Each character of the alphabet in the linguistic chain corresponds to the state of the process at a given time. At each new level of the series, the system enters a new state with a certain probability. The authors of the study proved the effectiveness of the proposed method for the analysis of time series of prices for shares of world-famous companies.

The way to detect anomalies in the time series of financial data, which is proposed in [11], is to detect anomalies using the ensemble approach. An LSTM-based autocorrect is used to eliminate input signal noise, an ARIMA model is used for prediction, the CNN network is used to correct the output of the predictive model, and confidence intervals are used as an anomaly detector.

However, despite the large number of existing methods for detecting time series anomalies, the "weak" point remains the choice of methods that are used for a particular time series. Also, it should be taken into account that the behavior of agents of the digital financial market is subject to structural changes in the context of a rapid change in the price of cryptocurrency, so the practical value of the study lies in the timely detection of anomalies in the market to correct the behavior of agents.

Objectives of the article

The purpose of the article is to study anomalies in the cryptocurrency market that affect the behavior of digital financial market agents. The object of the research is the time series of cryptocurrency prices based on data from CoinMarketCap – the world's most popular crypto price tracking site, a major provider of cryptographic data. The subject of the research is the methods of nonlinear dynamics.

The main material of the research

Consider the price dynamics of five cryptocurrencies with the largest capitalization in 2023: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), U.S. Dollar Coin (USDC) [12]. The volumes of capitalization of these cryptocurrencies are given in Table 1.

Daily data on the closing price of the selected cryptocurrencies was obtained using the *crypto2* library of the R environment [13] according to CoinMarketCap [14] and downloaded from the *Investing.com* website [15].

Table 1 – Capitalization volumes of the top 5 cryptocurrencies in 2023

The name of the cryptocurrency	**Amount of capitalization, billion dollars USA**
Bitcoin (BTC)	506.7
Ethereum (ETH)	209.5
Tether (USDT)	83.5
Binance Coin (BNB)	37.7
U.S. Dollar Coin (USDC)	28.3

Bitcoin (BTC), which was created in 2009 by Satoshi Nakamoto, is the original cryptocurrency. Like most cryptocurrencies, BTC runs on a blockchain, or ledger of transactions, distributed over a network of thousands of computers. The dynamics of the price of Bitcoin (BTC) for the period from May 01, 2016 to June 10, 2023 (2597 daily observations) is shown in Figure 1. The BTC price reached its highest value on March 13, 2021 ($61243.08) and November 8, 2021 ($67566.83). The significant increase in the price of BTC in 2017 was affected by: growing interest in the currency; an increase in the number of sellers who accepted payment in BTC; decrease in Bitcoin mining reward.

Ethereum (ETH) was created in 2013 and is the second most popular cryptocurrency that competes with Bitcoin. The main value of Ethereum is not only coins (ether), but also smart contracts. These are programs on the blockchain that transfer regular contracts to their digital version. In this case, the contract is monitored by a computer, not a person. The dynamics of the price of Ethereum (ETH) for the period from May 01, 2016 to June 10, 2023 (2597 daily observations) is shown in Figure 2. The Ethereum (ETH) price reached its highest values on May 11, 2021 ($4167.78) and November 8, 2021 ($4808.38). Users have the ability to deposit their ETH to an Ethereum 2.0 deposit contract. Keeping coins on this contract allows investors to receive passive rewards for staking the coin.

Tether (USTD) is the world's first stablecoin (cryptocurrency that is pegged to the value of fiat currency), which was created in 2014. Also, it is a cryptocurrency asset that is issued on the basis of the Bitcoin blockchain through the Omni Layer, Ethereum (ERC-20) protocols, TRON, EOS, Algorand, Solana and OMG Network. Each USTD unit is backed by a US dollar held in Tether Limited's

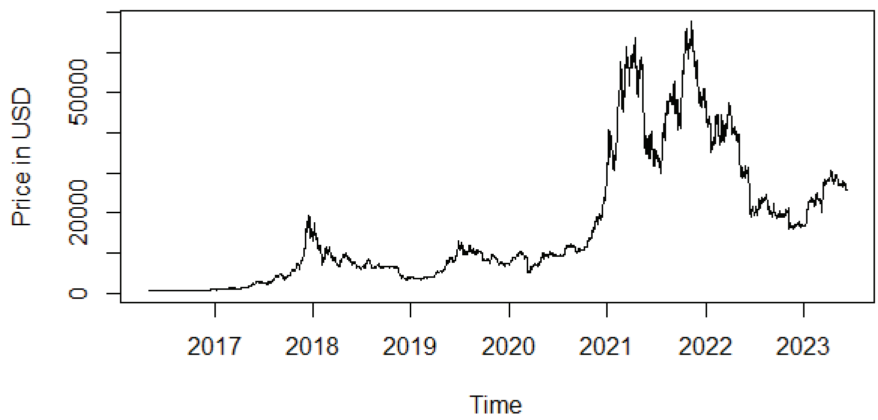

Fig. 1 – Bitcoin (BTC) price for the period from May 01, 2016 to June 10, 2023

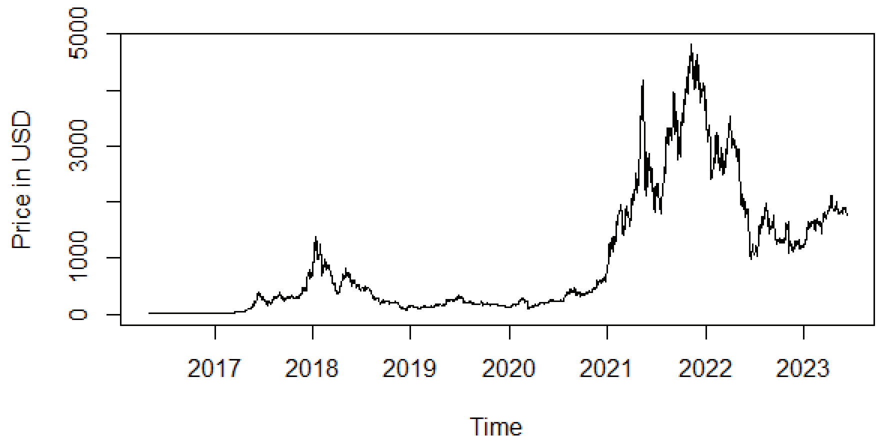

Fig. 2 – Ethereum (ETH) price for the period from May 01, 2016 to June 10, 2023

reserve and can be withdrawn using the Tether platform. Tether (USTD) is an important part of the cryptocurrency ecosystem. Tether (USTD) price dynamics for the period from April 14, 2017 to June 10, 2023 (2248 daily observations) is shown in Figure 3.

Binance Coin (BNB) is a form of cryptocurrency that can be used to trade and pay fees on Binance, one of the largest crypto exchanges in the world. Since its launch in 2017, the use of Binance Coin (BNB) has expanded beyond the boundaries of the Binance exchange platform. This cryptocurrency can now be used to trade, process payments, book travel, and sell and exchange for other forms of cryptocurrencies such as Ethereum or Bitcoin. The dynamics of the price of Binance Coin (BNB) for the period from November 09, 2017 to June 10, 2023 (2040 daily observations) is shown in Figure 4. The BNB price reached its highest values on May 3, 2021 ($676.56) and November 14, 2021 ($650.8).

U.S. Dollar Coin (USDC) is a stablecoin that is fully backed by dollar assets. USDC reserve assets are held

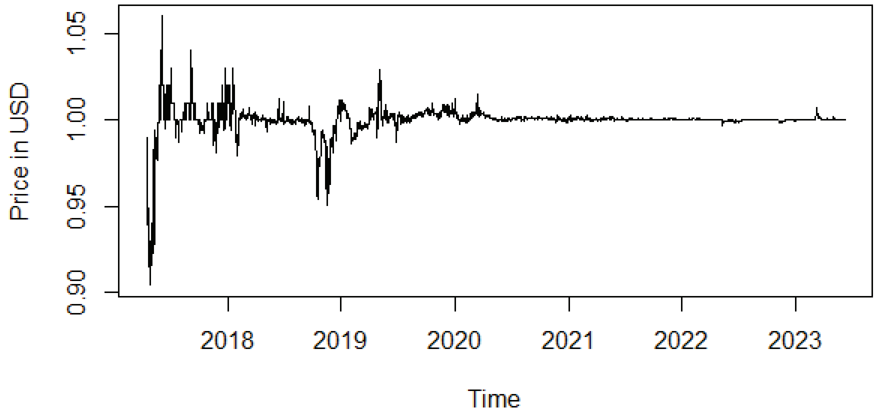

Fig. 3 – Tether (USTD) price for the period from April 14, 2017 to June 10, 2023

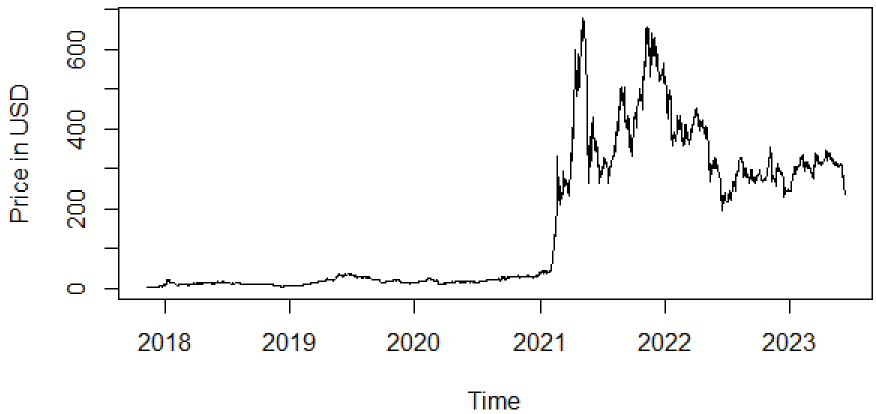

Fig. 4 – Binance (BNB) price for the period from November 09, 2017 to June 10, 2023

in accounts with regulated US financial institutions. U.S. Dollar Coin is operated by Centre, a consortium founded by cryptocurrency exchange Coinbase and fintech company Circle. Price dynamics U.S. Dollar Coin (USDC) for the period from December 6, 2018 to June 10, 2023 (1648 daily observations) is shown in Figure 5.

Despite the fact that the stablecoin Tether (USTD) is more widespread and recognized in the crypto community, U.S. Dollar Coin (USDC) is considered one of the most secure alternatives to centralized stablecoins that are pegged to the US dollar due to higher transparency, increased interoperability with different types of blockchain, and an improved legal framework.

The study of anomalies in the time series of selected cryptocurrencies was carried out in the R environment using the *timetk* library [16]. The *tk_anomaly_diagnostics()* method for anomily detection implements a two-step process for identifying time series outliers.

At the first step, the trend and seasonality are removed using the STL decomposition (Seasonal-Trend decomposition using LOESS) [17]. Decomposition removes the trend and seasonal components from observed values, leaving residuals for anomaly detection. The user can control two parameters: *frequency* and *trend*. The *frequency* adjusts the seasonal component, and the *trend* adjusts the trend window both automatically and according to user settings. The whole procedure of seasonal decomposition using STL consists of two cycles: external and internal. The external cycle consists of calculating the robust weights in terms of the median absolute deviation. The internal cycle includes the calculation of the trend and seasonal components.

The second step uses an interquartile range (IQR) of +/-25 from the median to detect anomalies. The default setting is $\alpha = 0.05$, and the limits are set by extending the 25/75 baseline by a coefficient of IQR = $0.15 / \alpha = 3$.

Application of the anomaly detection method for the Bitcoin (BTC) time series revealed 334 abnormal values, which accounted for 12.86% of the considered data. In Figure 6, anomalous values are marked with red dots.

Consider long-term (a week or more) anomalous periods. The first anomalous period is December 6–21, 2017, which accounts for the peak price of Bitcoin in 2017 ($19497.4, December16, 2017). Between December 8–15, 2020, Bitcoin crossed the $19000 mark per coin. The decline in business activity due to the COVID-19 led to the

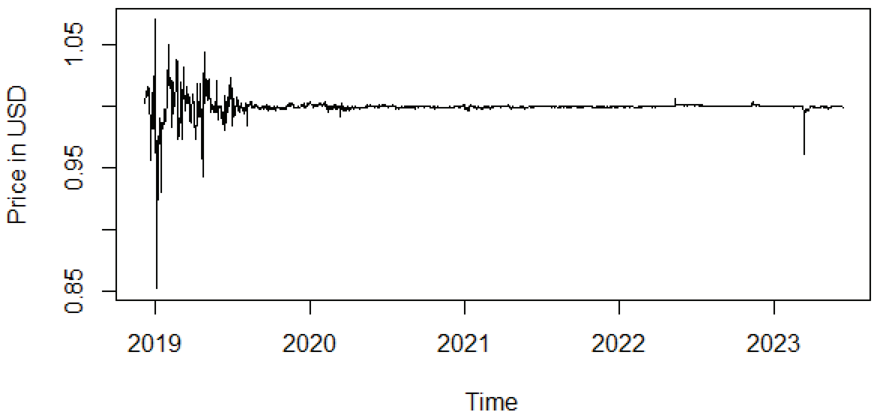

Fig. 5 – U.S. Dollar Coin (USDC) price for the period from December 06, 2018 to June 10, 2023

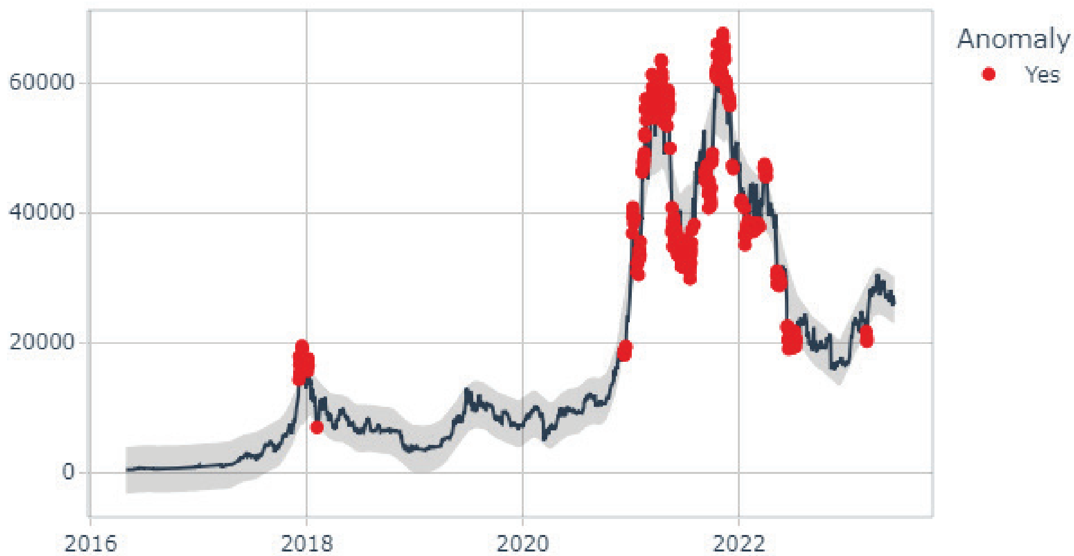

Fig. 6 – Bitcoin (BTC) price anomaly analysis

ISSN Print 2786-5150
ISSN Online 2786-5169

devaluation of the US currency. Against this background, institutional investors began to invest in Bitcoin. Also, one of the largest payment systems PayPal in 2020 allowed the use of cryptocurrencies for payments on its platform, which created a significant demand for such payment transactions.

Anomalies in the first half of 2021 are associated with the rapid growth of the Bitcoin price and the setting of monthly records in January-April 2021 (Table 2).

Table 2 – Bitcoin (BTC) price anomaly in January-April 2021

Abnormal periods	Monthly maximum price, 2021	
	Date	Price, $
23.01.2021–02.02.2021	08.01.2021	40797.67
11.02.2021–22.02.2021	21.02.2021	57539.94
09.03.2021–23.03.2021	13.03.2021	61243.08
26.03.2021–21.04.2021	13.04.2021	63503.46

However, after that, there is a fall in the digital asset to trading in the region of $48000 (anomalous period 26.04.2021–11.05.2021) with a further fall on 08.06.2021 up to $33472.63 (abnormal period 19.05.2021–02.06.2021). The anomalous period 19.06.2021–26.07.2021 is characterized by fluctuations in the price of Bitcoin in the range of $30000 – $40000.

The fall 2021 anomalies are associated with a new cycle of Bitcoin price growth and the setting of new monthly records in September-November 2021 (Table 3).

Table 3 – Bitcoin (BTC) price anomaly in September-November 2021

Abnormal periods	Monthly maximum price, 2021	
	Date	Price, $
08.09.2021–14.09.2021	06.09.2021	52633,54
19.09.2021–04.10.2021; 15.10.2021–26.10.2021	20.10.2021	65992,84
28.10.2021–17.11.2021	08.11.2021	67566,83

The Bitcoin exchange rate was affected by restrictions introduced in May 2021 in China. First, there was a ban on banks and payment systems to provide services with cryptocurrencies, and then new bans were introduced for miners and traders, which led to a large-scale exit of miners from the country. The sharp drop in the network hashrate was accompanied by a decline in the price of Bitcoin.

In addition, in 2021, Bitcoin was accepted as legal instrument of payment in El Salvador. Before Bitcoin was supported at the state level for the first time in the world, its value grew, but after the entry into force of the law, the value of the cryptocurrency collapsed.

The anomalous drop in the price of bitcoin at the beginning of 2022 (20.01.2022–03.02.2022) is associated with protests in Kazakhstan (January 2–11, 2022), since Kazakhstan ranks second in the world in Bitcoin mining. Also, the general collapse of the stock market influenced the fall of BTC due to the expectation of strengthening the US monetary policy. In February 2022, the price of Bitcoin rose above $45,000, then fell again to $35,000 amid geopolitical deterioration. The turning point occurred on March 22, 2022, when Bitcoin took a bullish course. At the peak on March 29, 2022, the price of the coin reached $47465.73 for the first time since the beginning of January. This corresponds to the anomalous period from March 27, 2022 to April 5, 2022.

The main reason for the fall in the price of Bitcoin in May-June 2022 is inflation in the United States, which increased to 8.6% in May. Against this background, the Federal Reserve System raised the key rate several times. One of the strongest collapses occurred on June 18, 2022 – to $19017.64 per coin. These events correspond to the anomaly of the time series, which was observed from June 13 to July 14, 2022.

The application of the anomaly detection method for the Ethereun (ETH) time series revealed 443 outliers, which accounted for 17.06% of the considered data. In Figure 7, anomalous values are marked with red dots.

Consider long-term (a week or more) anomalous periods of the Ethereun (ETH) time series. The rapid rise in the price

Fig. 7 – Ethereum (ETH) price anomaly analysis

of the ETH cryptocurrency at the end of 2017 ended on January 13, 2018 with a maximum exchange rate of $1380 at that time. This corresponds to the anomalous period of the time series from January 3, 2018 to February 1, 2018. Then the rate began to repeat the movements of bitcoin, which went into a deep peak. The systematic descent to the level of $378.68 (04.04.2018) corresponds to the anomalous period of the time series from March 24, 2018 to April 11, 2018.

The anomalous period of the time series from December 20, 2020 to January 2, 2021 precedes the price of Ethereun (ETH) again crossing the $1,000 per coin mark (Jan 4, 2021, $1,042.4).

In February 2021, the ETH altcoin reached $2000 (February 21, 2021, $1933.45), which corresponds to the anomalous period of the time series from February 3 to February 22, 2021. The time series anomaly from March 22 to March 28, 2021 corresponds to ETH price fluctuations from $1,500 to $1,700 per Ether.

The catalyst for the Ethereum (ETH) price spike in April 2021 and the local peak on May 11, 2021 ($4167.78) was an important network update – the developers of the cryptocurrency carried out the Berlin hard fork, which was part of the transition plan to Ethereum 2.0. This corresponds to the anomalous period of the time series from April 26 to May 18, 2021.

The time series anomaly from June 16 to September 3, 2021 corresponds to the ETH price fluctuations from $2,000 to $3,000 per Ether, and the time series anomaly from September 20 to October 4, 2021 corresponds to an approach to $3,500 per Ether.

The Ethereum (ETH) price reached its highest historical value on November 8, 2021 ($4808.38), which corresponds to the anomaly of the time series from October 28 to November 17, 2021. At the same time, the market capitalization of Ethereum (ETH) for the first time was $500 billion, which is equivalent to 20% of the total cryptocurrency market.

The anomalous period of the time series from November 19 to November 25, 2021 is characterized by an increase in the price of the altcoin ETH by almost $500 per week. The time series anomalies from November 27 to December 9, 2021 are characterized by sharp fluctuations in the price of ETH during this period. The time series anomaly from December 21 to December 27, 2021 precedes the collapse in the value of ETH to $3080.02 on January 8, 2022.

The reaction of the cryptocurrency market to the US Federal Reserve System meeting in January 2022 affected Ethereum (ETH). In 2022, the following anomalous periods were observed:

1) 17.01.2022–04.02.2022;
2) 18–27.02.2022;
3) 04–15.03.2022;
4) 24.03.2022–08.05.2022;
5) 11.06.2022–17.07.2022
6) 10–18.08.2022;
7) 26.10.2022–07.11.2022;
8) 28.12.2022–03.01.2023.

Thus, we can conclude that Ethereum (ETH) is more susceptible to market influences than Bitcoin (BTC).

The application of the anomaly detection method for the Tether (USDT) time series revealed 384 abnormal values, which accounted for 17.08% of the considered data. In Figure 8, outliers are marked with red dots.

Consider long-term (a week or more) anomalous periods for the Tether (USDT) time series. The anomaly of the series from April 17 to May 7, 2017 is characterized by the USDT price approaching $1 per unit of cryptocurrency. The next anomalous period from May 19 to July 12, 2017 is characterized by a stable USDT price near $1. In the period from September 1 to September 11, 2017, a maximum value of $1.04 per USDT is reached (September 4, 2017). The anomalous period from December 19 to 25, 2017 is characterized by USDT price less than $1 (December 20 and 21, 2017). In the period from December 27, 2017 to January 4, 2018, USDT price fluctuates at the level of $1.01 – $1.02 per coin. On January 16, 2018, USDT reached the level of $1.03, after which the cryptocurrency price began to fall (abnormal period from January 16 to

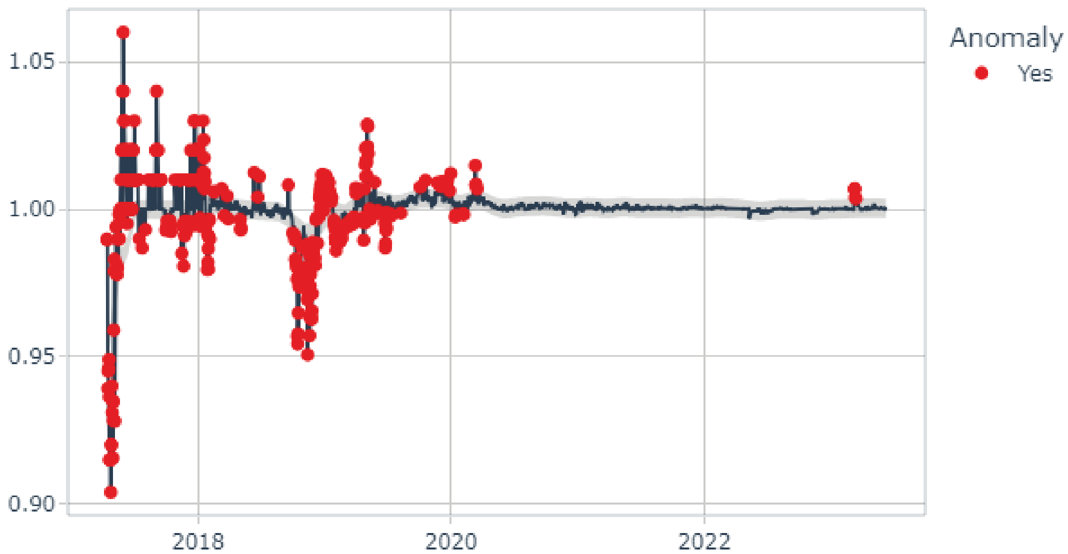

Fig. 8 – Tether (USTD) price anomaly analysis

ISSN Print 2786-5150
ISSN Online 2786-5169

22, 2018). Abnormal periods, which are characterized by USDT price around $0.99:

1) 27.01.2018–5.02.2018.
2) 29.01.2019–22.02.2019.
3) 23.03.2019–29.03.2019.
4) 23–30.06.2019.

Anomalous periods of the USDT time series, which are characterized by fluctuations of $0.99 – $0.97:

1) 08–26.10.2018.
2) 09–27.11.2018.

Anomalous periods of the time series, which are characterized by the return of the USDT price to the level of more than $1:

1) 17.12.2018p. – 19.01.2019.
2) 25.04.2019p. – 08.05.2019.

Since Tether (USDT) is a fiat-pegged stablecoin, there were no significant time series anomalies in 2020–2023. The Tether (USDT) crypto coin was created on the basis of the Omni Layer software protocol, which operates on the basis of the Bitcoin blockchain. Therefore, the stablecoin has a number of disadvantages that are inherent in bitcoin. For example, the authors of the cryptocurrency do not take steps to eliminate problems with the scalability of the crypto network, which in the future may cause a slowdown in the popularization of the asset among users. According to some experts, the need to deposit fiat funds to the account of the crypto network indicates that the anonymity of the participants in the cryptocurrency platform is inadequately ensured. Another disadvantage of Tether (USDT) is the lack of mining capability.

Application of the anomaly detection method for the Binance Coin (BNB) time series revealed 408 anomaly values, which accounted for 20% of the data considered. In Figure 9, anomalous values are marked with red dots.

Consider long-term (a week or more) anomalous periods for the Binance Coin (BNB) time series. Binance Coin (BNB) is the token of one of the largest crypto exchanges Binance and is one of the key elements of the cryptocurrency ecosystem. One of the important features of this cryptocurrency is that the coin can be used to reduce the commission on the Binance exchange. In addition, BNB is part of the Binance blockchain, which competes with Ethereum. The exchange coin has a higher level of scalability along with lower transaction fees.

The Binance Coin (BNB) time series anomaly from January 22 to February 9, 2021 is characterized by the fact that the price of the cryptocurrency crossed the border of $100 per coin (09.02.2021, $107.6). The next anomaly of the time series (February 19–25, 2021) is associated with the local high of $332.74 per coin on February 19, 2021 and a further decline in its value. During the anomalous period from March 18 to April 5, 2021, the price of Binance Coin (BNB) increased by almost $100.

The anomalous period from April 9 to June 1, 2021 is associated with an increase in the price of BNB to an all-time high (03.05.2021, $676.56) and a further fall in the price. Periods that are characterized by new waves of increase in the price of Binance Coin (BNB):

1) 08.07.2021–06.08.2021.
2) 19.08.2021–06.09.2021.
3) 20.09.2021–30.09.2021.
4) 29.10.2021–04.12.2021.
5) 04.08.2022–17.08.2022.
6) 30.10.2022–08.11.2022.

Periods characterized by a decrease in the price of Binance Coin (BNB) less than $400:

1) 20.01.2022–05.02.2022.
2) 20.02.2022–27.02.2022.
3) 12.04.2022–07.05.2022.

A period characterized by an increase in the price of Binance Coin (BNB) over $400: 27.03.2022–10.04.2022.

Periods characterized by a decrease in the price of Binance Coin (BNB) less than $250:

1) 12.06.2022–15.07.2022.
2) 15.12.2022–07.01.2023.

The state of affairs on the Binance platform directly affects the price of BNB. When the activity of traders on the crypto exchange increases, the demand for Binance

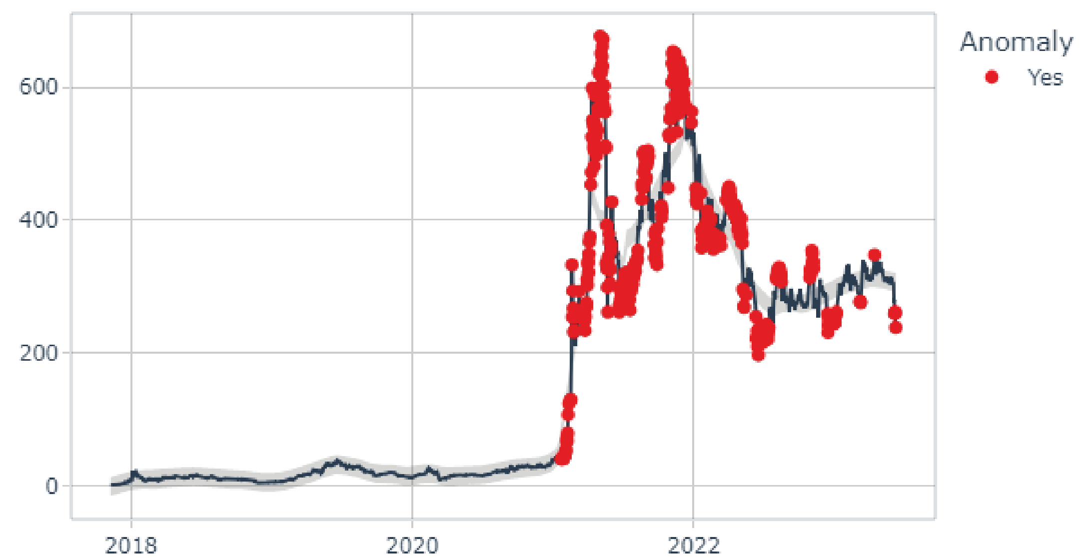

Fig. 9 – Binance Coin (BNB) price anomaly analysis

ISSN Print 2786-5150
ISSN Online 2786-5169

Coin also increases. Regular announcements related to the crypto exchange also positively affect Binance Coin. For example, the coin rate was influenced by the launch of the Binance Launchpad ICO platform, thanks to which startups were able to enter the market faster. Such projects increase interest in BNB as the scope of the cryptocurrency expands rapidly. Another reason for the rise in the price of BNB is the future burning of tokens. Burning is a process of reducing the number of coins in the public domain, which is usually carried out once a quarter.

The application of the anomaly detection method for the U.S. Dollar Coin (USDC) time series revealed 247 anomalies, which accounted for 14.99% of the considered data. In Figure 10, outliers are marked with red dots.

Consider long-term (a week or more) anomalous periods for the U.S. Dollar Coin (USDC) time series.

Anomalous periods of the USDC time series, which are characterized by price values less than $1:

1) 26.12.2018–20.01.2019.
2) 17.02.2019–02.03.2019.
3) 21–31.03.2019.
4) 02–12.04.2019.
5) 20–27.05.2019.
6) 05–14.06.2019.

Anomalous periods of the USDC time series, which are characterized by price values over than $1:

1) 06–18.12.2018.
2) 29.01.2019–14.02.2019.
3) 04–12.03.2019.
4) 14.04.2019–10.05.2019.
5) 17.06.2019–01.07.2019.

Since the U.S. Dollar Coin (USDC) is a stablecoin, the anomalies of the coin are similar to those of the Tether (USDT) coin. The difference is that USDC runs on the Ethereum blockchain.

Conclusion

The research revealed unexpected fluctuations in the cryptocurrency market for the top 5 cryptocurrencies by capitalization: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), U.S. Dollar Coin (USDC).

The dynamics of time series of prices of selected cryptocurrencies was analyzed. To identify anomalies in the time series of the bool, the R software environment was used, which is designed for statistical processing and data visualization. The anomaly detection method combines the STL decomposition (Seasonal-Trend decomposition using LOESS) and the interquartile range (IQR) +/-25 from the median.

According to the results of the research, it was revealed that Bitcoin (BTC) has the smallest share of anomalies in the total volume of the time series – 12.86%. The largest share of anomalies in the amount of 20% of the total volume of the time series belongs to the Binance Coin (BNB) cryptocurrency, which is explained by the peculiarity of the activity of the Binance crypto exchange.

The periods of time series anomalies for the altcoins Ethereum (ETH) and Binance Coin (BNB) largely repeat the periods of anomalies for the first cryptocurrency Bitcoin (BTC).

Time series anomalies for Tether (USDT) and U.S. Dollar Coin (USDC) stablecoins largely occur in 2018–2019 and are absent in 2020 and beyond. This can be explained by linking these cryptocurrencies to fiat currencies, namely the US dollar. And the presence of a reserve fund ensures the stability of the token exchange rate.

Identification of unusual observations (outliers, anomalies) in the time series of cryptocurrency prices allows you to track the impact of adverse events on the cryptocurrency financial market and correct the socio-economic behavior of digital financial market agents.

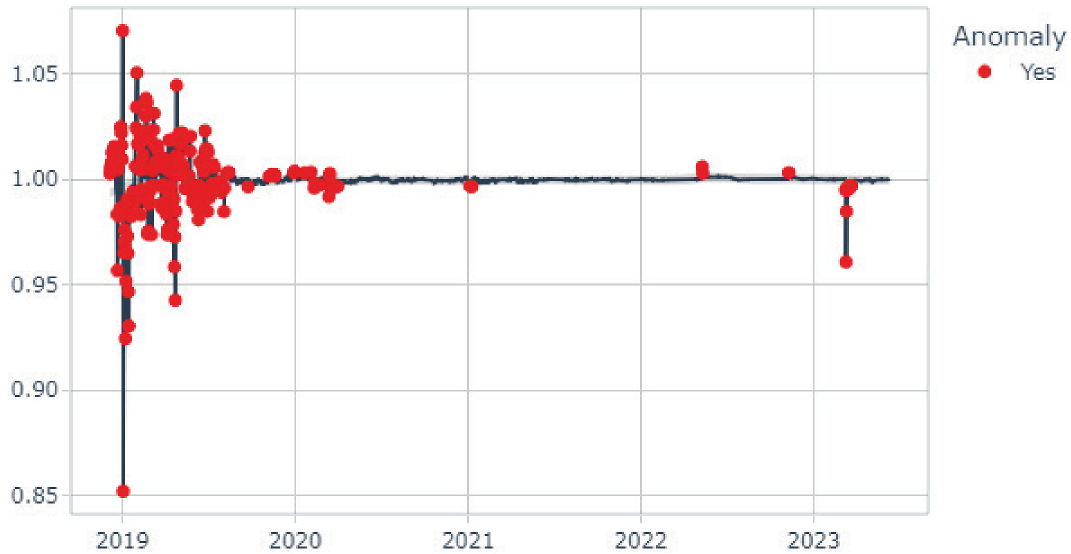

Fig. 10 – U.S. Dollar Coin (USDC) price anomaly analysis

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