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Crypto – Equity Market Interdependence Analysis

Anastasiia Buchko[1], **Anatoly Peresetsky**[2]

[1] National Research University Higher School of Economics,
11, Pokrovsky Blvd., Moscow, 109028, Russian Federation.
E-mail: aasergeeva@hse.ru

[2] National Research University Higher School of Economics,
11, Pokrovsky Blvd., Moscow, 109028, Russian Federation.
E-mail: aperesetsky@hse.ru

In recent years cryptocurrencies have gained popularity: institutional and retail investors as well as different trading companies started positively looking at crypto assets. As a result, the convergence level between cryptocurrencies and the traditional markets has changed a lot. Stocks deserve close attention because they are a key asset for many investors. This article explores the evolving relationship between crypto assets and the US stock market by focusing on the four largest cryptocurrencies: Bitcoin (BTCUSDT), Ethereum (ETHUSDT), Ripple (XRPUSDT), Binance Coin (BNBUSDT), and the US stock index (S&P500). Utilizing correlation analyses of returns and volatilities alongside Granger causality tests, the study reveals how these markets affect each other. To implement the analysis, 1-minute and 5-minute data for 4.5 years, from 2019 to mid-2024, was used. Employing intraday granular data distinguishes this study from earlier ones that used daily data, and also identifies conclusions that may be more interesting to market participants such as scalper traders. The results indicate that cryptocurrencies become more integrated with traditional financial markets during periods of global economic instability, such as COVID-19 in 2020 and geopolitical tensions in 2022. Moreover, according to Granger causality tests, connections become bidirectional in stressed years, indicating the mutual influence between stocks and cryptocurrencies. On the other hand, in quieter times, the level of interconnection is significantly reduced in terms of correlations. Granger causality results reveal mostly unidirectional relationships (the impact of the US stock market on all 4 cryptocurrencies) during calm periods.

Key words: cryptocurrency; stocks; S&P500; returns; volatility; correlations; Granger causality.

Anastasiia Buchko – Graduate Student.
Anatoly Peresetsky – Doctor of Sciences, Research Professor at the Department of Applied Economics.

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1. Introduction

Cryptocurrency is a form of digital asset that has been actively gaining popularity in recent years. The largest and the most popular crypto asset is Bitcoin, which was created in 2009. At the end of 2024, the market capitalization of Bitcoin was about $2 trillion, which is 2.5 times higher than at the end of the previous year[1]. For comparison, the capitalization of Apple, the world's largest company, was $3.75 trillion at the end of 2024 with an annual growth rate of only 25%[2]. The second most popular cryptocurrency is Ethereum with $0.45 trillion market capitalization. This is followed by other crypto assets such as Ripple, Binance coin and Dogecoin, as well as Tether and USDC stablecoins[3].

For a long time, cryptocurrencies have been on the periphery of the financial system, but now such assets have entered our lives quite tightly. Before the first significant growth of the cryptocurrency market in 2017, Bitcoin held the dominant market share, it alone accounted for about 85% of the total market capitalization. The first significant growth of the cryptocurrency market took place in 2017 when market capitalization expanded tenfold in a single year: from average values equal to $20 billion to roughly $200 billion. It happened due to several factors, including the Initial Coin Offering (ICO) boom[4]. Moreover, other cryptocurrencies besides Bitcoin have begun to gain significant popularity. For example, Ethereum rose in importance, featuring smart contract capabilities, enabling rapid token creation. As a result, according to CoinMarketCap, Bitcoin share decreased to around 40%, while Ethereum's share has increased from 9% to 17%; the capitalization of other cryptocurrencies also raised from 9% to over 40%.

One of the most significant turning points that reshaped the position of cryptocurrencies relative to other traditional asset markets was COVID-19. Macroeconomic instability and low interest rates have prompted investors to seek alternative asset classes. Consequently, many banks began to include cryptocurrencies in their investment portfolios[5], and public companies began to acquire crypto assets and hold them on their balance sheets[6]. In 2021, such big companies as Tesla and Square made significant investments in Bitcoin for $1.5 billion[7] and $210 million[8], respectively, reflecting broad acceptance. MicroStrategy also started buying large amounts of

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1 CoinMarketCap website. (https://coinmarketcap.com/charts/)

2 CompaniesMarketCap website. (https://companiesmarketcap.com/apple/marketcap/)

3 Stablecoins – assets, which price is pegged to another asset. Most often, this asset is the US dollar.

4 ICO – Initial Coin Offering. It is the combination of IPO model with crowdfunding (issuing tokens to raise funds for a blockchain project).

5 Markets Insider. (https://markets.businessinsider.com/news/currencies/13-top-banks-investing-cryptocurrency-blockchain-technology-funding-blockdata-bitcoin-2021-8)

6 The statistics of the Bitcoin volume on company accounts can be found on Bitcoin Treasuries website. (https://bitcointreasuries.net)

7 Yahoo Finance. (https://finance.yahoo.com/news/tesla-buys-billion-worth-of-bitcoin-133029552.html)

8 Binance. (https://www.binance.com/en/square/post/14909307659673)

Bitcoin repeatedly[9]. User-friendly apps have made crypto trading more accessible for new retail investors. Furthermore, countries around the world have begun to recognize cryptocurrencies as legal, and individual countries such as El Salvador and the Central African Republic have adopted Bitcoin as a legal tender. As a result, during 2020 and 2021 the overall crypto market capitalization increased again, multiplying nearly tenfold and surpassing the $2 trillion mark. Notably, despite this dramatic expansion, the relative market shares of the major cryptocurrencies remained unchanged. The unstable economic situation in 2022 has maintained the high popularity of cryptocurrencies, keeping the acquired capitalization level on average at the level of 2021.

The year 2024 was a new record year for the crypto market: the largest crypto assets, as well as other altcoins, updated their historical highs, and the total market capitalization exceeded $3 trillion for the first time in history. This is due to the continued interest from institutional players such as MicroStrategy and BlackRock, which continued to accumulate Bitcoin, as well as the statements of the new US president, which are quite positive for the industry.

Such big changes in the crypto industry have inevitably altered how these digital assets interact with other financial instruments. Stocks deserve close attention since they are a primary investment for diverse investor groups, including hedge funds, retail investors, HFT traders, scalpers, and others. For all investors – whether long-term portfolio managers or active traders – it is crucial to recognize the level of interconnection between the markets since diversification advantages can diminish as cross-asset linkages strengthen. When asset correlations rise, volatility in one market can more easily spill over into another, heightening the probability of shock transmission. Consequently, traditional investors risk destabilizing their portfolios, while intraday traders may face losses if they fail to adjust their risk parameters in time. In this context, his paper is devoted to the examination of the relationship between cryptocurrencies and the stock market. So, this study sets out to explore the following questions: has the relationship between the crypto assets and the US stock market changed over time? If so, how significant was the change? Did these changes coincide with periods of economic instability? And was the connection between markets unidirectional or bidirectional?

Cryptocurrencies as a research subject have gained increasing attention from different authors driven by the rapid development of crypto market. Some articles focus on forecasting cryptocurrency volatility using daily data [Caporale, Zekokh, 2019; Bergsli et al., 2022; Teterin, Peresetsky, 2024] and compare these models with those used for predicting stock market volatility [Aganin et al., 2023]. Most researchers deployed different GARCH (EGARCH, APARCH) and HAR models and found that the HAR tend to outperform GARCH models. Other authors try to find the interconnectedness between crypto and traditional assets, especially stocks. The conclusions in these studies highlight the evolution of the cryptocurrency market and the growing relationship between digital and traditional assets. This paper belongs to the second block of the investigations.

Early papers, until 2017, when the crypto market was still young, used Bitcoin as a proxy for the entire market. At that time, Bitcoin was regarded by researchers as a useful diversification tool in traditional investors' portfolios. For example, the empirical findings of [Briere et al., 2015] noted a low correlation of Bitcoin with other asset classes (stocks, bonds, currencies) and suggested that such a low level of relationship may offer diversification benefits and may improve the portfolio performance in terms of risk-return. [Dyhrberg, 2016] used the GARCH-

[9] Bitcoin Treasuries. MicroStrategy Bitcoin holdings. (https://treasuries.bitbo.io/microstrategy/)

based models to examine Bitcoin's reaction to various shocks in the FTSE index. Based on the evidence presented, until 2015 the returns of the main crypto asset were not affected by changes in the stock market. Similar conclusions were reached by [Bouri et al., 2017]. However, the authors expressed doubts that the situation may vary during the crisis, which meant the necessity of tracking the changes over a longer period.

After the first boom of cryptocurrencies in 2017, the main conclusions in the papers changed. Researchers, using different econometric tools, began to state not always a stable relationship between crypto and other traditional markets. For example, [Conrad et al., 2018] examined the relationship between Bitcoin and S&P500, [Malhotra, Gupta, 2019] between Bitcoin and five Asian stock indices. [Wang et al., 2020] studied how Bitcoin interacted with three major US stock indices: S&P500, Dow Jones and NASDAQ, using VAR model impulse response analysis and daily data from 2013 to 2018. Due to the main findings, the stock market standard deviation influence on Bitcoin standard deviation was higher than the impact level of BTC on equity indices. [Lopez-Cabarcos, 2021] also used daily returns of Bitcoin and S&P500 markets from 2016 to 2019 and applied GARCH-EGARCH models both on the entire time interval, as well as on four subsamples. Based on the results over the entire period under consideration, S&P500 volatility and Bitcoin volatility influenced each other. In subsample analysis, the authors identified intervals with bidirectional interconnectedness but also noted two periods (from March to December 2017 and the whole year 2018), when no relationship was observed. [Uzonwanne, 2021] analyzed volatility spillovers[10] between Bitcoin and five equity markets (S&P500, FTSE 100, CAC 40, DAX 30, Nikkei 225) using daily data from 2013 to 2018 with VARMA-AGARCH models. The article concluded that there was no significant short- or long-run connection between BTC and the French CAC 40. However, they have found evidence of shock spillovers from the UK FTSE and German DAX indices to the BTC market in the long run and no inverse relationship. The relationship in the short run between Bitcoin and the US S&P500 and Japanese Nikkei was unidirectional (from the stock market to the crypto asset), while in the long run, it was bidirectional.

The situation changed significantly after 2020 when COVID-19 happened. A growing number of researchers began to include the pandemic years in their studies, noting that stressful periods significantly alter the level of interconnectedness among assets. [Iyer, 2022] has examined return and volatility spillovers between two US equity indices (S&P500 and Russell 2000) and three major cryptocurrencies (Bitcoin, Ethereum, Tether) evolution, using daily data, VAR models and [Diebold, Yilmaz, 2012] approach. The findings indicate that post-COVID, bidirectional volatility and return spillovers increased significantly, while pre-pandemic asset interconnectedness was comparably lower. The same results were obtained using daily data from 2013 to 2021, which were gained by [Hung, 2022] for Bitcoin, S&P500, oil, and gold markets. [Akyildirim et al., 2025] also investigated the dynamic interactions between crypto assets and the major stocks of the NASDAQ Blockchain Economy Index[11] during COVID-19. Similarly, the results indicated that market links increased significantly during the pandemic, with clear evidence of unidirectional volatility spillovers running from cryptocurrencies to stocks. More extensive research was introduced by [Vuković et al., 2025], who explored how shocks from three

[10] Spillover – shock transmission from one market (or asset) to another one.
[11] Nasdaq website. (https://indexes.nasdaq.com/Index/Overview/RSBLCN)

major cryptocurrencies, Bitcoin, Ethereum, and XRP, transferred to traditional financial markets, including regional stock markets, bonds, and exchange rates. The study employed daily data over 6.5 years, from mid-2015 until the end of 2022, and utilized impulse response analysis within a BGVAR framework. Based on the main findings, the stock markets were most negatively affected by the shocks in Bitcoin, rather than the shocks in the other two cryptocurrencies. The regions that were most affected by these shocks were the USA, the UK, Brazil, and Germany. Additionally, the impact of shocks from Ethereum on stock indices was found to be statistically insignificant throughout the study period. Employing daily data [Attarzadeh et al., 2024] confirmed that crypto and traditional market interdependence is dynamic and shifts in tandem with economic events: during periods of stress the relations between markets increased and in stable periods the market interconnectedness level became lower. [Harb et al., 2024] using multivariate GARCH models and daily data showed that major cryptocurrencies and equity markets were largely unconnected. Nonetheless, they observed that the heightened volatility in the stock market during the pandemic shock period did have an impact on the volatility of both Bitcoin and Ethereum.

Few authors have included in their research the crisis that began in 2022. [Bampinas, Panagiotidis, 2024] explored how major global shocks, specifically the COVID-19 pandemic and the Russian-Ukraine conflict, influenced the dynamic linkages between stock indices and two main cryptocurrencies using a local Gaussian correlation approach. The authors split daily data into four periods: pre-COVID-19 (January 2019 – February 2020), post-COVID-19 (February – November 2020), pre-conflict (January 2021 – February 2022), and post-conflict (February – July 2022). Their findings reveal that cryptocurrencies became more closely aligned with traditional stock markets during the post-pandemic period, with correlations rising from negative or near-zero to roughly 0.3 – especially in Asian markets like China and Japan. A similar pattern emerged during the conflict period. Consequently, the authors concluded that Bitcoin and Ethereum did not act as safe-haven assets during stock market shocks, suggesting that investors should consider other diversification options. [Ali et al., 2025] analyzed intra-day 10-minute data using TVP-VAR models to investigate the connections between BTC, ETH, and individual US FAANG stocks during market crises. They observed that while asset relationships experienced short-lived changes during both turbulent periods, there was no evidence of shock transmission between markets.

Compared to the mentioned investigations, which were mainly focused on Bitcoin as a proxy to the whole crypto market, this research examines four main cryptocurrencies (Bitcoin, Ethereum, Ripple and Binance Coin). Rather than relying on crypto prices from one specific exchange, the study focuses on cryptocurrency indices, which aggregate prices from most major crypto exchanges. The main difference between this article and the previous ones is the use of more frequent data. While most studies rely on daily data, this paper utilizes 1-minute and 5-minute intervals that allow for capturing intraday dynamics and better aligning with market hours. Moreover, while earlier studies could be primarily useful for medium- and long-term investors, this research aims to provide insights for active market participants like scalper traders. This study includes a correlation analysis of returns and volatilities, as well as the Granger causality test, which was not common in the articles described above.

2. Data

To implement the analysis of crypto and stock market interactions, the main index of the US stock market – S&P500, and four cryptocurrency price indices: Bitcoin (BTCUSDT), Ethereum (ETHUSDT), Ripple (XRPUSDT), Binance Coin (BNBUSDT) were used. S&P500 index data was obtained from NASDAQ and NYSE market data. The data of crypto price indices was extracted from the Binance website.

As a result, the paper examines 1-minute data for 4.5 years: from January 1, 2019, to June 1, 2024. Additionally, all calculations were repeated on 5-minute data to ensure the stability of the obtained results.

2.1. Equity index description

S&P500 – one of the most popular equity indices in the world, that was launched in 1957. This is a market capitalization-weighted index of 500 publicly traded US companies from 11 major sectors. As the S&P500 covers approximately 80% of the total US equity market capitalization, it can be used as a benchmark for the American stock market performance. Like many other indices, S&P500 is not traded directly. However, it is calculated during the trading hours of its underlying stocks, which are regularly traded on the main US stock (NYSE, NASDAQ, CBOE) exchanges from 9:30 am to 4:00 pm Eastern Time.

2.2. Cryptocurrency index description

Cryptocurrency Price Index – is an index that is calculated by Binance every minute as a weighted average price of the crypto asset from major exchanges, such as Binance, Bybit, OKX, KuCoin, Gate.io, Coinbase, Kraken, Bitget and others.

$$P_{weighted,t} = \frac{\sum_{i=1}^{n}\left(P_{i,t} \cdot V_i\right)}{\sum_{i=1}^{n} V_i},$$

where n – the number of exchanges under consideration; $P_{i,t}$ – crypto asset price on the exchange i at each period t (1-min or 5 min); V_i – crypto asset trading volume on the exchange i for a particular day.

This index reflects a reliable benchmark for the fair crypto asset price, as it aggregates values from different sources rather than from one specific exchange. As cryptocurrency exchanges operate 24 hours a day, 7 days a week, crypto price indices are also updated continuously, without any opening and closing hours.

Cryptocurrencies were selected for analysis according to three criteria:

1. The assets should be large enough in terms of market capitalization to be able to influence such a large market as the US stock market. So, it was decided to take into consideration crypto assets, that were in top-10 by market capitalization for the entire period.
2. The assets should have been established no later than the end of 2018 to have a sufficient number of observations for the analysis before the first shocks in 2020 began.

3. The asset should not be a stablecoin, since stablecoins were created to provide price stability and to be resistant to volatilities.

As a result, the paper considers four crypto indices – BTCUSDT, ETHUSDT, BNBUSDT, and XRPUSDT.

Table 1.

Cryptocurrencies description

Crypto asset	Short name	Launch year	Market capitalization, $ (Dec. 2024)	Market Share, % (Dec. 2024)
Bitcoin	BTC	2009	2.01 tn	57
Ethereum	ETH	2015	445 bn	13
Binance Coin	BNB	2017	135 bn	4
Ripple	XRP	2012	100 bn	0.3

Source: CoinMarketCap website.

2.3. Data processing

To investigate the relationship between the two markets, the data obtained was processed according to the following procedure:

1. As crypto and S&P500 indices price values are presented in different time zones, the data was converted to a unified timestamp. Cryptocurrency prices are mostly shown in Coordinated Universal Time (UTC) to avoid confusion in different countries. At the same time, the S&P500 index follows Eastern Time (ET). As the US adheres to Daylight saving time practice[12], while bringing S&P500 data to UTC time, it was considered that ET refers to both: Eastern Standard Time (UTC-5) and Eastern Daylight Time (UTC-4), depending on the season.

2. To bypass the issues with limited trading hours on traditional US stock exchanges, cryptocurrency index data, which is updated 24/7, has been trimmed in line with the availability of S&P500 data. As a result, weekends, national American holidays, as well as non-trading hours on trading days (hours outside 9:30 am to 4:00 pm ET) were excluded from consideration.

3. To implement the statistical analysis of markets' interconnectedness, two key metrics: price returns and volatilities were calculated. Price returns are commonly understood as log-scaled returns. Volatilities were calculated using 1-minute high and low prices and applying the Parkinson estimator [Parkinson 1980].

$$Log\ Return_t = \ln\left(\frac{P_t}{P_{t-1}}\right),$$

where P_t – asset price at the period t; P_{t-1} – asset price at the previous period $(t-1)$.

[12] Daylight saving time practice – the practice of setting the clock forward by one hour starting from the second Sunday in March and ending in the first Sunday in November.

$$Volatility_t = \sqrt{0.361 \cdot \left(ln\left(\frac{P_t^{max}}{P_t^{min}} \right) \right)^2},$$

where P_t^{max} – asset maximum price for period t; P_t^{min} – asset minimum price for period t.

4. As the cryptocurrency market may experience price fluctuations outside the S&P500 index trading hours, the observations at the boundary of days were excluded.

5. The procedure of return and volatility calculations was repeated for 5-minute data.

Fig. 1 and Fig. 2 represent returns and volatilities for BTCUSDT and S&P500. Charts for other crypto assets look the same.

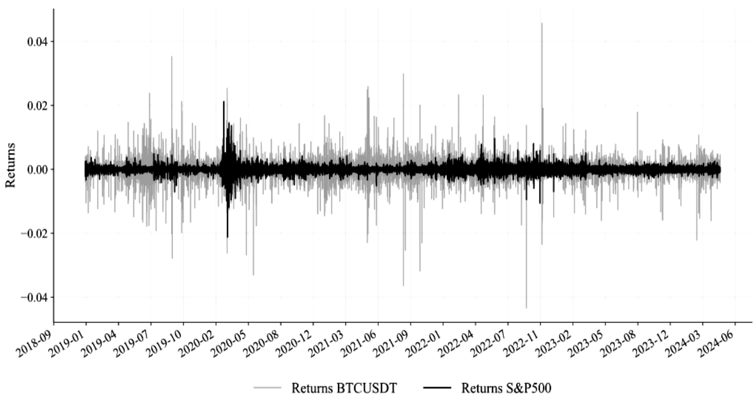


Fig. 1. Returns of BTCUSDT (grey line) and S&P500 index (black line), 1-minute data

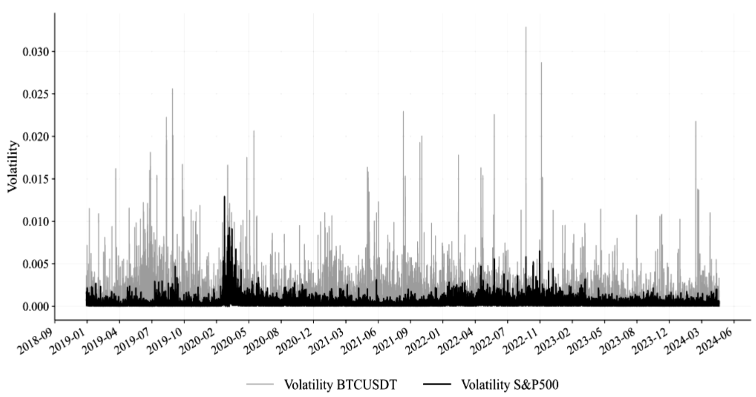


Fig. 2. Price volatility of BTCUSDT (grey line) and S&P500 index (black line), 1-minute data

3. Methodology

As a first step in assessing the relationship between the two markets, the pairwise correlations between the returns and volatilities of each crypto asset and S&P500 index were calculated. The correlations were evaluated separately for each year, starting from 2019, and dynamically using rolling windows.

The next step was dedicated to establishing the direction of influence between assets. One of the methods that can be used to examine it, is the Granger causality test [Granger, 1969]. Conducting such a test on both returns and volatilities provided insights into lead-lag relationships between the asset pairs and helped identify how the risk may be transmitted between them. The implementation of the Granger causality test included several steps:

1. Check for stationarity. Time series were checked for stationarity using the Augmented Dickey-Fuller test (ADF-test) [Dickey, Fuller, 1981], as both time series that were selected for the Granger causality test should be stationary.
2. Lag selection. The selected number of lags affects the estimated models in the next step. In this paper, for 1-minute data lags from one to ten were consistently used.
3. Model estimation. To implement the Granger causality test, the autoregressive (AR) model for time series y_t was evaluated.

$$y_t = c + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{p} \beta_i x_{t-i} + \varepsilon_t,$$

where y_t – dependent variable at time t (return or volatility of the first asset); x_t – independent variable at time t (return or volatility of the second asset); α_i – the coefficients of y_t lagged values; β_i – the coefficients of the independent variable x_t lagged values; p – the selected number of lags on the second step, $\varepsilon_t \sim WN\left(0, \sigma^2\right)$.

4. F-test. The null hypothesis of the Granger causality test assumes that past values of x_t do not provide additional predictive power for y_t model (or do not Granger cause y_t). The alternative hypothesis suggests that at least one of the x_t significantly differs from zero, which means that previous values significantly improve the prediction power of model y_t.

$$H0: \beta_1 = \ldots = \beta_p = 0.$$

In this paper, the tests were performed for each asset pair (in total, four asset pairs: S&P500 with BTCUSDT, ETHUSDT, BNBUSDT and XRPUSDT) for both returns and volatilities.

4. Main results

This section is divided into two parts: the first presents the correlation analysis, and the second outlines the findings from the Granger causality test. The results obtained for the 1- and 5-minute data are similar.

4.1. Correlation analysis

4.1.1. Return correlation analysis

The entire period under review was divided into six intervals of one year, starting in 2019 and ending in 2024. It is worth noting that the 2024 sample included data only up to June 2024. The analysis was carried out separately for return and volatility series, pairing each crypto index with the S&P500 index.

Based on the main findings (Fig. 3) for the 1-minute returns, there were no observable correlations in returns among any of the four asset pairs in 2019 (during the pre-pandemic time). The correlations between S&P500 and BTCUSDT, ETHUSDT, and BNBUSDT returns were around 0.004, whereas the S&P500 and XRPUSDT pair exhibited an almost zero correlation. However, after the onset of the COVID-19 pandemic in 2020, the situation changed and the correlations significantly increased for all the asset pairs: Bitcoin returns demonstrated the highest correlation with the US stock index returns equal to 0.19 followed by ETH – S&P500 pair with 0.18 correlation value. The connections with other crypto assets have also shown an increase, with the BNB – S&P500 pair reaching 0.16 and XRP – S&P500 pairs – 0.10. This suggests that crypto and equity returns were beginning to move in the same direction more often than before. In 2021, the correlation values remained largely unchanged with just a slight decrease from 2020. The second peak occurred in 2022 when the correlation for all asset pairs moved to moderate levels. The highest values, which turned out to be slightly above 0.50, continued to be seen between the US stock index and Bitcoin and Ethereum. For BNB and Ripple, the values reached 0.44 and 0.41, respectively. This marks a pronounced convergence in returns between the US stock market and the main crypto indices. Over the last 2 years, the overall correlation level between the cryptocurrencies and S&P500 returns decreased, but the annual values no longer fell below the level that was in 2020.

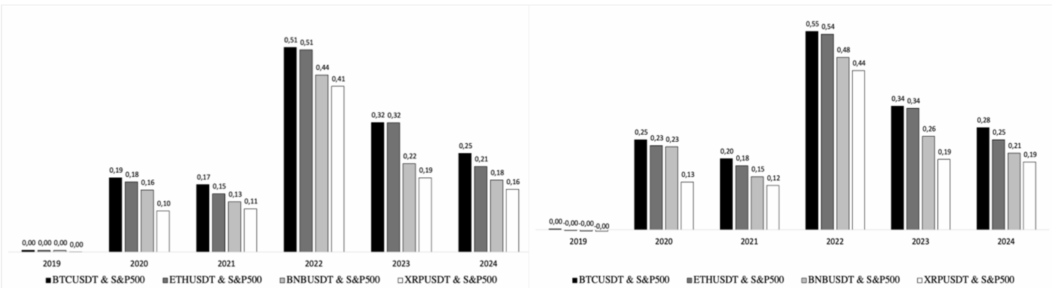


Fig. 3. Return correlations between crypto indices & S&P500 index,
1-minute data (left), 5-minute data (right)

To test the obtained results for robustness, return correlations for each asset pair using 5-minute data were calculated. According to Fig. 3, the derived findings correspond to the results that were acquired on the 1-minute data: correlations on the 5-minute data are slightly higher starting from 2020, but the overall trend remains the same. To the greatest extent, in terms of the return correlations, the most related crypto assets to the S&P500 after 2020 were

BTCUSDT and ETHUSDT, while the correlations for the XRPUSDT – S&P500 and BNBUSDT – S&P500 pairs were slightly lower.

To examine the changes in correlations between crypto and stock indices in more detail, a dynamic correlation graph was constructed using the 1-month (Fig. 4) and 3-month (Fig. 5) rolling window. Note that the values of the abscissa axis correspond to the right end of the window.

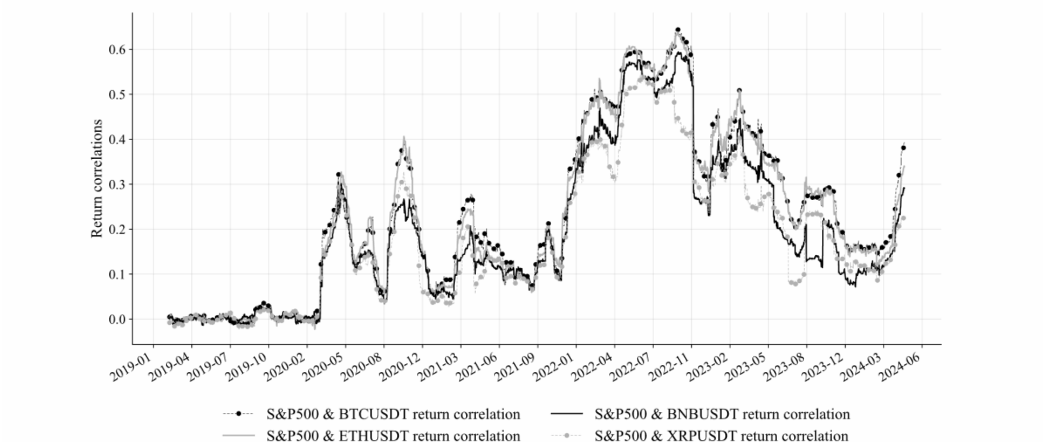


Fig. 4. Returns correlations between crypto indices & S&P500 index using 1-month rolling window, 1-minute data

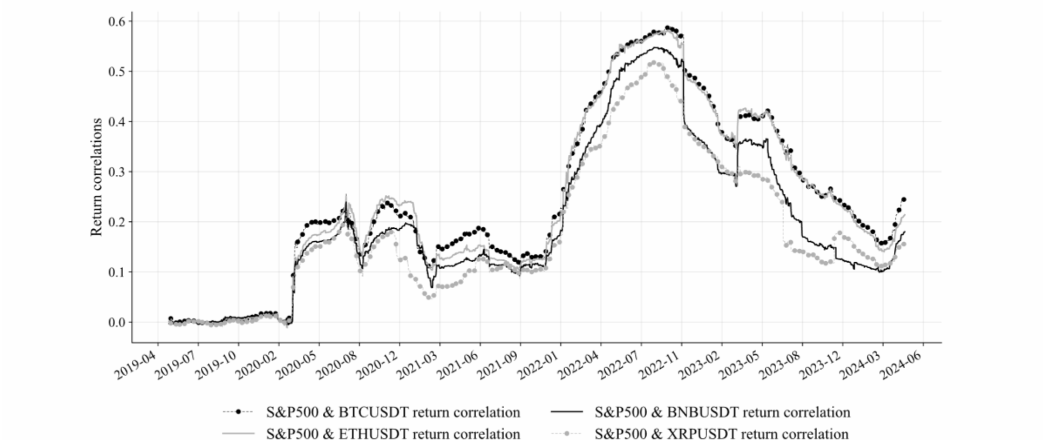


Fig. 5. Returns correlations between crypto indices & S&P500 index using 3-months rolling window, 1-minute data

According to Fig. 4 and Fig. 5, during 2019, all four crypto – S&P500 pair return correlations were close to zero, indicating that neither BTCUSDT, ETHUSDT, BNBUSDT, nor XRPUSDT moved in tandem with the US stock index. At the beginning of 2020, which coincides with the onset of COVID-19 and the change in the virus status from an epidemic to a pandemic, there has been a noticeable jump in correlations between S&P500 and all four crypto assets. The correlations for all the pairs have been increased from zero values to 0.1-0.2 range. During 2020 and 2021, BTC and ETH correlations with the S&P500 were higher than the correlations of the other two asset pairs. It is noteworthy that during certain periods, the return correlation in the ETHUST – S&P500 pair was even higher than in the BTCUSDT – S&P500 pair. At the beginning of 2022, the correlations of all four cryptocurrencies with the stock index increased sharply again. The connection level in Bitcoin – S&P500 and Ethereum – S&P500 pairs reached 0.60 in mid-2022. Ripple and S&P500 pair interconnectedness levels also tended to increase, though they usually remained slightly lower than the level of the index relationship with the other three cryptocurrencies. By early 2023, correlations decreased to 0.10–0.30 values, suggesting that cryptos and stock indices were no longer as tightly linked in terms of returns.

The results that were obtained for the 5-minute data: for the 1-month (Fig. 6) and 3-month (Fig. 7) rolling windows are close to those that were gained for the 1-minute data. There are similar patterns and absolute values of correlations.

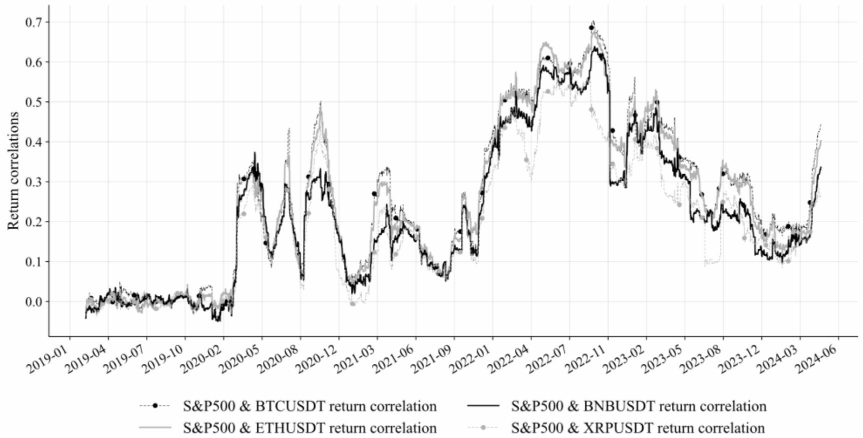


Fig. 6. Returns correlations between crypto indices & S&P500 index using 1-month rolling window, 5-minute data

Overall, the correlation between two markets steadily increased over time – this trend aligns with the gradual growth of the cryptocurrency market in terms of trading volumes and number of participants. However, during the whole period notable spikes were detected twice: in 2020, when COVID-19 happened, and in 2022 with the start of the military special operation. Both these periods may be potentially attributed to periods of economic instability and uncertainty.

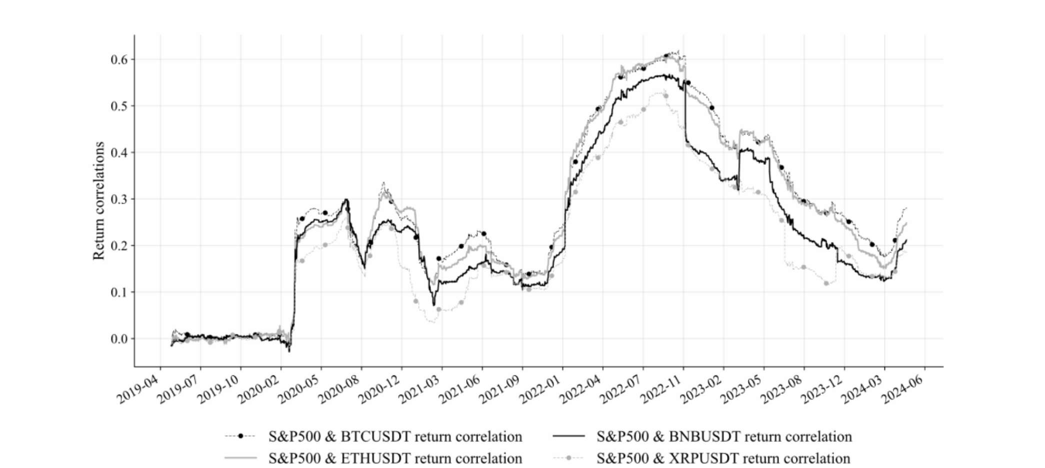


Fig. 7. Returns correlations between crypto indices & S&P500 index using 3-months rolling window, 5-minute dat

4.1.2. Volatility correlation analysis

The subsequent step involved conducting the same correlation analysis but focusing on volatilities rather than on returns. Both charts (Fig. 8) depict how the price volatility of each crypto index (BTCUSDT, ETHUSDT, BNBUSDT, and XRPUSDT) aligns with volatility in the S&P 500 over time. Firstly, the volatility correlations over the selected years will be described and then – the dynamic volatility correlations with the 1- and 3-month rolling windows.

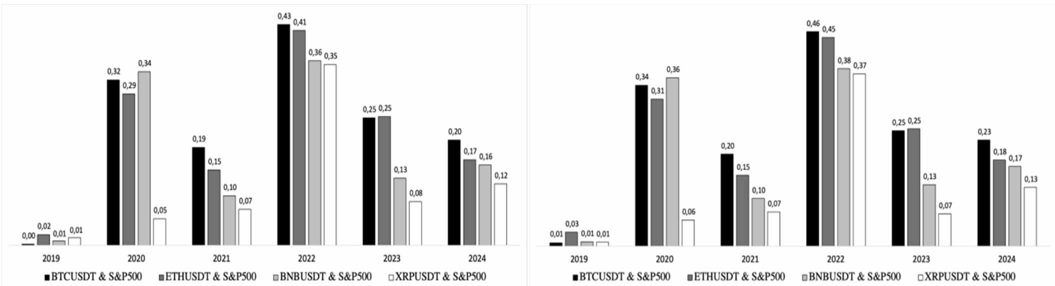


Fig. 8. Volatility correlations between crypto indices & S&P500 index, 1-minute data (left), 5-minute data (right)

Like in returns correlation analysis, there were no close connections between the two markets until 2020. In the COVID-year values increased for three main pairs, suggesting that fluctuations in these crypto assets and the S&P 500 became more connected during that time-frame. The most pronounced increases again occurred in 2022, with the maximum correlation values for Bitcoin – S&P500 and Ethereum – S&P500 assets pairs equal to over 0.40. After that, the connection level showed a small decrease for all asset pairs. It is noteworthy that XRPUSDT was least linked to the US stock market, with the only exception in 2022, when even in this pair the correlation increased to 0.35. The values obtained for the 5-minute data were also slightly higher than for the 1-minute data, but the general patterns were still preserved.

Fig 9 and Fig 10 represent volatility correlation dynamics.

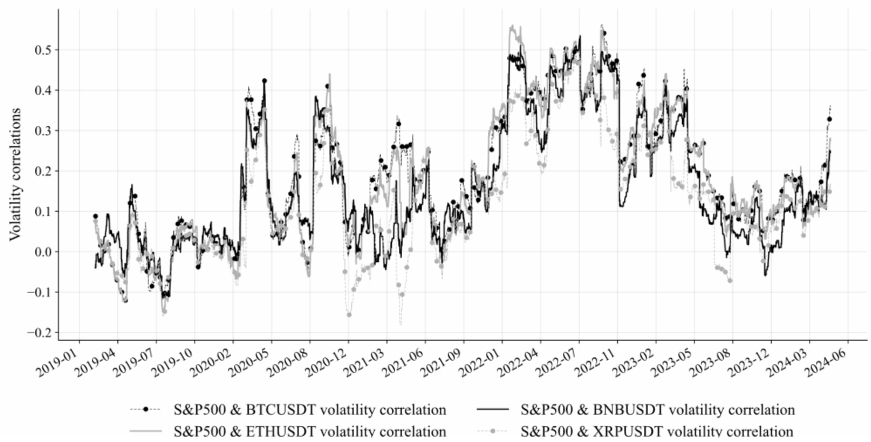


Fig. 9. Volatility correlations between crypto indices & S&P500 index using 1-month rolling window, 1-minute data

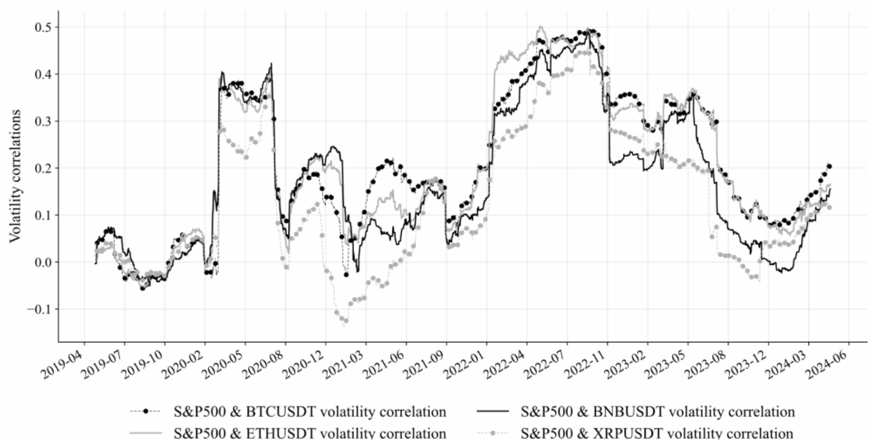


Fig. 10. Volatility correlations between crypto indices & S&P500 index using 3-months rolling window, 1-minute data

Referring to Fig. 9 and Fig. 10, it may be noted that volatility correlations exhibit patterns broadly similar to those of return correlations: negligible co-movements before 2020 and two peaks during the Covid-19 and 2022 with maximum values closed to 0.4 and 0.5 respectively. It was followed by a retreat into moderate correlations in 2023 and 2024. In a similar way to returns, the volatility correlations in the BTCUSDT – S&P500 and ETHUSDT – S&P 500 pairs were almost always higher than in the other two asset pairs, because these two cryptocurrencies have the largest capitalization. What was also remarkable depending on the chosen time interval, the connectivity level of the US stock index with the Bitcoin index was lower than with the Ethereum index (like at the beginning of 2022). Moreover, it can be noticed that the volatility correlations in 2020 were on average higher than the returns correlation level, however, in 2022 the situation reversed. 5-minute data charts (Fig. 11 and Fig. 12) were similar to 1-minute charts for both 1- and 3-month rolling windows.

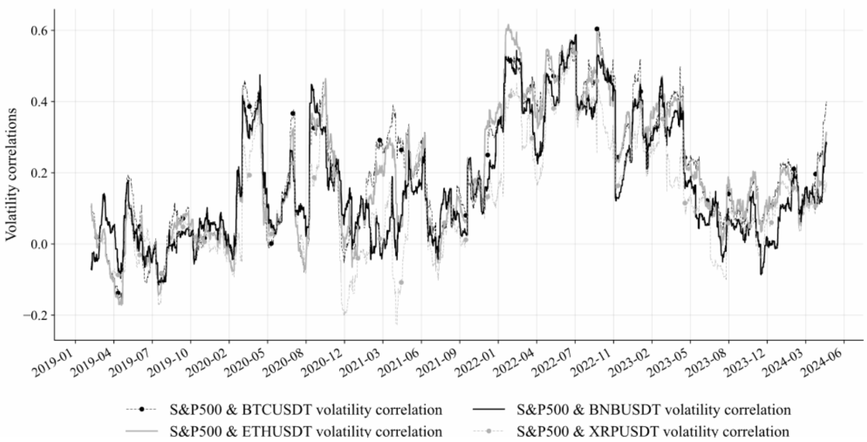


Fig. 11. Volatility correlations between crypto indices & S&P500 index using 1-month rolling window, 5-minute da

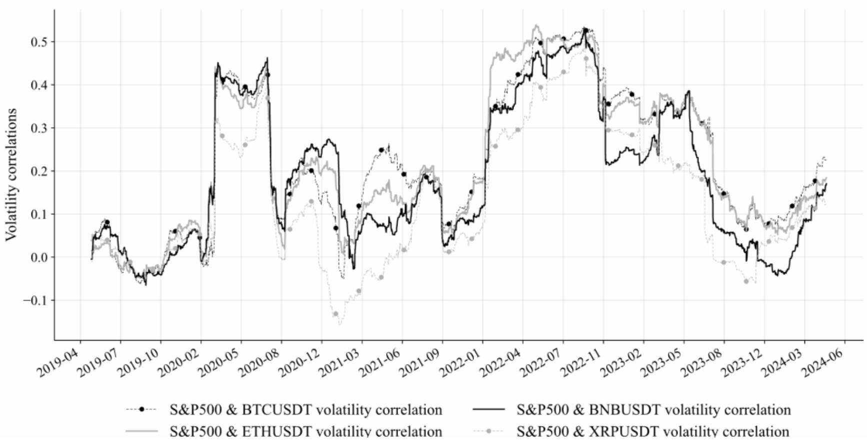


Fig. 12. Volatility correlations between crypto indices & S&P500 index using 3-months rolling window, 5-minute data

To sum up, each pair of crypto and S&P500 indices may have different correlations in terms of volatilities and returns, but all of them generally had the same interconnectedness trend. Whenever broader market stress triggered volatility in the US stock market, crypto indices appeared to experience similar swings and the same was true for returns.

4.2. Granger causality

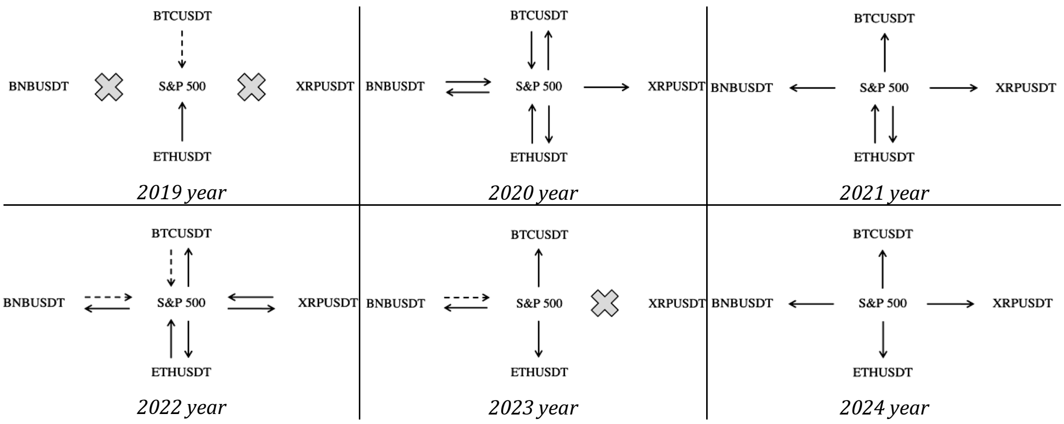
The next stage of the research involved conducting the Granger causality test to determine the direction of influence between the assets. In this part, the 1-minute volatility and return data was again split into six intervals of one year each.

Before implementing the Granger causality test itself, each time series was tested for stationarity using the ADF test. The test results demonstrated that all series were stationary at the 5% significance level.

For each year, ten Granger causality tests were conducted, corresponding to lags 1 through 10 (1 to 10 minutes). Lags from 1 to 3 were classified as short-run influence patterns, whereas the results for 7–10 lags were defined as long-run effects. This approach reveals how movements in one market can have or not have immediate and delayed impacts on another market.

4.2.1. Returns Granger causality analysis

Fig. 13 corresponds to the Granger causality test for short-term connections, 1–3 lags (1–3 minutes delay), and Fig. 14 relates to more long-term relationships (7-10 minutes delay) between markets' returns. According to the results, during 2019 crypto assets and the stock market showed minimal interdependences: no significant (5% significance level) causal relationships between the two markets were detected in the long-run period. For some short-run lags, there was an unstable impact from ETH and BTC on the S&P500, and at the same time, no reverse effect was observed.

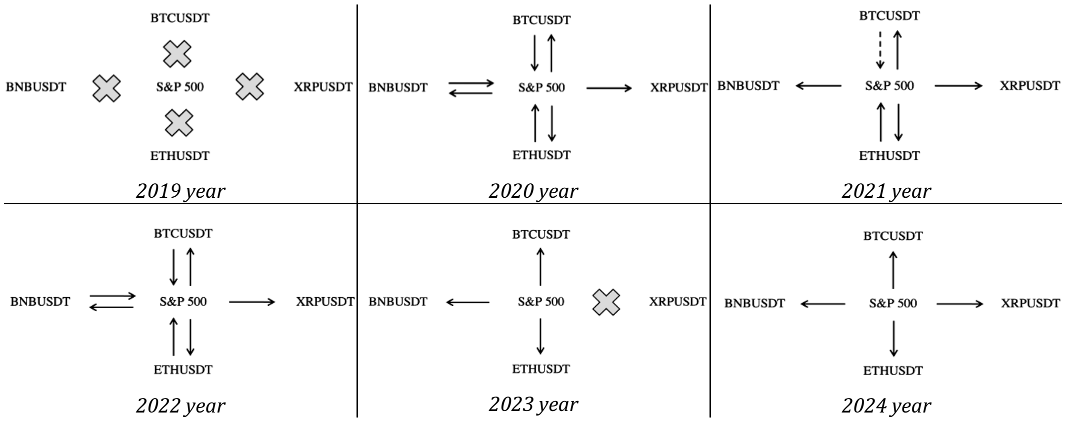


Notes. Solid arrow – a statistically significant effect at a 5% significance level at each lag. Broken arrow – a statistically significant effect at a 5% significance level not at each lag. Cross – no significant relationships at any adequate significance level.

Fig. 13. Granger causality tests for 1–3 lags (short-run effects) on returns, 1-minute data

However, significant changes happened in 2020: S&P500 started to influence all the crypto assets in short- and long-terms, while only three cryptocurrencies (BTC, ETH, BNB) showed a significant impact on the US stock market.

Notably, in 2021, the impact of the stock market has remained unchanged in both the short- and the long-runs: S&P500 granger-caused all four crypto indices on a 5% significance level, suggesting that stock market movements informed crypto returns. Conversely, Bitcoin and Ethereum exhibited some capacity to affect the S&P 500: BTC only in the long term and ETH in both the short and long term. At the same time, Binance Coin and Ripple did not show consistent influence on stock index returns in 2021. In the following 2022 year, the relationships between the two markets were significantly strengthened again: the results for the short-run revealed bidirectional effects for each crypto-equity index pair. In the long run, however, one exception emerged – Ripple did not significantly affect the S&P500.



Notes. Solid arrow – a statistically significant effect at a 5% significance level at each lag. Broken arrow – a statistically significant effect at a 5% significance level not at each lag. Cross – no significant relationships at any adequate significance level.

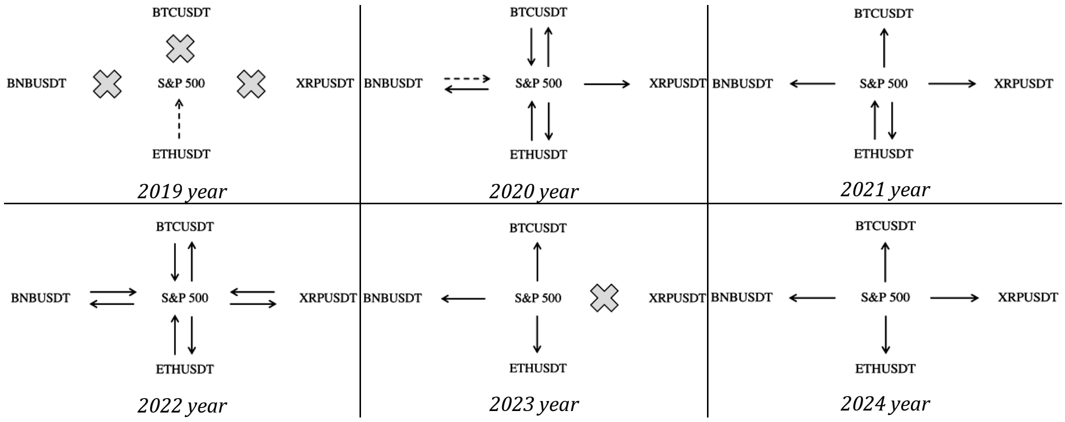
Fig. 14. Granger causality tests for 7–10 lags (long-run effects) on returns, 1-minute data

In 2023, the pattern shifted toward a more one-sided relationship, where the stock index influenced the crypto market (specifically three cryptocurrencies: BTC, ETH and BNB). Cryptocurrencies in turn did not show any significant influence on the S&P 500. This asymmetry continued in 2024 when the US equity index influenced all four cryptocurrencies in both short and long terms, but none of the crypto assets demonstrated a reverse effect.

These findings support the correlation analysis results: before the market shock in 2020, two markets tended to operate independently. However, during periods of instability, markets converged strongly and began to influence each other, as demonstrated in 2020 and 2022. At the same time, the US stock market started to exert a more permanent and stable impact on cryptocurrencies rather than the opposite, as the influence of the stock market on crypto assets was also detected in 2021 and 2023 years, which did not apply to shock ones.

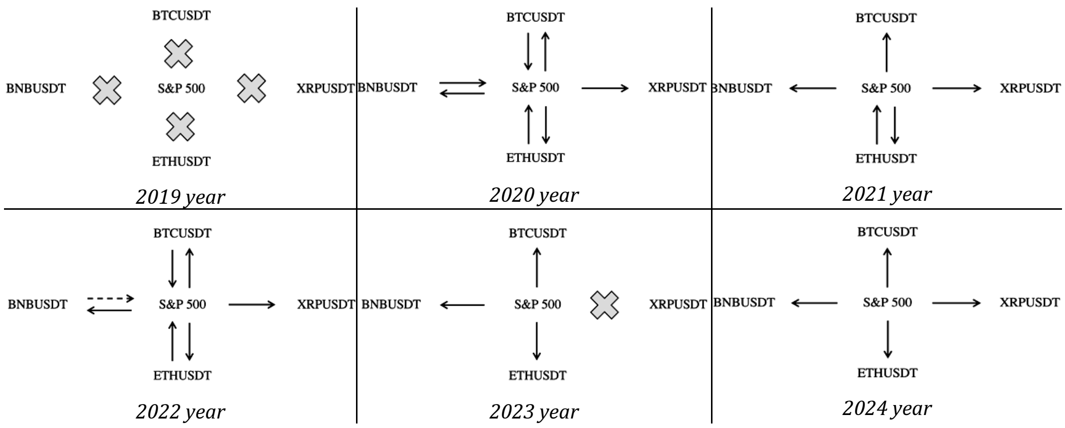
4.2.2. Volatility Granger causality analysis

Same Granger causality test results were acquired for 1-minute volatility data. The short- (1–3 minutes delay) and long-term (7–10 minutes delay) connections of crypto assets and S&P500 are represented on Fig. 15 and Fig. 16 respectively. Both markets were moving independently before 2020: no influence was detected in either direction between any cryptos' and S&P500 volatilities, whether in the short run or the long run. In 2020 a statistically significant bidirectional relationship was observed in all asset pairs, except XRP – S&P500. These findings are generally consistent with the previous results. In 2021, the level of interconnection decreased. ETH – S&P500 appeared the only pair in which two-way relationships were observed. In other cases, there was a unidirectional impact from the US stock index in both, the short- and long-run.



Notes. Solid arrow – a statistically significant effect at a 5% significance level at each lag. Broken arrow – a statistically significant effect at a 5% significance level not at each lag. Cross – no significant relationships at any adequate significance level.

Fig. 15. Granger causality tests for 1–3 lags (short-run effects) on volatilities, 1-minute data



Notes. Solid arrow – a statistically significant effect at a 5% significance level at each lag. Broken arrow – a statistically significant effect at a 5% significance level not at each lag. Cross – no significant relationships at any adequate significance level.

Fig. 16. Granger causality tests for 7–10 lags (long-run effects) on volatilities, 1-minute data

During 2022, the bidirectional significant influence was again detected in each pair, which confirmed that 2022 increased cross-market linkages in terms of both volatilities and price movements. After 2022, the markets' connection level decreased considerably. Mostly, only one-way relationships were observed: the stock market influenced the cryptocurrencies.

To sum up, volatility-based Granger causality results reinforce the view that economic shocks trigger cross-market relationships, which then partially disappear but never completely revert to the minimal linkages found before COVID-19.

4.3. Results discussion

Based on the obtained findings in the investigation, the greatest level of interconnectedness between crypto and US stock markets was observed in 2020 and 2022, two years of potential global economic stress. In 2020 the world faced uncertainty due to COVID-19, which led to market crashes in March 2020 and volatile recovery phases. The introduced monetary policies in different countries raised concerns about inflation and fiscal sustainability. In 2022 the military special operation in Ukraine started and it affected global inflation levels and triggered a dramatic increase of interest rates around the world. As a result, unstable economic conditions and high market volatility in these years led to synchronous movements due to increased risk aversion by investors.

To validate whether these years indeed coincided with increased uncertainty, the TEU, Twitter-based Economic Uncertainty, index was selected. The data was gained from the Economic Uncertainty website and turned out to be available till mid-2023[13]. This index expresses the amount of uncertainty, that was expressed in the social network X (previously Twitter) over time. In [Pogorelova, 2024] paper, this index was also analyzed alongside the VIX index, which will be detailed below.

Fig. 17 confirmed the previously mentioned statements: firstly, the TEU index values dramatically increased in February – March 2020, reflecting the onset of COVID-19, and the second rise started in 2022 likely linked to the geopolitical tensions. It is worth noting that in other years, the index values were not so high, which is also consistent with gained lower levels of markets' connectivity in terms of return and volatility correlations and Granger causality.

To better understand the sentiment in both markets over time, it was decided to additionally consider two «fear indices»: VIX for the S&P500 market and the Fear & Greed index for crypto assets. VIX, or Volatility Index, measures the market anticipations of near-term volatility in the S&P500 and reflects the investor's expected market risk level. The data was obtained from the CBOE website[14] and it covers the entire period under consideration in the study (Fig. 18).

Crypto Fear & Greed index assesses the sentiment of the crypto market. It aggregates several factors, like market volatility, volume, public interest in social media and other trends. The data was obtained using CoinMarketCap API and Alternative.me website[15]. Fear & Greed index values vary from 0 to 100, which relates to extreme fear and greed respectively. Since the

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[13] Economic Policy Uncertainty website. (http://policyuncertainty.com/twitter_uncert.html)

[14] The VIX index is calculated by CBOE – Chicago Board Options Exchange. (https://www.cboe.com/tradable_products/vix/vix_historical_data/)

[15] Alternative.me. (https://alternative.me/crypto/fear-and-greed-index/), CoinMarketCap. (https://coinmarketcap.com/charts/fear-and-greed-index/)

scale in this index is reversed (the lower the index value, the greater the fear) from the one used in VIX, it was decided to mirror the values relative to the abscissa axis, so 0 value corresponds to greed, 100 – to fear (Fig. 19).

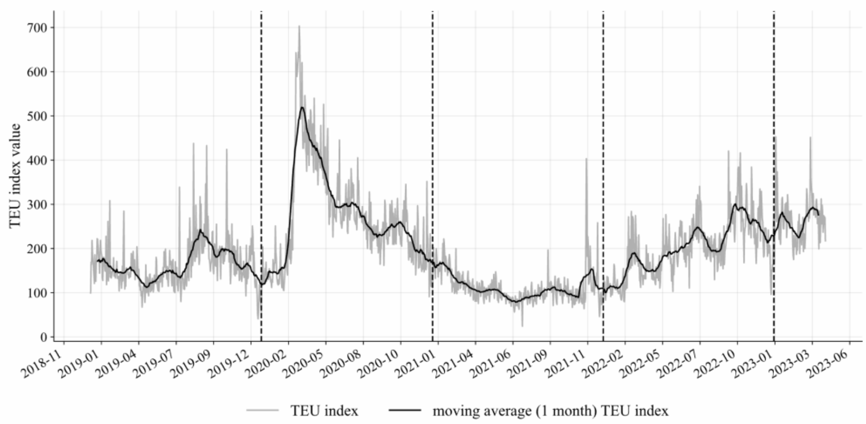

Fig. 17. Twitter Economic Uncertainty index (2019–2023)

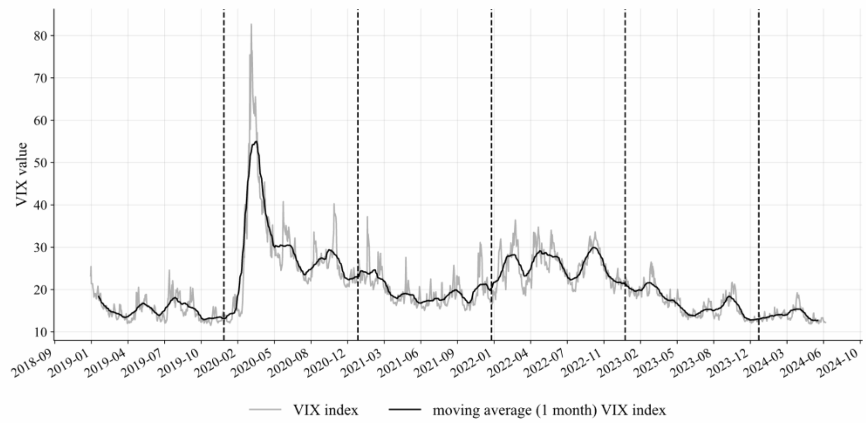

Fig. 18. VIX index (2019–2024)

Both charts (Fig. 18 and Fig. 19) also show sharp peaks in 2020 and 2022, reflecting fear and volatility in both markets. The increased fear corresponds to a risk aversion behavior among market participants. In these environments investors move in or out all their assets, reflecting flight-to-safety sentiment, and such a collective reaction causes the rise in connections across markets. After 2022, both markets calm down and investor behavior becomes more independent, this corresponds to the lower levels of interconnection obtained in previous chapters. It is important to note that the COVID-year significantly impacted the crypto market by attracting investors from traditional markets, who were looking for alternative returns. Therefore, until 2020, similar investor behaviors could not have such a strong effect on market connectivity.

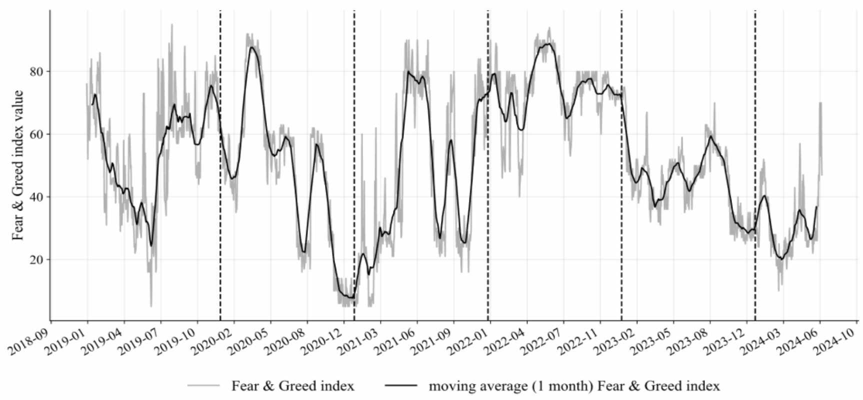

Fig. 19. Fear & Greed crypto index (2019–2024)

5. Conclusion

The study examined the relationship between the cryptocurrency market (represented by the four largest crypto assets: BTC, ETH, BNB and XRP) and the US stock market (S&P500), focusing on how the level of interconnection has changed over time. The investigation involves calculating correlations between the returns and volatilities and determining the direction of asset relationships through Granger causality tests. One of the most distinctive aspects of this paper is the use of granular 1-minute and 5-minute data, which allowed to create potentially valuable findings for active market participants like scalper traders.

Throughout the study, it became apparent that before COVID-19 crypto assets and the US stock market did not have close relationships, as the level of return and volatility correlations were negligible. This finding is consistent with the conclusions of reviewed articles that included the pre-COVID period in their analyses. During other stable economic periods (like the period after 2022), the connectivity between the two markets tends to decrease, reflecting more independent behaviors. However, during episodes of high uncertainty, such as the COVID-19 pandemic in 2020 and geopolitical tensions in 2022, the connections between crypto and stock markets increased. This was evidenced by raised correlations in returns and volatilities in both years. Using a different method (TVP-VAR model) and daily data, [Attarzadeh et al., 2024] similarly argued that stock-cryptocurrency interconnections intensify during periods of stress and diminish during calmer times.

The two largest cryptocurrencies: Bitcoin and Ethereum turned out to be the most interconnected with S&P500. The returns correlation between them and the US stock index peaked at 0.3 and 0.6 in 2020 and 2022, while the correlations of volatility reached 0.4 and 0.5, respectively in these years. Similar conclusions regarding the increasing interconnectedness of markets during times of uncertainty have been highlighted in the previous studies of [Bampinas, Panagiotidis, 2024] and [Iyer, 2022], who used daily data. However, their findings were particularly relevant and interesting to institutional investors. One of the key results of our paper is that, even at the intraday level, we observe heightened synchronization in market volatility during periods of economic uncertainty. Immediate reactions to news, earnings reports, SEC rulings, social media activity, or even tweets from figures like Elon Musk can further drive this intraday synchronization. These dynamics are especially important for high-frequency traders.

At the same time, Ripple was least correlated with the S&P500. Even though after 2022 both markets calmed down and the relationship between them weakened, the level of correlations has never fallen below those before COVID-19. This indicates structural changes in the cryptocurrency market and reflects that the crypto assets are approaching the classic stock market in their behavior.

Granger causality tests provided additional insights into the relationship of the asset. In times of high uncertainty, the tests often indicated bidirectional connections in both long and short terms, suggesting that not only the traditional market influenced crypto markets, but crypto assets also affected the US stock market. In quieter periods, interconnections became more unidirectional, and more often S&P500 Granger caused some crypto assets. The bidirectional relationships in such years sometimes have been found between main crypto assets (Bitcoin and Ethereum) and the S&P500. Ripple again became the less connected to the US stock market: and often, no relationship was observed in this pair in quiet years.

Thus, it can be assumed that due to the constant growth of crypto market trading volumes and a number of traditional market participants who invest in cryptocurrencies during periods of high instability, the crypto and stock markets will show the same behavior as in 2020 and 2022, and levels of convergence may be even higher. This, in turn, indicates that the crypto market is losing its diversifying function, especially in stressed periods. As these results confirm earlier daily data studies, not only investors but also active players like scalper traders should be aware of interconnected risks.

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Анализ взаимосвязи рынка акций и криптовалют

Бучко Анастасия Алексеевна[1], **Пересецкий Анатолий Абрамович**[2]

[1] Аспирант, Национальный исследовательский университет
«Высшая школа экономики»,
11, Покровский бульвар, Москва, 101000, Россия.
E-mail: aasergeeva@hse.ru

[2] Д.э.н., профессор, Национальный исследовательский университет
«Высшая школа экономики»,
11, Покровский бульвар, Москва, 101000, Россия.
E-mail: aperesetsky@hse.ru

В последние годы рынок криптовалют становится все более популярным: институциональные и розничные инвесторы, а также различные торговые компании начали положительно относиться к криптоактивам. В результате уровень взаимосвязи между криптовалютами и традиционными рынками сильно изменился. Акции заслуживают пристального внимания, поскольку являются ключевым активом для многих инвесторов. В этой статье исследуется развивающаяся взаимосвязь между криптоактивами и фондовым рынком США, основное внимание уделяется четырем крупнейшим криптовалютам: Bitcoin (BTCUSDT), Ethereum (ETHUSDT), Ripple (XRPUSDT), Binance Coin (BNBUSDT) и фондовому индексу США (S&P500). Используя корреляционный анализ доходностей и волатильностей, а также тесты на причинность Грейнджера, исследование показывает, как два рынка взаимосвязаны. Для проведения анализа были использованы 1-минутные и 5-минутные данные за 4,5 года, с 2019 г. до середины 2024 г. Использование внутридневных данных отличает это исследование от предыдущих, в которых преимущественно использовались ежедневные данные. Более гранулярные данные также позволяют сделать выводы, которые могут быть интересны активным участникам рынка, таким как трейдеры-скальперы. Результаты показывают, что криптовалюты становятся более связанными с традиционными финансовыми рынками в периоды глобальной экономической нестабильности, такие как COVID-19 в 2020 г. и геополитическая напряженность в 2022 г. Более того, согласно тестам на причинность Грейнджера, в стрессовые годы связи между рынками становятся двунаправленными, что указывает на взаимное влияние рынков друг на друга. С другой стороны, в более спокойные периоды уровень корреляций снижается, а тесты на причинность Грейнджера выявляют преимущественно однонаправленное влияние фондового рынка США на все четыре криптовалюты.

Ключевые слова: криптовалюты; акции; S&P500; доходность; волатильность; корреляции; причинность по Грейнджеру.