Regional COVID-19 cases and Bitcoin volatility: Assessment through the Markov switching prism

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Abstract: *The 21st century has become the century of technology, which has spread to the currency market, presenting the international economic system with a new challenge – the challenge created by digital currency, which has determined a change in the rules of operation in the market. The main property of cryptocurrencies in general, and Bitcoin in particular, is constant volatility and mutual sensitivity to each other. This article aims to analyze the cryptocurrency market landscape from both short-term and long-term perspectives. Additionally, the article seeks to quantitatively assess the contradictions, trends, and patterns of price volatility in Bitcoin by employing the framework of Markov switching during the period spanning from 2020 to 2022. The Markov switching model was used in the study. In this study, the factors influencing volatility on different modes of the Markov switch are the COVID-19 pandemic and the Pearson correlation statistical method. The Chi-squared test was estimated to identify the connection between Bitcoin volatility switching modes and the COVID-19 pandemic spread. This analysis enables international investors to diversify with maximum efficiency and returns using available hedging tools. However, several open questions remain for future research. Future studies can analyze different cryptocurrencies' volatility. This research helps to assess the nature of the relationship of cryptocurrencies in statistics (the correlation of cryptocurrencies as of December 1, 2021, when no significant events in the financial market and political upheavals were recorded) and dynamics (the Markov switching models for the post-pandemic period of 2020–2022). The article contributes to understanding the interdependence and sensitivity of different cryptocurrencies in relation to each other.*

Keywords: *GARCH model, Chi-squared test, Bitcoin volatility modes, Pearson correlation method, statics and dynamics analysis.*

JEL Classification: *E41, E51, P24.*

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Introduction

In recent years, there has been a rapid development of new digital products – cryptocurrencies. During this period, Bitcoin has become a leader in the global market of cryptocurrencies. The explosive profitability and diversification opportunities worked as incentives for introducing financial derivatives into cryptocurrencies (Kim et al., 2021a). During periods of panic in the financial markets, cryptocurrencies play the role of a potential haven where investment flows are directed (Corbet et al., 2022). Several studies indicate that the volatility dynamics between Bitcoin and major financial asset classes (gold, oil, foreign exchange, stocks, and bonds) were weak or negative before the pandemic and turned positive during the pandemic (Maghyereh & Abdoh, 2022). Unlike stock exchanges, digital currency forecasting and trading appear to be more consistent and predictable (McCoy & Rahimi, 2020). It should be pointed out that Bitcoin is the world's leader in terms of capitalization, which amounted to more than USD 138 billion. This new financial asset has great diversification opportunities for international investors, allowing the use of new and optimal hedging strategies.

Modeling can explain financial asset volatility, which is important in financial markets when forming diversified portfolios of crypto assets, increasing awareness and knowledge of market participants, and effectively controlling investment risks. The Markov switching is effective for predicting Bitcoin volatility. This model has been used in several studies to describe the volatility dynamics of Bitcoin prices (Chkili, 2021; Le & David, 2014). This method is valuable for obtaining three capabilities at once: isolating heterogeneous volatility regimes, creating a map of regime switches to determine volatility dynamics, and finding the optimal number of states to capture the heteroscedasticity of the Bitcoin regime (Chappell, 2019).

The GARCH model is of relevance too. The advantage of the GARCH model is that it combines with other models. This is what is being developed in recent research, where hybrid GARCH models are being developed that contain elements of the Markov switch calculation to account for volatility modes (Ardia et al., 2019; Walther et al., 2017). The volatility forecasts depend on the order of the GARCH models and the selected machine learning model. The Bitcoin volatility studies often show that the summation ensemble methodology based on higher-order hybrid GARCH models has proven to be a winner. This methodology improves the accuracy of volatility forecasts (Aras, 2021).

Bitcoin, Bitcoin Cash, XRP, and Ethereum show volatility that is incomparable (Hafner, 2020). Yousaf and Ali (2020) employed the VAR-DCC-GARCH model to examine the return and volatility transmission among Bitcoin, Ethereum, and Litecoin during the pre-COVID-19 and COVID-19 periods. They found that the return spillovers differed across both periods for the Bitcoin-Ethereum, Bitcoin-Litecoin, and Ethereum-Litecoin pairs (Yousaf & Ali, 2020). A problem is volatility valuation. In 2014, a structural shift in Bitcoin yields was noticed by Bariviera (2017). Bouri et al. (2019) found inconsistent results with sliding windows and static models. Some progress has been made in this area by Yin and Wang (2022) who employed the prediction model based on the intrinsic generation mechanism (chaos) of Bitcoin's daily return volatility from an econophysics perspective.

The authors suggested that chaotic artificial neural network models have a good prediction effect by comparing these models with the existing artificial neural network (ANN) models. However, not only are the properties and behavior of cryptocurrencies in the market given a lot of research but also anomalies are analysed. Firstly, anomalies in the underlying blockchain transaction network are investigated. Secondly, the price anomalies of various cryptocurrencies individually and in comparison with each other are of interest. The price correlation studies for different cryptocurrencies, such as Ethereum, Bitcoin Cash, Dash, and Monero have shown that only a few cryptocurrencies show significant price growth rates compared to Bitcoin (Meynkhard, 2020). One of the reasons for these anomalies is the manipulation of pump-and-dump prices, as this is how scammers try to force traders to buy cryptocurrencies at artificially inflated prices (pumping). This manipulation is followed by the second part of the scam, the quick sale of all assets (dumping) to make super profits. According to Li et al. (2021), such activity leads to short-term bubbles characterized by sharp increases in prices, volume, and volatility. Prices peak within minutes, followed by a reversal. These same researchers have investigated long-term pump-and-dump patterns, in which pump signals fail to reach the buy target for days or weeks.

Guesmi et al. (2019) proposed to use GARCH models as multivariate spaces to explain the volatility dynamics of Bitcoin and its indicators. They use the DCC-GJR-GARCH tool, which more optimally characterizes the specifics of volatility modeling between Bitcoin and other assets. Thus, using Bitcoin in a portfolio consisting of gold, oil, or stocks significantly reduces the portfolio risk.

Continuing this same analysis of Bitcoin volatility dynamics, Katsiampa (2017) applies several GARCH-type models to explain the price volatility of Bitcoin. He draws a computationally sound conclusion – the component GARCH (CGARCH) model is appropriate for Bitcoin returns estimates. Twelve GARCH models were used by Chu et al. (2017) for seven cryptocurrencies. Researchers concluded that the IGARCH model with normal distributions includes fewer values of the information criteria and, hence is a better ft-model. Conrad et al. (2018) proposed the GARCH-MIDAS model to describe the causes of short-term and long-term Bitcoin volatility.

Their main conclusion is that S&P 500 volatility negatively affects the long-term volatility of cryptocurrencies. However, the S&P 500 volatility risk premium positively impacts long-term Bitcoin volatility. The scholar found that there is a significant relationship between long-term Bitcoin volatility and Baltic Dry Index. Bitcoin volatility is related to global economic activity. Urom et al. (2020) have shown that secondary volatility effects among Bitcoin and other assets are significantly amplified during extreme global market fluctuations.

In terms of the optimal formation of an investment portfolio and the achievement of the most profitable diversification, market analysts and traders tend to choose the volatility forecasting model that will most effectively describe the further fluctuation of the cryptocurrency. Several studies come to this conclusion (Malepati et al., 2019). Degiannakis et al. (2018) found that traders and investors try to forecast all their future investments in terms of uncertainty. This is necessary to assess risks, which subsequently allows for the most optimal composition of the investment portfolio and the selection of appropriate hedging instruments. Malepati et al. (2019) point out that volatility acts as a tool for measuring risk in financial markets.

Moreover, the authors suggest that the quantification of uncertainty is a key component in assessing the value of cryptocurrency in the financial market and helps to assess the degree of investment risk. A considerable body of literature exists on Bitcoin forecasting performance. Some authors suggested that forecast combination techniques outperform individual models in prediction accuracy (Wei et al., 2022). The authors selected among 295 individual prediction models three machine learning approaches, specifically, neural networks, support vector machines, and gradient boosting approach. They examined the forecasting ability of the three models and suggested that forecast combination techniques outperform individual models in prediction accuracy.

The economic situation and structural changes in the global economic system from 2020 to the present are largely shaped by the consequences arising from the COVID-19 pandemic. The increasing integration of international financial markets has been a significant factor contributing to the substantial and rapid spread of market risks (Liu et al., 2022). Therefore, it is not surprising that the COVID-19 pandemic has resulted in significant damage to virtually all sectors of global economic activity, emerging as a “black swan” event for financial transactions (Yarovaya et al., 2022). Like other asset markets, the cryptocurrency market has undergone crisis manifestations, prompting a natural interest in examining the relationship between Bitcoin volatility and the spread of the COVID-19 pandemic. In response to the crisis amid COVID-19 in the United States and Western Europe, there was an increase in the issuance of national currencies, leading to liquidity excess and heightened investor inclination to allocate funds to digital currencies, the prices of which surged (OECD, 2020). Subsequently, the ascent of cryptocurrency prices decelerated following China’s decision to implement measures prohibiting the issuance and circulation of digital currencies in the country. In 2020, as a response to the crisis arising from the COVID-19 pandemic, central banks in developed countries augmented the issuance of national currencies, resulting in an increased risk appetite among major investors and a growing interest in cryptocurrencies (Boar & Wehrli, 2021).

Of particular interest is the interplay between regional COVID-19 cases and cryptocurrency volatility. Simultaneously with the crisis manifestations of the pandemic in the economic sphere, governments sought various mechanisms to curb its impact, while investors endeavored to formulate individual strategies to capitalize on the market situation effectively. Furthermore, this novel “black swan” event is undeniably intriguing for research as a volatility factor, given that volatility indicators are key instruments for forecasting and studying the functioning of Bitcoin in the financial asset market.

Hence, the objective of this article is to analyze the cryptocurrency market landscape from both short-term and long-term perspectives. Additionally, it aims to quantitatively assess the contradictions, trends, and patterns of Bitcoin price volatility through the lens of Markov switching from 2020 to 2022. The focus of the research is specifically placed on the impact of the COVID-19 pandemic on Markov switching regimes, ultimately enabling investors to ascertain portfolio composition, discern Bitcoin price dynamics, and determine risk levels. In this context, the COVID-19 pandemic may function as a litmus indicator of high or low Bitcoin volatility in the future. Despite some studies attempting to investigate the volatility properties of Bitcoin using various model types, there exists a gap in the analysis of the specific influence of COVID-19 on Bitcoin volatility and the Markov switching of its volatility regimes. Addressing this gap will contribute to expanding existing scholarly research and providing crucial information to financial analysts, international investors, and risk managers regarding risk assessment, securities valuation, risk management, and portfolio allocation.

1. Theoretical background

Bitcoin was designed as a peer-to-peer monetary system and to function as a currency, it should be stable and supported by the government. At the same time, the price volatility of Bitcoin is extreme and can be up to 10 times higher than the volatility of exchange rates, which negatively affects its investment opportunities (Baur & Dimpfl, 2021). As for the analysis of Bitcoin behavior studies, it should be noted that there is no definitive concept of the nature of Bitcoin and cryptocurrencies. Several authors, for example, indicate that Bitcoin is a commodity, that has the same properties as gold (Rambaccussing & Mazibas, 2020), other authors (Dyhrberg, 2016) indicate that Bitcoin is the same monetary unit as the dollar; therefore, performs all functions of money. The author points out that, in this vein, the main function is moneymaking.

The onset of the COVID-19 pandemic has heightened research interest in the issue of cryptocurrency volatility. The pandemic not only spread at an unprecedented speed but also assumed truly global proportions, covering more than 30 countries, regions, and territories in just a month and a half. Almost immediately, in response to the economic consequences of the pandemic, studies began to emerge on its impact on cryptocurrencies. Researchers have concluded that cryptocurrency market volatility exhibits a swift response to news reports related to COVID-19 (Baek et al., 2020). For instance, there is evidence supporting the notion that news containing panic-inducing information about the consequences of COVID-19 increased cryptocurrency volatility. Studies have explored the correlation between mortality statistics and the heightened market volatility exacerbated by a sense of panic (Chen et al., 2020).

The correlation method in modern research shows a strong relationship among cryptocurrencies. Thus, for example, the level of correlation between Bitcoin and other cryptocurrencies has grown since the beginning of 2017 and somewhat halted its growth in mid-2018. High growth is proved by research that found a correlation between cryptocurrencies that use the proof of work mechanism to verify transactions compared to those that use other cryptographic algorithms (Lahajnar & Rozanec, 2020). In addition, the authors identified a strong positive relationship between the 20 influential cryptocurrencies, with most of the correlation coefficients exceeding 0.7 (Davies, 2021). Other studies indicated a high positive correlation between cryptocurrencies and their volatility index across all investment horizons (Agyei et al., 2022). A fundamentally important discovery was made by Akyildirim et al. (2020a), revealing a strong positive relationship between financial market stresses and cryptocurrency correlations that change over time. These correlations increase significantly during periods of high stress in financial markets. In this case, fear of contagion in financial markets and volatility increase affect new financial products – cryptocurrencies (Akyildirim et al., 2020b).

Jiang et al. (2018) and Mensi et al. (2019) suggested shaping volatility modeling by introducing additional factors. In this paper, the researchers talk about the long-term memory factor. At the same time, Mensi et al. (2019) analyzed two cryptocurrencies and found evidence for the Bitcoin market's long-term memory. Models investigated by scientists that include a long-term memory factor have modifications like FIGARCH and hyperbolic GARCH (HYGARCH). Moreover, Charles and Darné (2019) found that the FIGARCH model shows the best performance in the sample for a lot of virtual currencies.

Soylu et al. (2020) focused directly on volatility, and not only on Bitcoin, but compared two other cryptocurrencies to Bitcoin and used GARCH family models. Their modeling was based on three separate models for each currency. Researchers looked at the long-term memory factor in volatility. However, GARCH models were not compared with Markov switch and FIGARCH. Bitcoin volatility research should consider this comparison. Several related studies (Katsiampa, 2019; Pal & Mitra, 2019; Tan et al., 2021) considered volatility between Bitcoin prices and commodity and financial markets.

Modern publications analyze the role of the pandemic in predicting the conditional volatility of five important cryptocurrencies – Bitcoin, Dash, Ethereum, Litecoin, and XRP. Based on the application of the asymmetric TGARCG model, studies revealed a significant role of pandemic indicators in predicting conditional volatility for all five cryptocurrencies. These findings will help investors adopt the right strategies and optimize trading operations (Apergis, 2022).

Pesaran and Timmermann (2007) considered a cross-validation method for selecting the window size under a single discontinuity. The cross-validation method is about an estimate including a breakpoint that improves the trade-off between variance and bias. Examples of different window selections include Fang et al. (2018) discussing the long memory phenomenon in Bitcoin markets and the CSI 300 including a sliding window (200 observations). Markov models are used to understand the highly speculative, loosely regulated, and decentralized cryptocurrency market. Giudici and Abu Hashish (2020) studied Bitcoin prices' switch between "bullish," "stable," and "bearish" modes. Koki et al. (2022) considered returns for three highly capitalized cryptocurrencies: Bitcoin, Ripple, and Ether. Like Giudici and Abu Hashish (2020), they established that the invisible Markov structure differentiated between "bullish," "stable," and "bearish" modes for the Bitcoin series; for ether and ripple, it parted periods with different numbers of risk and return. Kim et al. (2021b) employed the invisible Markov model to see how cryptocurrency markets conduct and react to social attitudes under different modes.

At the same time, Dyhrberg (2016) suggested that Bitcoin hedging can be considered using GARCH models. Baur et al. (2018) continued Dyhrberg's (2016) study. The researchers found that cryptocurrencies' returns, volatility, and correlation differ from gold and the U.S. dollar, Bouri et al. (2019) modeled long-term volatility employing semi-parametric and parametric methods. Their data confirm shocks' constancy and no return to the average in level series; they also find Bitcoin dynamics' structural changes. Cheikh et al. (2020) shared this view, using the smooth transition GARCH model, they found evidence of an asymmetric inverted response for most cryptocurrencies. Good news largely impacts volatility compared to bad news. The present study uses time series and asymmetry coefficient and compares GARCH models with FIGARCH and Markov switch that employ long-term memory (no research considered this before). The present study considers an effective model for Bitcoin volatility prediction. Studying the interrelationship of various cryptocurrencies, the authors use a high-frequency analysis of the correlation of futures contracts through the effectiveness of Bitcoins. Ultimately, they found that significant consequences for pricing are associated with both fraudulent activities and regulatory concerns in the markets (Akyildirim et al., 2020a). The analysis of correlations between key cryptocurrencies, stock indices, bonds, and gold prices contributes to more efficient management of cryptocurrency portfolios (Aslanidis et al., 2019).

Thus, some studies have attempted to explore the relationship between cryptocurrencies and the volatility properties of Bitcoin using different types of models. Nevertheless, researchers have not arrived at a definitive conclusion regarding the exclusive effectiveness of employing a particular analytical tool. Each model has its proponents ready to advocate for its applicability in forecasting cryptocurrency volatility. As previously mentioned, a significant body of work is dedicated to the application of models from the GARCH family, which have proven effective in forecasting the volatility of traditional financial instruments. However, it is emphasized that asymmetric

GARCH models such as EGARCH, APARCH, and TS-GARCH outperform standard GARCH modeling in terms of forecast accuracy when it comes to currency forecasts, including cryptocurrencies (Amirshahi & Lahmiri, 2023). Early researchers of cryptocurrency volatility asserted that the classical GARCH model with a sudden intensity of returns is well-suited for analyzing extreme price movements, indicative of an immature market. This modeling approach was suitable for analyzing Bitcoin volatility in 2014 when the cryptocurrency market was essentially in its nascent stages but has since undergone substantial changes (Mostafa et al., 2021). Later researchers, identifying a set of superior models and employing over 1000 GARCH models for forecasting the volatility of popular cryptocurrencies, concluded that standard GARCH models are insufficiently effective in modeling their volatility primarily due to the existing long-memory effect. Simultaneously, criticism extended to the consideration of the challenge of forecasting short-term daily cryptocurrency volatility. In this context, it is demonstrated that comparing forecasts of realized Bitcoin volatility reveals that HAR models outperform GARCH models based on daily data (Bergsli et al., 2022).

However, despite a substantial body of critical research, none of it specifically addressed the impact of COVID-19 on Bitcoin volatility and the Markov switching models of its volatility post-pandemic. The net mutual correlation among cryptocurrencies in a static context has not been explored in the post-pandemic period. Additionally, the analysis of interrelationships among cryptocurrencies in both short-term and long-term perspectives, along with a quantitative assessment of contradictions, trends, and patterns in Bitcoin price volatility and Markov switching from 2020 to 2022, emerges as a pertinent and nontrivial task.

2. Research methodology

The GARCH model allows for the description of the conditional variance of financial income series (Bollerslev, 1986). GARCH model with Markov switching is the main calculation method. The choice of modeling is predicated on the inadequacy of standard GARCH models, as previously mentioned, in effectively capturing cryptocurrency volatility. The refinement of the model is necessitated by existing long-memory effects in cryptocurrencies, regime-switching, and multifractality. Moreover, combined forecasts enhance predictions compared to those obtained from individual models, and regime-switching models can assist in addressing the challenge of accounting for structural changes in the cryptocurrency market (Panagiotidis et al., 2022).

This model is as follows (Equation (1)):

$$\begin{aligned} y_t &= v_{st} + a_{1,st}\, y_{t-1} + a_{2,st} y_{t-2} + \\ &+ a_{3,st} y_{t-3} + a_{n,st} y_{t-n} + \varepsilon_t,\ \ \varepsilon_t \sim N(0,\sigma^2_{st}) \end{aligned} \tag{1}$$

From the basics of modeling theories, one can say that models with Markov switching were developed by Goldfeld and Quandt (Goldfeld & Quandt, 1965). These dynamic measurement models are used to analyze time series using time-varying parameters that correspond to the state the process is in. The autoregressive model with order p, AR( ), N states for probable modes, $s_t \in \{1, 2, 3, ..., N\}$, is MS( ) – AR($p$) and is shown in the Equation (1).

Autoregressive models are characterized by the estimation of mode changes, which is done by likelihood function maximization with the EM algorithm, where “E” are integrals and “M” are equations with no analytical solution. The Markov switching heteroskedasticity model is more flexible when it describes financial series, in which conditional mean structure discontinuities and unconditional variance of the data generation process are common. To analyze the volatility of Bitcoin, the study chose a model that describes the volatility of Bitcoin prices. For this purpose, the study used a Markov switching-GARCH model with two states, which has the form of a system of equations as follows:

$$z_t = \begin{cases} a_0 + \beta z_{-1} + \varepsilon_t, & s_t = 0 \\ a_0 + a_1 + \beta z_{-1} + \varepsilon_t, & s_t = 1 \end{cases} \tag{2}$$

where: $\beta < 1$, and ε_t is contrasted to zero average and variance σ^2_ε.

This is the easiest system AR (1), i.e., the standard process with mean values $\alpha_0/(1 - \beta)$, if $s_t = 0$. If $s_t = 0$, the process switches to a state s_t from 0 to 1. Based on the above, one can say that the model describes two basic states of the unobservable variable s_t. The resulting indicator z_t can control distributions with both zero state s_t and a single state, while it is s_t that is the switch between these modes.

Descriptive statistics for the original time series present: mean (0.17), SD (0.82622), asymmetry (−1.877), and kurtosis equal to 20.88. Fig. 1 depicts the series of returns and prices. Information is crucial as volatility is primarily a parameter that characterizes the dynamics of price changes, reflecting the breadth of the price movement range over a fixed period. Therefore, the value of this parameter aids in assessing how rapidly the price changes during the current period in comparison to the preceding ones.

There are low prices for 2013–2017. Then, they increase and reach a maximum in 2021–2022. However, the series has peaks and is not stable. The series further fluctuates from USD 20,000 to USD 60,000. Returns show volatility clustering, which advocates the option of GARCH models to depict Bitcoin market volatility dynamics.

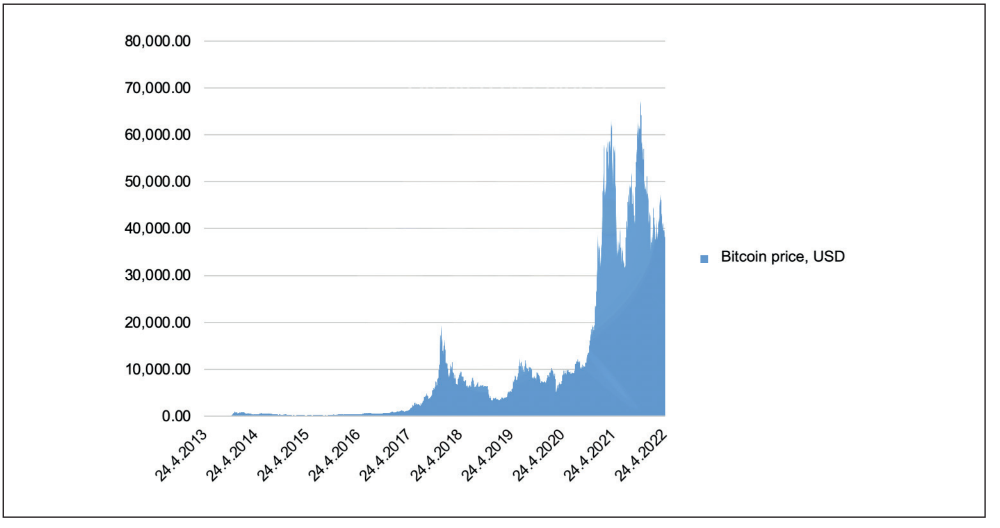

Fig. 1: Evolution of Bitcoin prices (April 2013–April 2022)

Source: own (based on Investopedia (2023))

The overall volume of Bitcoin purchases has increased since 2019, reaching its peak in 2021. Understanding this phenomenon may be grounded in the consideration of external socio-economic factors. During this period, a pivotal external factor could be attributed to COVID-19. Given that one of the distinctive features of the cryptocurrency market is that significant events lead to heightened investor enthusiasm (Liu & Tsyvinski, 2021), manifestations of the pandemic could have increased the demand for Bitcoin, coinciding with price growth (Fig. 1) and an elevation in market capitalization. The mean Bitcoin return is positive and equals 0.1773%, while the volatility, which is measured by the standard deviation, showed high values and amounted to 8.2%. The asymmetry statistics showed a negative result, which may indicate frequent small gains and a few large losses.

The Jarque-Bera test statistic is significant at 1%, and this finding is confirmed by the deviation from the Gaussian distribution. The Engle test shows heteroskedasticity for returns of up to 5 lags and stimulates using GARCH models. Panel B shows the unit root tests, i.e., Phillips-Perron (PP) and extended Dickey-Fuller (ADF) tests. The two tests are valid at 1% significance. Consequently, the null hypothesis of the unit root for the studied series can be rejected.

However, the reasons for increased volatility for 2020–2022 must be studied. For this, an exogenous influence factor was the COVID-19 data set. Fig. 1 shows the unctioning trend in the markets. It was decided to use beincrypto.com to obtain data on the Markov-switching Bitcoin volatility for 2019–May 2022. UNICEF data on COVID-19 incidence were used. The Chi-squared test for several EECCA countries was used to test the claim. Fig. 2 depicts data on the quantity of sick people (the COVID-19 incidence) in Armenia, Azerbaijan, Belarus, Moldova, Kyrgyzstan, Kazakhstan, Tajikistan, and Uzbekistan. The rationale for the research sample is elucidated by the fact that the countries comprising the Commonwealth of Independent States (CIS) today represent the post-Soviet space with developing economies. These countries lack surplus funds in their state budgets, prompting their governments, following the dissolution of the socialist system, to seek financial resources outside the national economy. Furthermore, after the global financial crisis and the decline in global oil prices in 2020–2021, the issue of compensating for the decline in budgetary revenues has become even more pressing for them. Simultaneously, it is essential to note that in the CIS countries, a financial market is only beginning to emerge against the backdrop of the decentralization of financial instruments. The potential of CIS countries is of interest in terms of the future dynamics and trends in the development of the financial market. Therefore, it seems expedient to test the proposed model on the cryptocurrency market in the region of developing countries in Asia.

Fig. 2 shows disease growth dynamics in the analyzed countries; incidence increased in November 2020. One can consider the connection between Bitcoin exchange rate volatility and the incidence in China, as this state was the first to face the disease growth. The lockdown was in the regions with high disease levels and not the whole country; this should be analyzed with the Chi-squared tool.

Below is the Pearson correlation analysis between cryptocurrencies in the short- and long-term perspective. The empirical data on the prices of the top fifteen financial instruments as of the beginning of December 2021 were used for a static analysis of the relationships between cryptocurrencies (Fig. 3).

Fig. 3 demonstrates a staggering price gap for different cryptocurrencies, from USD 48,700 for Bitcoin (BTC) to 0.58 for Crypto.com coin

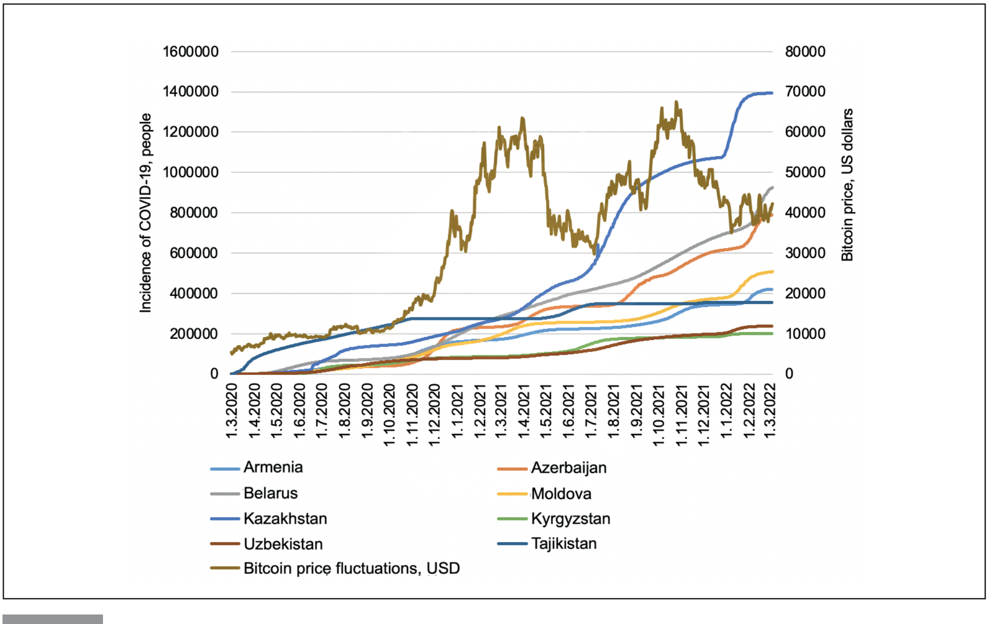

Fig. 2: **Bitcoin fluctuations and COVID-19 incidence 2020–2022**

Source: own (based on WHO (2023))

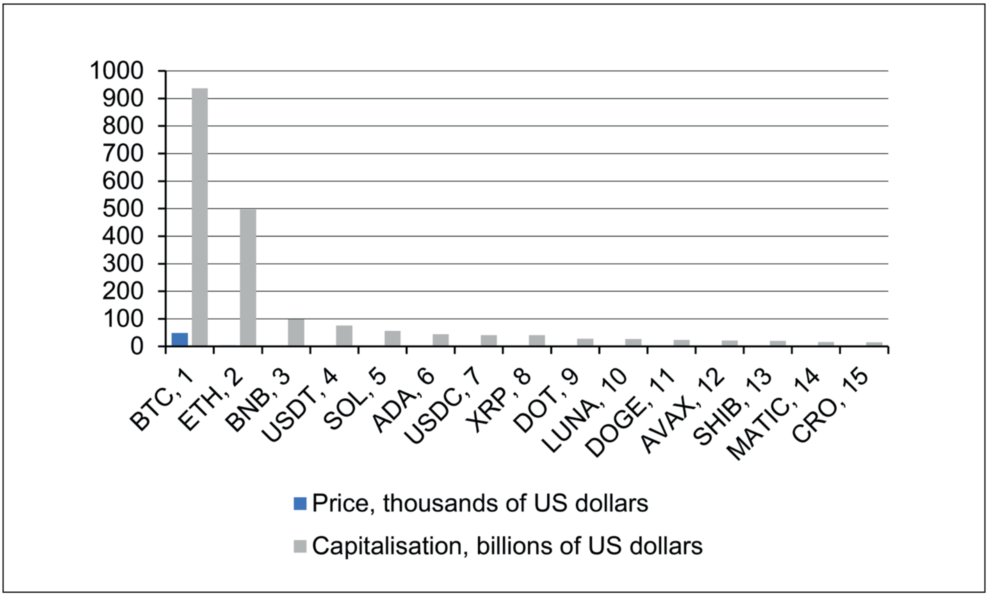

Fig. 3: Cryptocurrency prices and market capitalization

Source: own (based on CoinMarketCap (2023))

(CRO), and a 60-fold gap in their capitalization (937.2 and USD 14.98 billion for the respective cryptocurrencies). An overview of cryptocurrency prices in the context of capitalization shows their relationship and follows the main cryptocurrency – Bitcoin.

3. Research results

Conditional volatility is tested first. Two popular tests are applied, i.e., Robinson's semi-parametric Gaussian criterion (GSP) and logarithmic periodogram regression test (GPH). The estimation is shown in Fig. 4.

There are some high volatility periods. There are two periods of Bitcoin market sharp spikes: November 2020–January 2021 and November 2021–January 2022. As Bitcoin demand is not seasonal, due to similar periods in 2019–2020 and 2018–2019, one must add the COVID-19 disease peak and related restrictions.

Tab. 1 depicts the evaluation and tests for the Markov switching GARCH model.

All parameters of the standard GARCH model that have been calculated are positive and greater than 0. Thus, Bitcoin returns current conditional volatility is influenced by its past shocks and past conditional volatility. The coefficient β is seen as high and close to 1, namely, there is Bitcoin market volatility. Conditional variance is stationary as the sum of GARCH and ARCH coefficients is less than one. This outcome is consistent with several previous studies. Katsiampa (2019) studied the cryptocurrency market volatility dynamics. He showed that the studied market is volatile.

There are two mode types: a mode of low volatility (mode 1), and a mode of high volatility (mode 2). As for conditional variance, Bitcoin volatility is almost 3 times higher in mode 2 compared to mode 1. Mode 1 is more stable compared to Mode 2. In 2021, there was a maximum of 267 days in mode 2, and 72 days in 2022. The probability of staying in the high volatility mode is 0.9908, which is a mean duration of 108 days. There are turbulent and alternating stable periods. The high volatility mode is less stable. The Markov switching model allows for identifying different volatility modes.

The study points to the likely impact of switching volatility modes and COVID-19 incidence as the period of pandemic peaks stabilizes the Bitcoin exchange rate in the high

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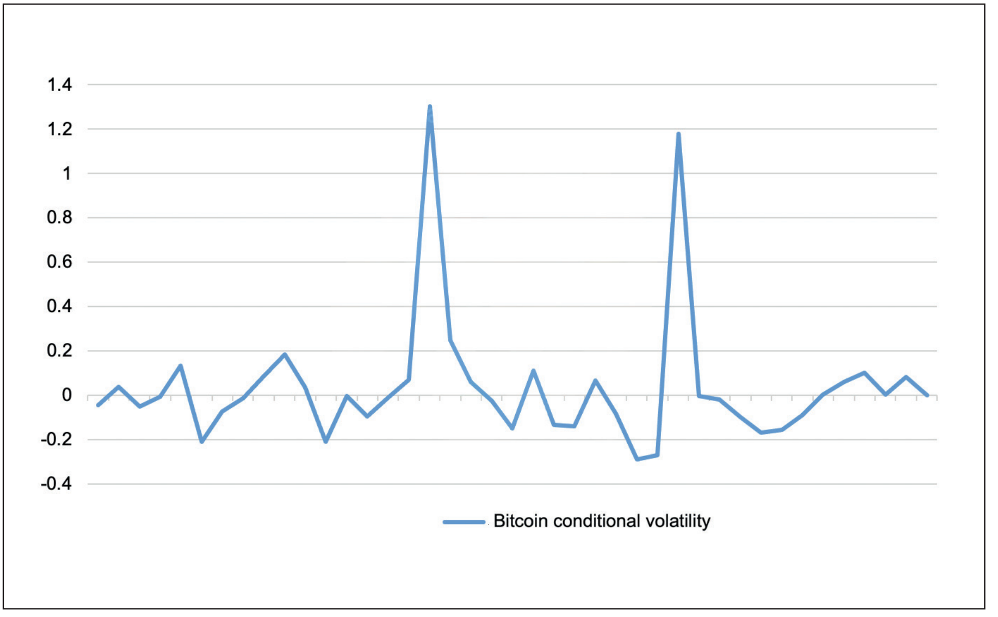

Fig. 4: Bitcoin conditional volatility estimation

Source: own (based on the data of Bitcoin prices from Binance (2023) and CoinMarketCap (2023))

Tab. 1: Evaluating Markov switching GARCH model

Indicators	GARCH model
μ	0.172011523
ω	0.824857467
α	0.024581282
β	0.311707841
Student *t*-test	20.404472740
Standard error	0.037759143
Multiple *R*	0.993627458
***R*-square**	0.987295525
Normalized *R*-square	0.986236819

Source: own

mode of volatility. The Chi-squared test results are shown in Tab. 2.

In Kazakhstan and Azerbaijan, the Chi-squared test is bigger than the tabulated value; therefore, Bitcoin volatility and COVID-19 are linked (correlation ranges from 0.80 to 0.99). If the correlation is below 0.5 (Kyrgyzstan), it is considered low. As for Armenia, Moldova, Tajikistan, Uzbekistan, Belarus, and Russia, no such correlation was found. Fig. 5 illustrates the number of sick people and Bitcoin volatility in Kazakhstan.

Tab. 2: Chi-squared test results

Country	Chi-squared	Critical value of Chi-squared	Chi-test (*P*) value
Armenia	628.35	847.13	0.9890
Azerbaijan	3,304.75		0.5175
Belarus	134.40		0.9915
Kazakhstan	1,974.62		0.8601
Kyrgyzstan	308.97		0.2137
Moldova	752.90		0.9893
Russia	127.80		0.9996
Tajikistan	189.21		0.7008
Uzbekistan	157.43		0.9787
China	1,976.29		0.9987

Source: own (based on WHO (2023))

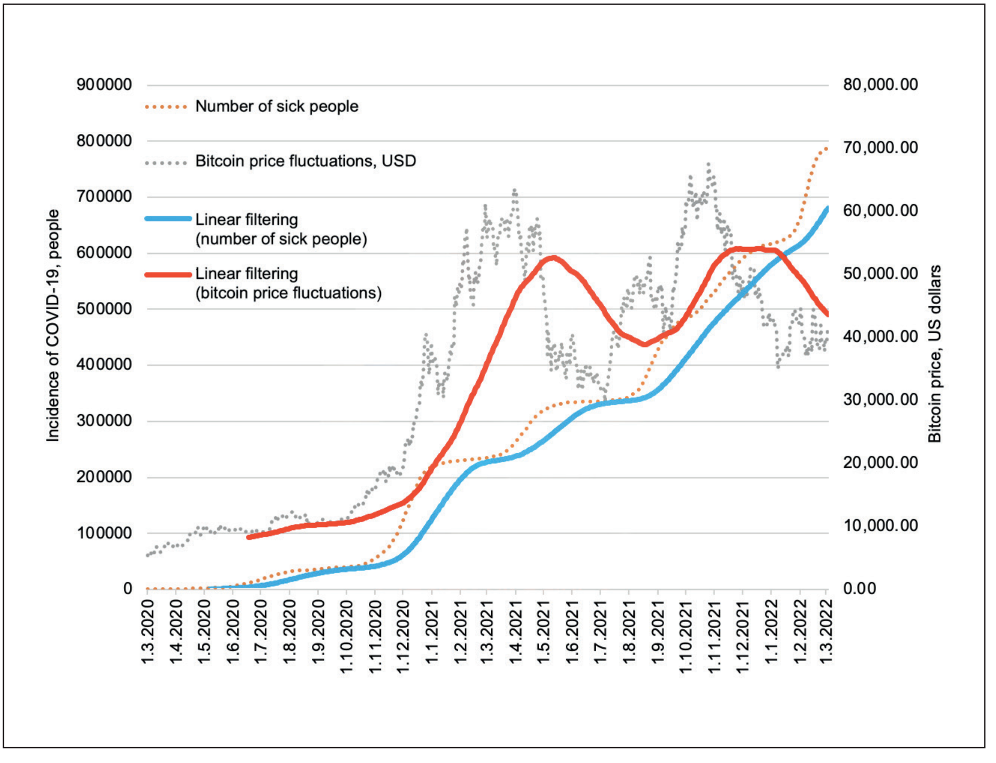

Fig. 5: Comparing the dynamics of Bitcoin volatility and the number of sick people in Kazakhstan for March 2020–March 2022

Source: own (based on the data of Bitcoin prices from Binance (2023), CoinMarketCap (2023), and WHO (2023))

The graph of disease dynamics partially coincides with the graph of volatility dynamics (Fig. 6). To analyze the figure, a trend with linear filtering was used, which allows evaluation of the link between the number of sick people and Bitcoin fluctuations, which shows that at the start of the pandemic incidence slightly increased and Bitcoin was in a low-volatility mode (March 2020–June 2020). Nevertheless, growing morbidity and the introduction of COVID-19 restrictions by countries from November 2020 to May 2021 defined a Bitcoin quote's highly volatile mode. Fig. 6 depicts the number of sick people and Bitcoin volatility in Azerbaijan.

The linear filtering trend illustrates comparable disease and Bitcoin volatility trends as well. There are peak growth periods (April 2021 and October 2021) and peak decline periods (July 2021 and September 2021). Yet the peaks of morbidity and switching of volatility modes do not match. In the high volatility mode, the COVID-19 morbidity changes its tendency a few times: from November 2020 to January 2021 (rapid morbidity growth with a low Bitcoin volatility state). This is also true for other study periods. One should note that the charts wave-like match each other in the spots of increasing and decreasing Bitcoin prices and the number of cases.

Chi-square for China is 1,976.29 and the tabular value is 847.125. There is a disparity between 1,976.29 > 847.125, meaning the number of COVID-19 episodes in China correlates with the volatility of Bitcoin. To examine the relationship in detail, the authors built a graph with a linear filtering method (Fig. 7).

The calculations lead to the conclusion that the quotation and volatility of Bitcoin are not characterized by a dependency on cases of COVID-19. As a conjecture, this can be clarified by the fact that the Chinese government did not implement total isolation for the entire country but instead intensified quarantine restrictions for regions with the highest infection rates. This measure aimed to preserve the functioning of the economic sector in areas

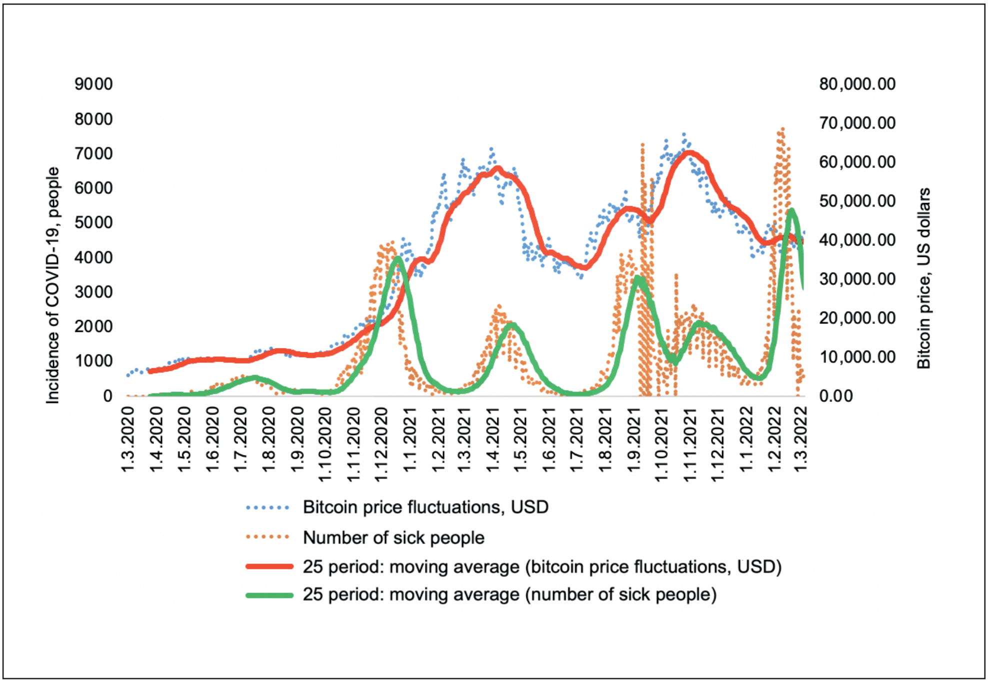

Fig. 6: Comparison of Bitcoin volatility dynamics and the number of patients in Azerbaijan for the period March 2020–March 2022

Source: own (based on the data from Binance (2023), CoinMarketCap (2023), and WHO (2023))

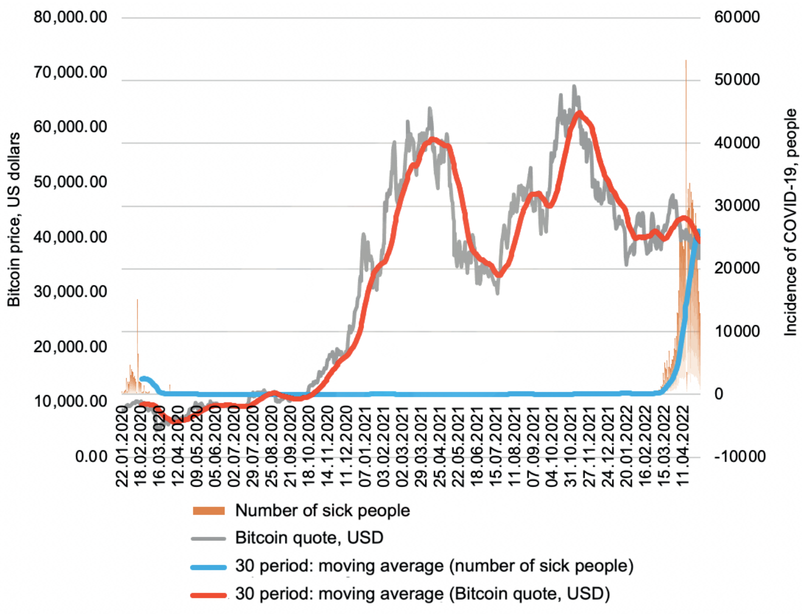

Fig. 7: **Comparison of the Bitcoin volatility dynamics and the quantity of ill people in China for January 2020–March 2022**

Source: own (based on the data from Binance (2023), CoinMarketCap (2023), and WHO (2023))

where the infection rate was not as high. However, it is noteworthy that subsequently, impediments to entrepreneurial development due to the pandemic created long-term challenges for China's economic growth (Li & Li, 2023). The analysis used the daily price (start and end of the day) and weekly returns of 11 significant cryptocurrencies on financial markets tied to the USD exchange rate as of December 1, 2021: Bitcoin, Ethereum, Binance Coin, Tether, Cardano, XRP, USDC, Dogecoin, Litecoin, Tron, Bitcoin Cash. Tether and USDC (CoinMarketCap, 2023).

The formula used to calculate the correlation coefficient is:

$$r = P_{closing}\,(t_1) - P_{closing}\,(t_1{-}1)\;/P_{closing}\,(t_1{-}1) \quad (3)$$

where: t – a unit of time; $P_{closing}(t_1)$ – the closing price of the cryptocurrency at the start of the day; $P_{closing}(t_1{-}1)$ – the closing price of the cryptocurrency at the end of the day.

The correlation matrix of the daily prices of cryptocurrencies from the short-term perspective is presented in Tab. 3.

The correlation analysis of the cryptocurrencies presented in the Tab. 3 indicates a positive (moderate) correlation among them. In this case, Bitcoin, due to its market capitalization, has a significant impact on the cryptocurrency market. Therefore, the matrix presented is the correlation between Bitcoin and other currencies. The most strongly correlated with Bitcoin are Ethereum, Litecoin, and TRX, with investors who consistently and risk-free invest in their purchases and optimize their portfolios. There is a strong positive correlation among Binance Coin, Tron, Cardano, and Bitcoin Cash, and a low negative correlation between Tether, and USDC. Moderate positive correlation is present for XRP and Binance Coin, and between XRP, Ethereum, and Litecoin.

The following is a correlation matrix between weekly returns over the long-term perspective (Tab. 4).

Tab. 3: Correlation matrix between daily prices of cryptocurrencies (1 day; 12/1/2021)

	BTC	ETH	BNB	USDT	ADA	XRP	USDC	DOGE	LTC	TRX	BCN
BTC	–										
ETH	0.86	–									
BNB	0.81	0.84	–								
USDT	0.05	0.12	0.14	–							
ADA	0.78	0.80	0.81	0.02	–						
XRP	0.44	0.45	0.45	−0.01	0.55	–					
USDC	0.15	0.09	0.12	−0.12	0.11	0.12	–				
DOGE	0.77	0.76	0.73	−0.02	0.75	0.72	0.20	–			
LTC	0.86	0.87	0.85	0.16	0.80	0.49	0.16	0.75	–		
TRX	0.85	0.84	0.83	0.11	0.79	0.52	0.11	0.82	0.89	–	
BCN	0.81	0.78	0.76	0.08	0.76	0.52	0.07	0.76	0.86	0.81	–

Source: own (based on the data from Binance (2023) and CoinMarketCap (2023))

Tab. 4: Correlation matrix of weekly cryptocurrency returns (1 week; 12/1/2021)

	BTC	ETH	BNB	USDT	ADA	XRP	USDC	DOGE	LTC	TRX	BCN
BTC	–										
ETH	0.86	–									
BNB	0.77	0.76	–								
USDT	−0.28	−0.16	0.01	–							
ADA	0.70	0.66	0.76	−0.03	–						
XRP	0.73	0.62	0.62	−0.32	0.66	–					
USDC	−0.03	0.04	0.05	0.32	0.01	−0.01	–				
DOGE	0.85	0.79	0.68	−0.37	0.65	0.79	0.00	–			
LTC	0.88	0.82	0.81	−0.21	0.74	0.74	0.01	0.81	–		
TRX	0.77	0.73	0.66	−0.32	0.56	0.66	−0.06	0.77	0.76	–	
BCN	0.81	0.75	0.62	−0.45	0.48	0.70	−0.01	0.80	0.81	0.73	–

Source: own (based on the data from Binance (2023) and CoinMarketCap (2023))

Comparing the correlation analysis in the short and long term, it becomes clear that the relationship between the prices of Bitcoin and other cryptocurrencies is significantly stronger in the short term, although in the range from 0.05 to 0.89. Ethereum and Litecoin are strongly correlated with Bitcoin. In addition, there is a strong correlation between Binance Coin, Tron, Cardano, and Bitcoin Cash. A negative correlation has been found between Tether and USDC. Moreover, the correlation between cryptocurrencies is much stronger during price declines than during their increase, reducing investment portfolio diversification's effectiveness.

4. Discussion

The COVID-19 pandemic implications for cryptocurrency markets are troubling in terms of risk management and investment. Bitcoin price volatility information can adversely impact financial market participants. Furthermore, this study examines how the COVID-19 pandemic affects the correlation between COVID-19 infections and Bitcoin volatility. However, this paper considers the BTCF market for empirical analysis, given its certain benefits. As expected by the authors of this study, Corbet et al. (2021) affirmed in their study how Chinese financial markets reacted first to the onset of the COVID-19 pandemic in Wuhan and the ensuing lockdown of the cities. Researchers have suggested identifying the impact of shifts in cryptocurrency markets with indices reflecting the effect of COVID-19 on Chinese financial markets, as measured by real-time investor sentiment. Their study, however, is based on contrasting the effect of COVID-19 and traditional flu on financial market indicators, while the current study is based on the effect of COVID-19 on Bitcoin volatility, i.e., the study describes a narrower area.

The comparative correlation analysis in both short-term and long-term perspectives reveals that the association between Bitcoin prices and those of other cryptocurrencies is significantly stronger in the short-term horizon. However, as recent studies show, as market volatility and financial stress increase, correlations become stronger (Akyildirim et al., 2020a). Ethereum and Litecoin exhibited a close association with Bitcoin. The findings demonstrate a robust correlation among Binance Coin, Tron, Cardano, and Bitcoin Cash, while a negative correlation is observed between Tether and USDC. This conclusion extends prior research that forecasted the conditional volatility of several major cryptocurrencies such as Bitcoin, Dash, Ethereum, Litecoin, and XRP (Apergis, 2022). It reaffirms the assertion that optimizing investment portfolios requires information on the interrelationships among cryptocurrencies, as well as the patterns or contradictions in their alignment with the primary currency, Bitcoin. Our study on cryptocurrency correlations in 2021–2022 aligns with research conducted in earlier periods, such as 2017–2018, where strong correlations between cryptocurrencies were identified based on proof-of-work mechanisms (Lahajnar & Rozanec, 2020), including significant correlations among 20 cryptocurrencies with coefficients exceeding 0.7 (Davies, 2021). An intriguing regularity was discovered by Akyildirim et al. (2020a): a strong positive correlation exists between financial market stresses and cryptocurrency correlations, which change over time. Increased volatility consistently amplifies the interdependence among cryptocurrencies (Akyildirim et al., 2020b).

The study has advanced approaches to the utilization of GARCH models and showcased their capabilities, thereby extending the postulates formulated earlier. Thus, Baur et al. (2018) and Katsiampa (2017) support the conclusions concerning the usage of autoregressive conditional heteroskedastic (GARCH) models and their versions in the single-mode form to simulate Bitcoin volatility. Kodama et al. (2017), on the contrary, stressed the applicability of Markov-switching autoregressive models to Bitcoin. The researchers thus confirmed the Markov-switching GARCH model to be the most effective model. Tiwari et al. (2018) proposed to use long memory parameter estimates with overlapping windows every 300 observations of daily returns when modeling with a Markov switching GARCH model, or to enter a complementary long memory parameter, which completely supports the selection of the model. Zargar and Kumar (2019) used non-intersecting quarterly rolling windows of about 100 days. Ardia et al. (2019) examined volatility by using sliding windows of 1,000 daily logarithmic returns but utilizing these Markov-switching models can provide more precise and better results, which has already been confirmed by the study. Conrad et al. (2018) proposed various approaches to simulating and projecting the volatility of the Bitcoin market. Their results show that the Bitcoin market is characterized by long memory, mode switching, and multifractality. The present study did not investigate this aspect, that is, the long memory factor was not included in the model because the study objective was to determine the effect of the exogenous pandemic factor on Bitcoin volatility. However, the present study authors agree with the second part of the results of Conrad et al. (2018), which show that multifractal Markov switching processes are superior to all other models of the GARCH family in modeling Bitcoin market volatility on both long and short timeframes. American scientists support the conclusions regarding the use of autoregressive conditional heteroscedastic (GARCH) models and their versions in single-mode form for modeling the volatility of Bitcoin (Baur et al., 2018; Katsiampa, 2017). In addition, the analysis of the volatility of cryptocurrencies often uses the summation ensemble methodology based on hybrid GARCH models, which enhances the accuracy of volatility forecasts (Aras, 2021).

An important next step in this study may be to check the hypotheses by Mensi et al. (2019), who observed that incorporating a long-term memory factor into the conditional variance greatly improves the forecasting of cryptocurrency prices. Dyhrberg (2016) shared the same idea. The author found that a structural change and long-memory volatility model, such as FIGARCH with gaps, is better than every other model in characterizing and forecasting the volatility of futures and spot oil prices. This research format was not used in this article. Still, it can be effective for future studies for comparison because the GARCH model with Markov switching is the basic model for studying Bitcoin volatility, which was investigated without any additional elements introduced (Chkili et al., 2012; Sosa et al., 2019). Some researchers demonstrated that long-run memory is considerably reduced when regime change is considered (Charles & Darné, 2019; Mensi et al., 2019). Their findings show that the evidence of long memory attenuates in magnitude and/or statistical significance when a series of gap-adjusted returns is used.

Conclusions

This work attempts to determine a proper model to depict Bitcoin price volatility dynamics using Markov switching GARCH, and mode switching is driven by volatility clustering, which is considered using raw time series as an example. This analysis assists investors and portfolio managers in gaining an accurate valuation of assets and selecting possible diversification opportunities that Bitcoin acquired. This provides the best hedging strategies by selecting suitable derivatives and value-at-risk valuations.

It has been revealed that two switching volatility modes are possible: i) mode 1 – low volatility; and ii) mode 2 – high volatility. One exogenous factor affecting Bitcoin switching modes was the COVID-19 morbidity growth factor. This is because the increase in Bitcoin value, number of transactions, and capitalization occurred at the start of the pandemic. The study showed that of all the countries analyzed, only in Kazakhstan did the pandemic influence the switching of volatility modes of Bitcoin quotes more. In Azerbaijan, the peaks and drops of the incidence match the Bitcoin price peaks, but the volatility switch from low to high does not rely on the prevalence of COVID-19 in the country. One should note that the effect of COVID-19 on Bitcoin volatility differs considerably by region, according to the government measures taken to control the disease.

Correlation analysis of cryptocurrencies revealed a positive moderate correlation among them, with Bitcoin exerting a stronger influence on other currencies due to its market capitalization. The most strongly correlated with Bitcoin are Ethereum, Litecoin, and TRX. There is a strong positive correlation between Binance Coin, Tron, Cardano, and Bitcoin Cash, and a low negative correlation between Tether and USDC. A moderate positive correlation is present for XRP and Binance Coin and among XRP, Ethereum, and Litecoin. A comparative analysis of the correlation coefficients of cryptocurrencies in the short- and long-term perspective showed that the price correlations of Bitcoin and other cryptocurrencies are much stronger in the short term perspective.

The following guidelines are suggested as directions for future research work: i) develop and model investment strategies with more than two modes; ii) model these investment strategies using MS, MS-ARCH, or MS-GARCH models with non-uniform likelihood functions in each mode; iii) use asymmetric models in Bitcoin volatility parameters and the likelihood functions; and iv) include the effects of financial transaction costs, as well as other market risks not included here, such as slippage (or fluctuations in the exercise price), foreign exchange risk, or any other risk or impact due to the influence of exogenous variables or events not included in the used MS model.

Hence, as a theoretical contribution, this research can be characterized as an additional contribution to the literature on the application of Markov Switching (MS) models to actively manage investment portfolios in cryptocurrency markets. Additionally, it is anticipated that the research findings will contribute to further exploration of the advantages of active investing utilizing MS GARCH models.

The practical implications of this research hold significance for financial strategic planning. They are directed towards investment management professionals, as the use of constant-dispersion MS models and MS-GARCH models enables the attainment of alpha or excess returns compared to a passive strategy. This provides the opportunity for one or multiple investors to denominate funds in dollars. The study introduces an approach for cryptocurrency market participants that aids in better understanding the manifestations of cryptocurrency volatility associated with the occurrence of "black swan" events and facilitates the adoption of more informed and effective strategies amidst market turbulence. Such a combined approach, involving the use of the MS-GARCH model, enhances forecasts and thereby minimizes risks associated with unfounded decisions. In conclusion, the anticipated results are economically significant, as accurate volatility forecasts provide crucial information for portfolio allocation decisions and risk management. While the promising outcomes of this study are encouraging, the direct positive impact of the proposed calculation may be more effectively expanded by considering other exogenous factors and incorporating multi-modality in the presence of dynamic price changes.

Future research endeavors should delve into the causes behind the observed divergent behavior in the volatility of various cryptocurrencies and assess whether MSGARCH models outperform GARCH models in forecasting volatility across different cryptocurrencies. Additionally, it is imperative to expand the list of examined countries, investigate the correlation between Bitcoin volatility and the spread of the COVID-19 pandemic, and explore this factor's impact on other cryptocurrencies.

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