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DYNAMIC INTERRELATIONSHIPS AMONG BITCOIN, BONDS, AND SECTORAL INDICES IN INDIA: EVIDENCE FROM PRE- AND POST-COVID-19

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Abstract

This study employs the Maximal Overlap Discrete Wavelet Transform technique to analyze the wavelet-based correlations between Bitcoin, bond markets, and thirteen sectoral stock indices in India over the period from 2017 to 2023, focusing on the comparison of pre-and post-COVID-19 pandemic effects. The aim is to investigate the dynamic interrelationships and to understand the impact of the COVID-19 pandemic on these financial assets. The study period is divided into pre-COVID-19 and post-COVID-19. Findings from the study reveal a minimal negative correlation between Bitcoin, bond markets, and the sectoral stock indices in the pre-COVID era, indicating a lack of significant interdependence among these assets. However, the scenario changes markedly in the post-COVID period, shifting towards a positive correlation. This shift suggests that the COVID-19 pandemic has altered the relationship dynamics, leading to a more interconnected financial environment where movements in Bitcoin have begun to show a significant positive correlation with the movements in bond and sectoral stock indices in India. The study contributes to the existing literature by providing empirical evidence of how external shocks, such as the COVID-19 pandemic, can influence the correlation patterns among different financial assets. It highlights the importance of considering the changing dynamics in financial market correlations for investors, policymakers, and researchers in portfolio diversification, risk management, and financial stability analysis. Further, it underscores the role of alternative investments like Bitcoin in the evolving market landscape, particularly in response to global crises.

JEL classification: G01, G15
Keywords: Bitcoin, Indian Financial Markets, MODWT, Wavelet Analysis, COVID-19

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Introduction

The advent of cryptocurrencies is one of the most significant developments to impact the financial world in recent years. Cryptocurrencies have proliferated and are now popular assets in global financial markets (Białkowski, 2020; Fang et al., 2021; Li et al., 2021), attracting media attention, individual investors, institutional investors, and regulators and becoming an essential and emerging topic in several fields of academic research (Angerer et al., 2021). One of the earliest and best-known cryptocurrencies, Bitcoin, was first introduced by Nakamoto (2008), and since its inception, it has grown from $0 in October 2009 to more than $26,000 in June 2023 (CoinMarketCap.com, 2023).

With the backing of several investment banks and the launch of Bitcoin futures and options by Chicago Mercantile Exchange (CME), Bitcoin began to establish itself as a prominent asset class among institutional and retail investors. Due to its highly volatile nature, there is ongoing debate over whether Bitcoin is a currency, an investment, or a speculative asset. While some studies, such as Bouoiyour et al. (2019) and Su et al. (2020), argue that Bitcoin has hedging abilities on par with the US Dollar and gold and may serve as an asset in a diversified investment portfolio, other studies suggest that Bitcoin is a purely speculative asset that does not fulfill any of the traditional functions of money, such as acting as a store of value. For example, Baur et al. (2018) and Yermack (2015) have found that Bitcoin is primarily used for speculative purposes and are not widely accepted as a means of payment or store of value. These studies caution that Bitcoin is a risky investment and may not be suitable for all investors.

Given this uncertainty about Bitcoin's character, the issue of its causal relationship with other financial assets, such as stocks, bonds, currencies, and commodities, must be addressed (Corbet et al., 2020; Hung, 2020; Ji et al., 2018; Maghyereh & Abdoh, 2020). Thus, establishing this association will not only help international investors in better portfolio allocation, but policymakers will be able to understand its dynamics and effects on financial market stability although only a handful of studies such as Majumder (2022), Hung (2021), Jana and Sahu (2023), Murty et al. (2022), Rijanto (2023) have investigated this relationship specifically within the context of the Indian stock market. Using various methodology such as GARCH and wavelet coherence, the studies collectively examine Bitcoin's relationship with India's stock market indices, particularly Nifty, across various market conditions. Pre-pandemic analyses suggest Bitcoin acts as a hedge but not a safe haven. However, during COVID-19, its correlation with Nifty varied, showing potential as a diversifier in normal times but not consistently as a safe haven during stress. Yet, the most of these studies are based on the broad-market based capitalisation indices, ignoring the benchmark sectoral indices which could have different correlation dynamics as suggested in a recent study by Kyriazis et al. (2023). The study found that the relationship between benchmark US sectoral indices, cryptocurrencies, and metals varies, reflecting different levels of connectedness across these assets during crises. Thus, a study is needed to comprehend the complete picture of Bitcoin's influence on wider market behaviours, particularly how different industries are affected by global health emergencies in the other developed and emerging markets.

With one of the world's economies with the most significant growth rate, India has seen a rise in the use of Bitcoin and other cryptocurrencies. According to Statista's 2022 Cryptocurrency Adoption Survey, India has seen tremendous growth in cryptocurrency adoption from 7% in 2019 to 25% in 2022. While contemplating several possibilities, including banning their usage and creating its digital currency, the Indian government has not yet controlled cryptocurrencies. It is critical to comprehend the connection between Bitcoin and the Indian financial markets in this context.

Thus, the study aims to provide a comprehensive understanding of the dynamic relationships between Bitcoin with bonds and 13 major sectoral markets of India during pre- and post-COVID periods at short-, medium-, and long-term scales in a pairwise manner. T he sectors explored in this study include both private and public sector entities. For instance, the Energy sector (oil and gas), Financial services and the Public Sector Undertakings (PSU) Bank indices include public sector undertakings. The study predominantly focused on the private sector entities, but it is not solely limited to them.

The study uses one of the popular wavelet approaches, i.e., Maximum Overlap Discrete Wavelet Transform (MODWT), to analyze the scale-based relationship between Bitcoin and financial markets in India during the pre and post-Covid pandemic. This wavelet methodology has several advantages. Initially, this technique uncovers insights from the series over both time and frequency dimensions while preserving all data points. Secondly, the decomposition process allocates the series' variance evenly across various time scales without omitting any. Lastly, this method does not require the data series to maintain stationarity.

The findings reveal a shift in correlation patterns between Bitcoin and different market sectors before and after the COVID-19 pandemic. Pre-COVID, correlations across sectors fluctuated, with some sectors like Consumer Durables (CD) and Fast-Moving Consumer

Goods (FMCG) showing moderate negative correlations at longer scales. Post-COVID, there is a noticeable shift towards positive correlations, especially at medium scales. Notably, sectors such as Health and Information Technology (IT) demonstrate strong moderate positive correlations, suggesting a closer co-movement with the primary asset class in the aftermath of the pandemic. This could be attributed to the rising acceptance of Bitcoin in India as investment and payments where only private sectors can invest in and create their own Bitcoin investment portfolios. Moreover, in India, Bitcoin and other cryptocurrencies are classified as "virtual digital assets". This classification indicates recognition for tax purposes, but they are not considered legal tender. Conversely, the Auto sector shows a significant negative correlation at the longest scale post-COVID, indicating divergent behavior compared to other sectors.

The present study contributes to the existing literature in the following ways. First, this research enhances existing literature by extending the Jana and Sahu (2023) as well as Rijanto (2023) analyses to include bonds and major sectoral indices, areas previously overlooked. As different financial assets are traded based on these sector indexes, understanding Bitcoin's correlation across various sectors is crucial for participants in the financial market. Second, it clarifies the impact of the COVID-19 epidemic on these financial relationships, addressing ambiguities in earlier studies. Finally, by employing the MODWT for decomposition, this study innovatively identifies correlations across various scales. This approach offers a nuanced understanding of temporal dynamics, presenting a significant advancement in assessing financial market correlations and their resilience or vulnerability during global crises.

The results of this study have important implications for regulators and investors. Investors may make wise investment decisions by comprehending the time-scaling-based relationship between Indian financial markets. Regulators and policymakers may use the results of this study to create the proper rules and regulations for the Indian cryptocurrency sector. The remainder of the paper is structured as follows: The relevant literature is reviewed in Section 2, the data and methodology are explained in Section 3, the empirical results and discussion are shown in Section 4, and Section 5 concludes.

Literature review

Academics and investors alike are studying cryptocurrencies as alternative assets to diversify the risks associated with traditional investments. In recent years, cryptocurrencies have gained immense popularity and are being discussed as an essential part of a diversified portfolio (Deniz & Teker, 2020). Recently, some researchers have looked into the potential of cryptocurrencies as an asset class to diversify traditional market risk.

The literature on cryptocurrencies has lately grown to include two crucial topics: the value of cryptocurrencies as an alternative investment asset (Baur et al., 2018; Hong, 2017) and how cryptocurrencies and other conventional assets are related in terms of risk and return (Chowdhury, 2016; Conlon & McGee, 2020; Corbet et al., 2020; Mariana et al., 2021; Gil-Alana et al., 2020; Goodell & Goutte, 2021; Li & Miu, 2023). Several pieces of research have evaluated the appropriateness of cryptocurrencies as an asset class to diversify traditional stock market risk. In keeping with the study's goal, we concentrate on research examining the interaction between cryptocurrencies and traditional asset markets.

Using the daily data from 2015-2018, Gil-Alana et al. (2020) studied the cointegration between the six major cryptocurrencies and traditional asset classes, such as gold, stock, and bond, in the US. The study found no cointegration between the assets and suggested investing in Bitcoin would help to diversify the portfolio with traditional assets. Similarly, Corbet et al. (2020) used daily data of three primary cryptocurrencies, i.e., Bitcoin, Ripple, and Litecoin, and other mainstream asset classes such as the US$ Broad Exchange Rate, MSC GSCI Total Returns Index, the COMEX closing gold price, the SP500 Index and, VIX and the Markit ITTR110 index and studied their relationship. They observed cryptocurrency's highly disconnected nature from the mainstream asset classes.

Along similar lines, Li and Miu (2023) examined the correlation of three cryptocurrencies with the S&P 500 and FTSE 100 stock market indices. The study pointed out that the relationship is dependent upon market volatility. During normal market conditions, cryptocurrency and the stock market experience weak or negative correlation, but during the pandemic phase, the relationship turned positive, hampering cryptocurrencies' perspective as a safe haven for investors. Along these lines, Conlon and McGee (2020) studied the safe haven property of Bitcoin against the S&P 500 and observed both prices moving synchronously during the COVID-19 pandemic. Thus, the studies found that cryptocurrencies do not possess any safe haven properties and should not be invested in during an economic downturn.

On the contrary, Mariana et al. (2021) found that cryptocurrency shared a negative correlation with the S&P 500 during the pandemic phase. The study used the daily data of the S&P 500 and two major cryptocurrencies, i.e., Bitcoin and Ethereum, and concluded that both cryptocurrencies have short-term safe haven properties. Similarly, Bouri et al. (2020) examined the

the safe haven properties of Bitcoin, gold, and commodities. They found that Bitcoin exhibits superior returns over gold and commodities in extreme adverse movements in stock indices. However, the benefit of diversification could vary according to different investor horizons and the time-frequency of the investment.

In the Indian context, a limited number of studies examined this relationship, for example, Hung (2021); Jana and Sahu (2023); Majumder (2022); Murty et al. (2022); Rijanto (2023) examined the dynamic linkages between Bitcoin prices and other conventional asset classes in India using wavelet transform frameworks. The study found the relationship between them at low, medium, and high frequencies in the pre-Covid timeframe. The study also confirmed the existence of a unidirectional connection between Bitcoin and other assets in India, although, the sample period was restricted to the pre-Covid timeframe. Extending this limitation, Murty et al. (2022) studied the safe haven properties of Bitcoin in the pre- and post-pandemic period using GARCH volatility analysis. Pre-pandemic analyses suggest Bitcoin acts as a hedge but not a safe haven. However, during COVID-19, its correlation with Nifty varied, showing potential as a diversifier in normal times but not consistently as a safe haven during stress.

In another related study, Jana and Sahu (2023) explored the relationship between major cryptocurrencies and the Nifty-50 index during normal and crisis periods, employing wavelet coherence analysis. Their research uncovered diverse outcomes, notably highlighting an enhanced association between cryptocurrencies and the Nifty index exclusively in the period following the pandemic. This analysis provides additional insights into the evolving dynamics of financial markets in response to global crises. Similarly, Majumder (2022) suggests that before the pandemic, Bitcoin served as a hedge against the Indian equity market but did not qualify as a safe haven. During the pandemic, the relationship between Bitcoin and Indian equity markets, particularly the Nifty index, became more complex, with varying degrees of correlation. However, the studies are mostly based on the various broad market-based indices such as Nifty 50, Nifty Small Cap 100, and Nifty Midcap 150, ignoring the sectoral indices which could have different correlations with Bitcoin in the pre- and post-pandemic period. While Rijanto (2023) explored the shifts in co-movement patterns between Bitcoin and technology stock indices in India and China during the pandemic, it is important to note that studies focusing on other sectors have not yet been conducted. This leaves a gap in understanding Bitcoin's relationship with broader market dynamics outside the technology sector, especially in global health crises and their impact on various industries.

Thus, the current study tries to fill this void by examining the relationship between Bitcoin and benchmark sectoral stock and bond indices, in a pre-and post -Covid pandemic in India. The results will provide a better picture of the use of Bitcoin in the portfolio mix in crisis and non-crisis periods.

Data and methodology

The study covers the period from January 1, 2017 (when Bitcoin trading commenced actively) to June 30, 2023. Following the existing research e.g., Goodell and Goutte (2021) as well as Huang et al. (2021) the study period is divided into two sub-samples. The division was established on March 11, 2020, when COVID-19 was designated a pandemic by WHO. As a result, the pre- and post-COVID-19 eras are represented by the dates January 1, 2017, to March 10, 2020, and March 11, 2020, to December 3, 2022, respectively.

To thoroughly analyze indices across a broad array of sectors with utmost precision, the thirteen sectoral indices representing Indian financial markets were examined. These include NIFTY Auto, NIFTY Consumer Durables, NIFTY Financial Services, NIFTY FMCG, NIFTY Health, NIFTY IT, NIFTY Media, NIFTY Metal, NIFTY Oil & Gas, NIFTY Pharma, NIFTY Private Bank, NIFTY PSU Bank, and NIFTY Realty. Other than sectoral indices, the CCIL All Sovereign Bond Index (CASBI) was also included in the analysis to provide a better picture of Indian asset markets. For econometric analysis, these time-series variables were obtained at daily intervals, and then these were transformed into their logarithmic returns for the final analysis. The calculation of logarithmic returns for each series utilized the formula:

$$R_{i,t} = ln(P_{i,t} / P_{i,t-1}) \tag{1}$$

where, $P_{i,t}$ and $P_{i,t-1}$ represent closing prices at t and t - 1 of the i^{th} time series.

The research data of the major sectoral indices, CASBI, and Bitcoin prices were sourced from NSE (National Stock Exchange), CCIL (Clearing Corporation of India Ltd.), www.coinmarketcap.com website, and MCX exchange, respectively.

Maximal Overlap Discrete Wavelet Transform (MODWT)

The MODWT decomposes financial return series into components across various time scales. This method is particularly advantageous as it allows for retaining the original sample size throughout the transformation, facilitating a more nuanced analysis that considers both time and frequency domains.

Time Series Decomposition

Let R_n represents the return series of an asset at time (n). We select appropriate mother Ø and father Ψ wavelets - typically from the Daubechies family - due to

(j). For this study, the return series are decomposed at six levels (J = 6), allowing for a comprehensive analysis across different investment horizons. This multi-scale approach aids in observing the variance and correlation behavior as it evolves over time, providing a granular understanding of the underlying market dynamics. These scales are categorized as follows:
- Short-term: scales 1 and 2.
- Medium-term: scales 3 and 4.
- Long-term: scales 5 and 6.

The decomposition yields two sets of coefficients for each scale: approximation coefficients A_n, which represents events that unfold over extended periods and are infrequent in occurrence. Conversely, the other component D_j focuses on generating detailed elements that are brief and occur at higher frequencies. The mathematical expressions for the overall process are given by:

$$V_{i,t} = \phi A_n + \sum_{j=1}^{n} \psi D_j \quad (2)$$

The next step is to compute the variance of the detail coefficients at a given scale $\lambda_j = 2^{j-1}$ which is indicative of the volatility present within the corresponding time frame, and is represented as follows (Gençay et al., 2002):

$$\sigma_r^2(\lambda_j) = \frac{1}{N_j} \sum_{t=L_j-1}^{N-1} D_{j,t} \quad (3)$$

Where r denotes either bitcoin (b) or sectoral (c) returns series. Also, $L_j = (2^j - 1)(L - 1) + 1$ is the number of coefficients unaffected by the boundary. When used on a stationary time series, the wavelet-variance estimator remains impartial and yields a mean value of zero $D_{j,t}$ for any time scale due to the differencing process incorporated in the filter, as Percival and Walden (2000) outlined. The Covariance between the detail coefficients of two different return series (bitcoin and sectoral stock returns) is estimated to assess their interrelationship at each scale:

$$Cov_{b,c}(\lambda_j) = \frac{1}{N_j} \sum_{t=L_j-1}^{N-1} D_{j,t} \quad (4)$$

Correlation Analysis

Utilizing the estimated variances and covariances, the wavelet-based correlation for each scale can be calculated as follows:

$$\rho_{b,c}(\lambda_j) = \frac{Cov_{b,c}(\lambda_j)}{\sigma(\lambda_j)\sigma_c^2(\lambda_j)} \quad (5)$$

Where correlation $\rho_{b,c}(\lambda_j)$ elucidates the co-movement of assets, with values near +1 or -1 indicating strong positive or negative relationships, respectively, and values near 0 implying weak or no correlation.

Significance Testing

To ascertain the statistical significance of the wavelet-based covariances and correlations, Percival and Walden (2000) highlight that the wavelet variance estimator needs to be impartial, ensuring that the level of variance remains consistent across different time scales during the decomposition process. Furthermore, they introduce the concept of a variable confidence interval that adjusts in response to the estimation of variance, Covariance, or correlation at various scales. Specifically, for a significance level of 5% (p = 0.05), the confidence interval, expressed as (1 - p) × 100%, is determined by its lower and upper bounds.

$$CI_{v_r^2(\lambda_j)} = \begin{bmatrix} v_r^2(\lambda_j) - \theta^{-1}(1-p).\sqrt{\mathrm{var}(v_r^2(\lambda_j))}, \\ v_r^2(\lambda_j) + v_r^2(\lambda_j) - \theta^{-1}(1-p).\sqrt{\mathrm{var}(v_r^2(\lambda_j))} \end{bmatrix} \quad (6)$$

Under the assumption that θ^{-1} (1 - p) corresponds to the (1 - p) percentile of the Gaussian distribution and this principle is consistently applied throughout the analysis.

Wavelet Filter Selection

Consistent with prior studies (Al Rababa'a et al., 2021; Alomari et al., 2021; Dajcman, 2015), Daubechies least asymmetric wavelet with a length of eight (D8) is applied. This filter is chosen for its advantageous properties in representing volatile time series data, while its asymmetric nature ensures the generation of optimally smooth wavelet coefficients.

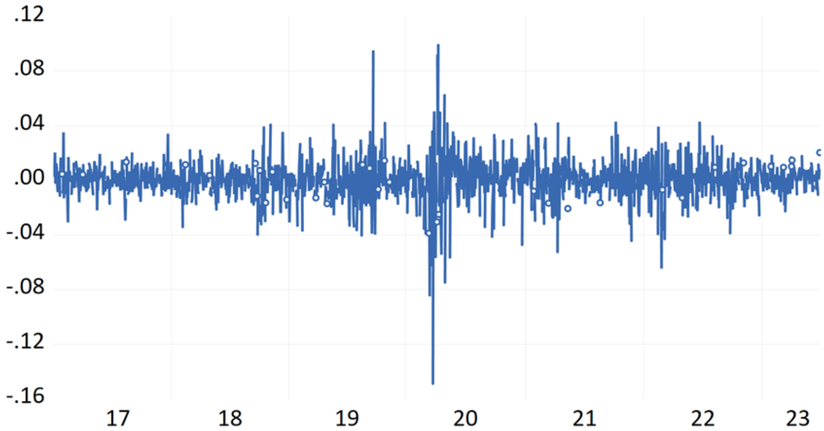
Results and discussion

Descriptive analysis

Figure 1 shows the logarithmic returns of the time series variables considered for the study, which include Bitcoin and various major sectors of Indian financial markets. Visual inspection confirms that Bitcoin has the highest return variations over the study period. In the context of sectoral returns, the most significant fluctuations are seen in the Realty and Metal sectors. At the same time, bonds exhibit the least variability, affirming their status as a safe haven. It is also important to note that from the end of 2019 to early 2020, which witnessed the swift spread of COVID-19, all the time-series variables being analyzed demonstrated extremely high volatility.

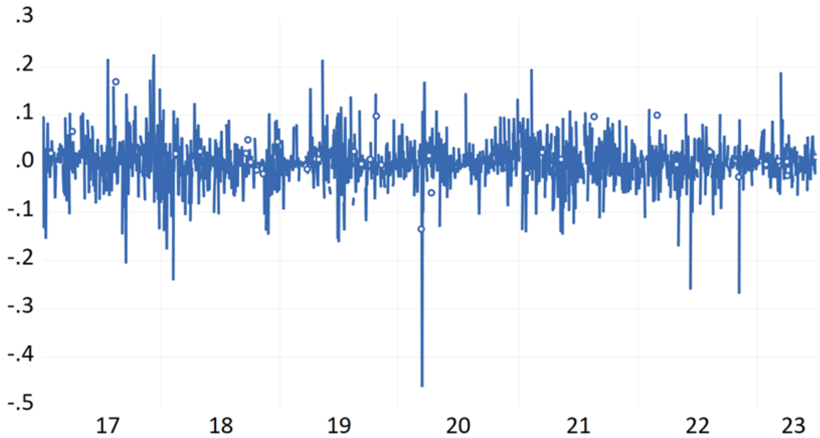
Furthermore, Table 1 presents the descriptive statistics for the examined variables. Notably, Bitcoin emerged as the top-performing asset throughout the analyzed timeframe with the highest mean return, succeeded by Consumer Durables, Realty, IT, Financial Services, and FMCG, whereas the Media sector displays negative performance. However, the high volatility associated with cryptocurrency diminishes its appeal for risk-neutral and risk-averse investors. Additionally, the Jarque-Bera normality test and ADF test for stationarity were employed. The results showed normally distributed returns with no presence of unit root in the study variables. Figures 1 to 15 Returns plot of the time -series variables.

Figure 1: Returns plot of the time-series variables (Auto)



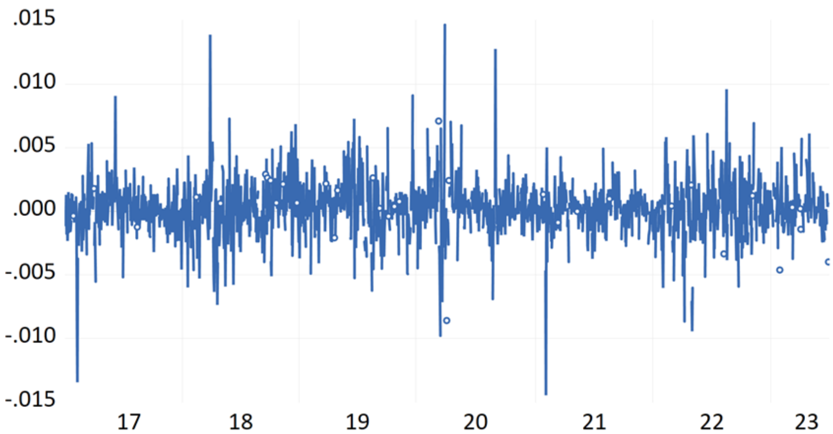
Source: Authors' calculation; NSE.

Figure 2: Returns plot of the time-series variables (Bitcoin)



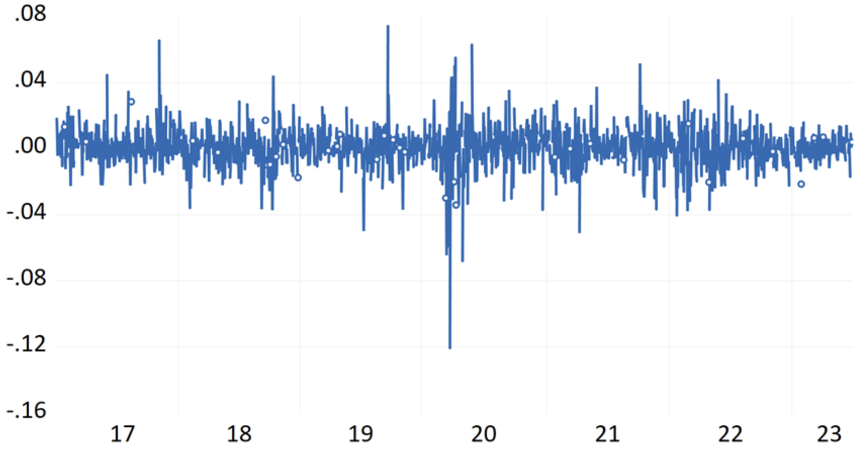
Source: Authors' calculation; NSE.

Figure 3: Returns plot of the time-series variables (Bond)



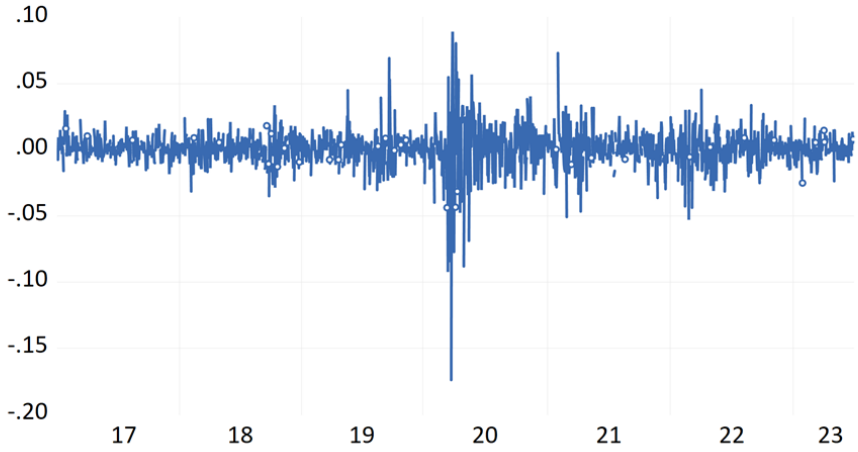
Source: Authors' calculation; NSE.

Figure 4: Returns plot of the time-series variables (Consumer durables)



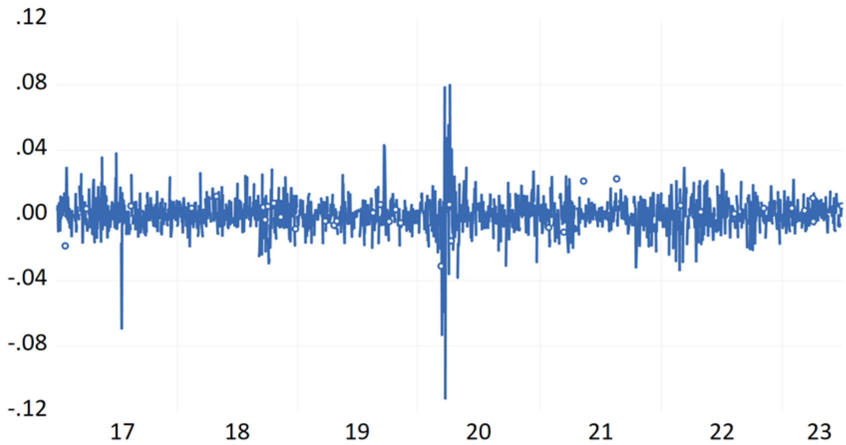
Source: Authors' calculation; NSE.

Figure 5: Returns plot of the time-series variables (Financial Services)



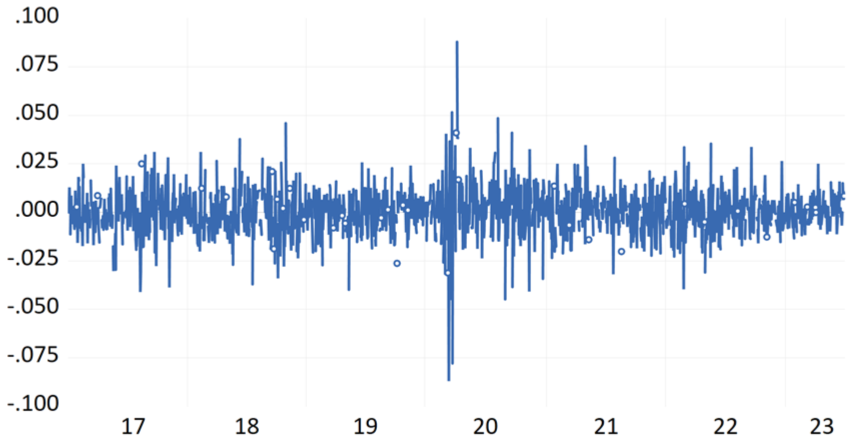
Source: Authors' calculation; NSE.

Figure 6: Returns plot of the time-series variables (FMCG)



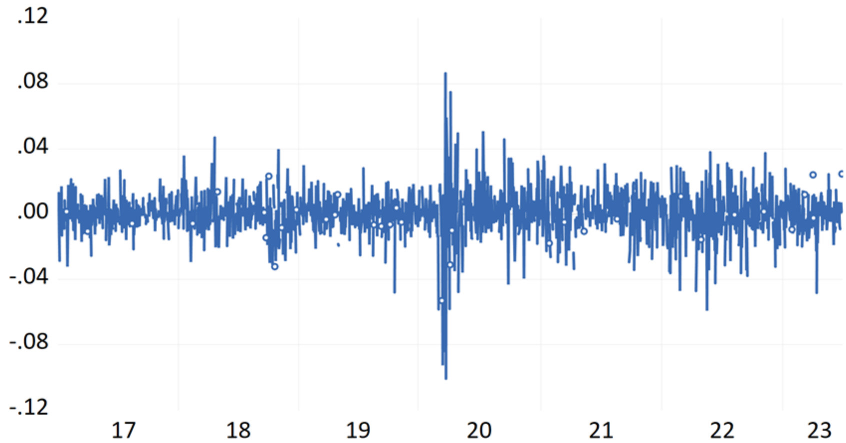
Source: Authors' calculation; NSE.

Figure 7: Returns plot of the time-series variables (Health)



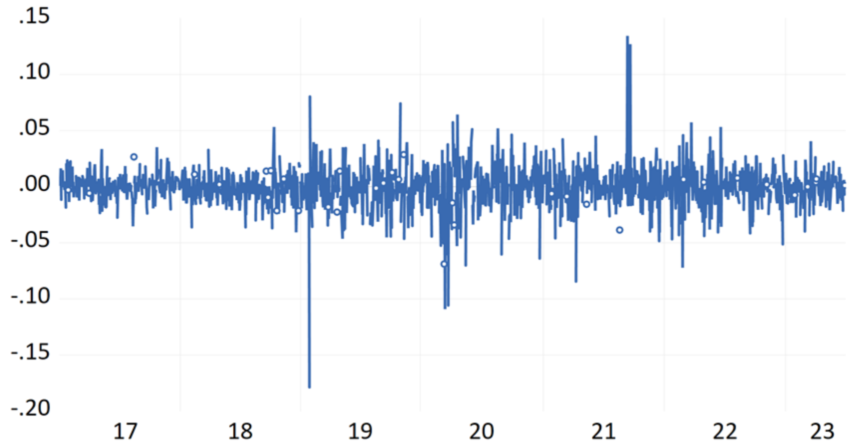
Source: Authors' calculation; NSE.

Figure 8: Returns plot of the time-series variables (IT)



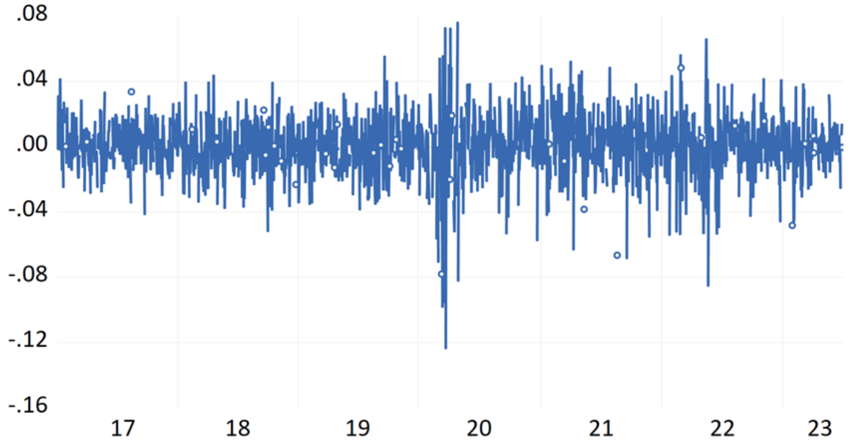
Source: Authors' calculation; NSE.

Figure 9: Returns plot of the time-series variables (Media)



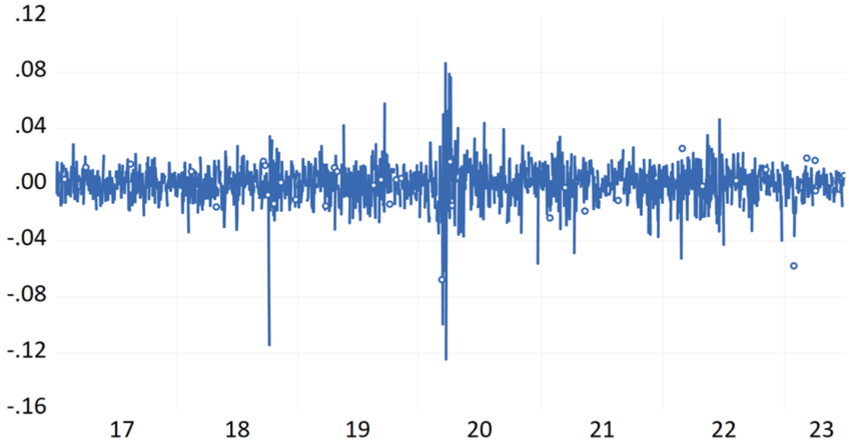
Source: Authors' calculation; NSE.

Figure 10: Returns plot of the time-series variables (Metal)



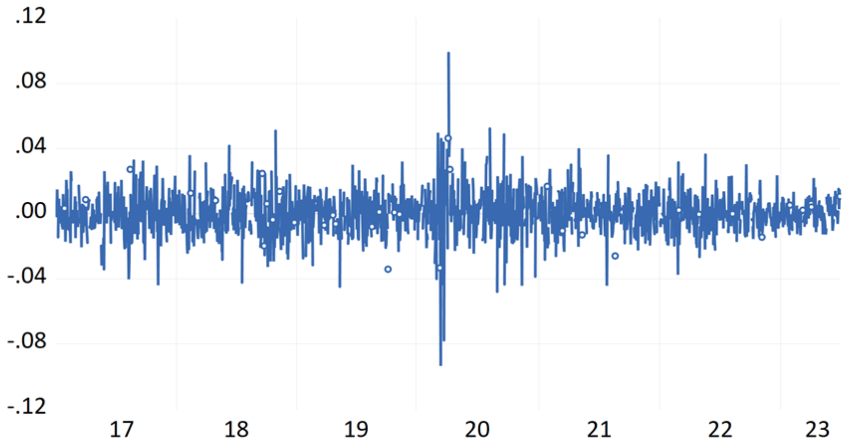
Source: Authors' calculation; NSE.

Figure 11: Returns plot of the time-series variables (Oil & Gas)



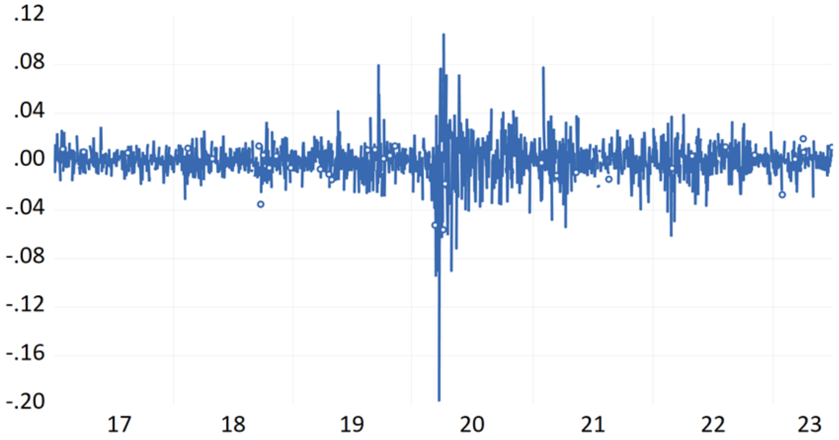
Source: Authors' calculation; NSE.

Figure 12: Returns plot of the time-series variables (Pharma)



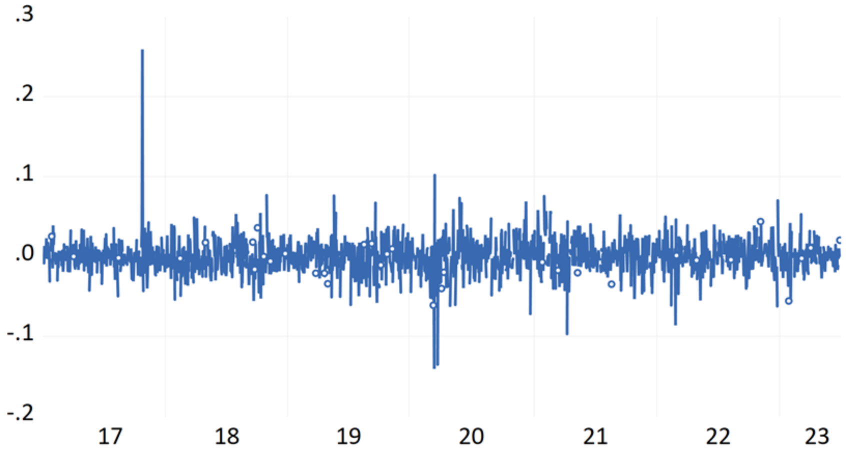
Source: Authors' calculation; NSE.

Figure 13: Returns plot of the time-series variables (Private Bank)



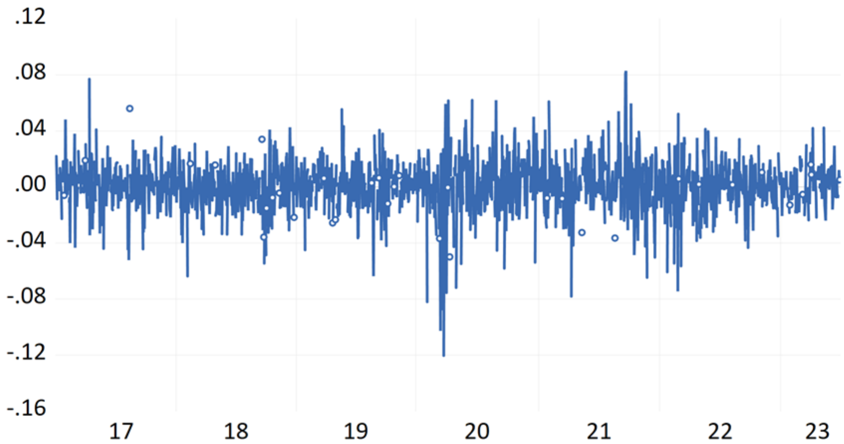
Source: Authors' calculation; NSE.

Figure 14: Returns plot of the time-series variables (PSU Bank)



Source: Authors' calculation; NSE.

Figure 15: Returns plot of the time-series variables (Realty)



Source: Authors' calculation; NSE.

Table 1: Summary statistics of the returns of the variables for the whole sample period

	Bitcoin	Auto	Bond	CD	FS
Mean	0.0022	0.0003	0.0003	0.0008	0.0006
Median	0.0017	0.0007	0.0002	0.0009	0.0010
Maximum	0.2257	0.0990	0.0147	0.0741	0.0891
Minimum	-0.4612	-0.1491	-0.0145	-0.1204	-0.1736
Std. Dev.	0.0480	0.0147	0.0022	0.0124	0.0146
Skewness	-0.7161	-0.5793	0.0258	-0.6365	-1.3514
Kurtosis	11.6649	14.9747	9.0269	12.5536	21.7702
Jarque-Bera	5161.3200***	9685.1900***	2430.8600***	6216.0140***	24065.0200***
ADF Test	-40.3500***	-39.7200***	-32.2500***	-37.3200***	-16.6900***
	FMCG	**Health**	**IT**	**Media**	**Metal**
Mean	0.0006	0.0003	0.0007	-0.0003	0.0005
Median	0.0005	0.0002	0.0009	0.0003	0.0010
Maximum	0.0799	0.0880	0.0828	0.1345	0.0760
Minimum	-0.1120	-0.0869	-0.1022	-0.1788	-0.1233
Std. Dev.	0.0106	0.0119	0.0130	0.0182	0.0187
Skewness	-0.5161	-0.0929	-0.6382	-0.5319	-0.5677
Kurtosis	18.4280	8.7102	10.7696	14.3820	6.3685
Jarque-Bera	15999.0100***	2184.1900***	4148.6110***	8744.8000***	845.5400***
ADF Test	-41.7100***	-38.3900***	-42.2000***	-39.6200***	-41.1200***
	Oil & Gas	**Pharma**	**Pvt Bank**	**PSU Bank**	**Realty**
Mean	0.0004	0.0002	0.0005	0.0002	0.0007
Median	0.0009	-0.0001	0.0009	0.0001	0.0015
Maximum	0.0868	0.0986	0.1049	0.2595	0.0830
Minimum	-0.1244	-0.0935	-0.1970	-0.1411	-0.1205
Std. Dev.	0.0139	0.0130	0.0156	0.0217	0.0187
Skewness	-1.0158	0.0334	-1.4188	0.7527	-0.4926
Kurtosis	14.7205	8.4771	25.2127	18.3461	6.6448
Jarque-Bera	9468.5400***	2007.6900***	33555.8100***	15910.6100***	953.9400***
ADF Test	-39.8800***	-39.1300***	-38.4200***	-39.3600***	-37.2500***

Note: *** denotes a 5% level of significance; CD, FS, Pvt Bank refers to Consumer Durables, Financial Services, and Private Bank, respectively

Source: Author's own work.

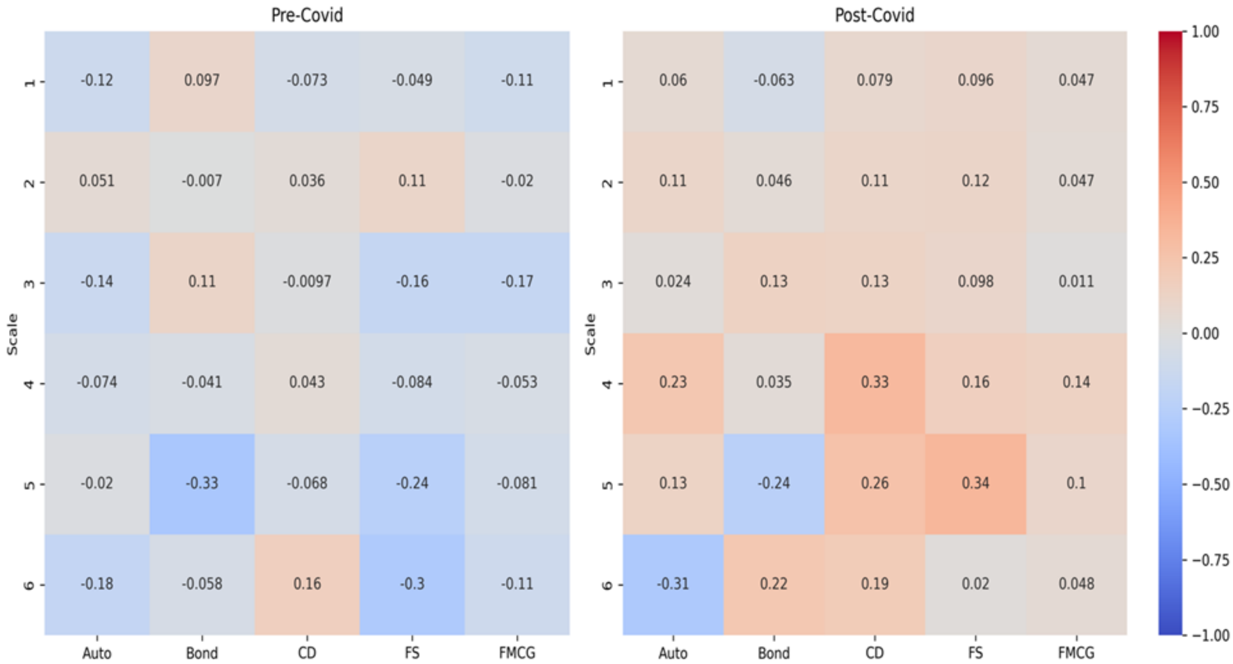
Moving forward to the main analysis, the study employs wavelet correlation to study the association of Bitcoin with India's bond and major sectoral markets in the pre- and post-Covid periods. Figure 1 - 3 displays the heatmaps to compare the results better. The left side of the figures show a pre-Covid relationship while the right side demonstrates the post-Covid era results.

Pre-Covid analysis

As depicted by the wavelet correlation-based heatmaps, the pre-COVID correlation landscape presents a subtle picture of the relationship between Bitcoin and the diverse spectrum of India's sectoral and bond markets across multiple scales. The analysis indicates a general tendency towards weak to moderate negative correlations, particularly at larger scales, suggesting a divergence in market behavior over the longer-term pre-pandemic period.

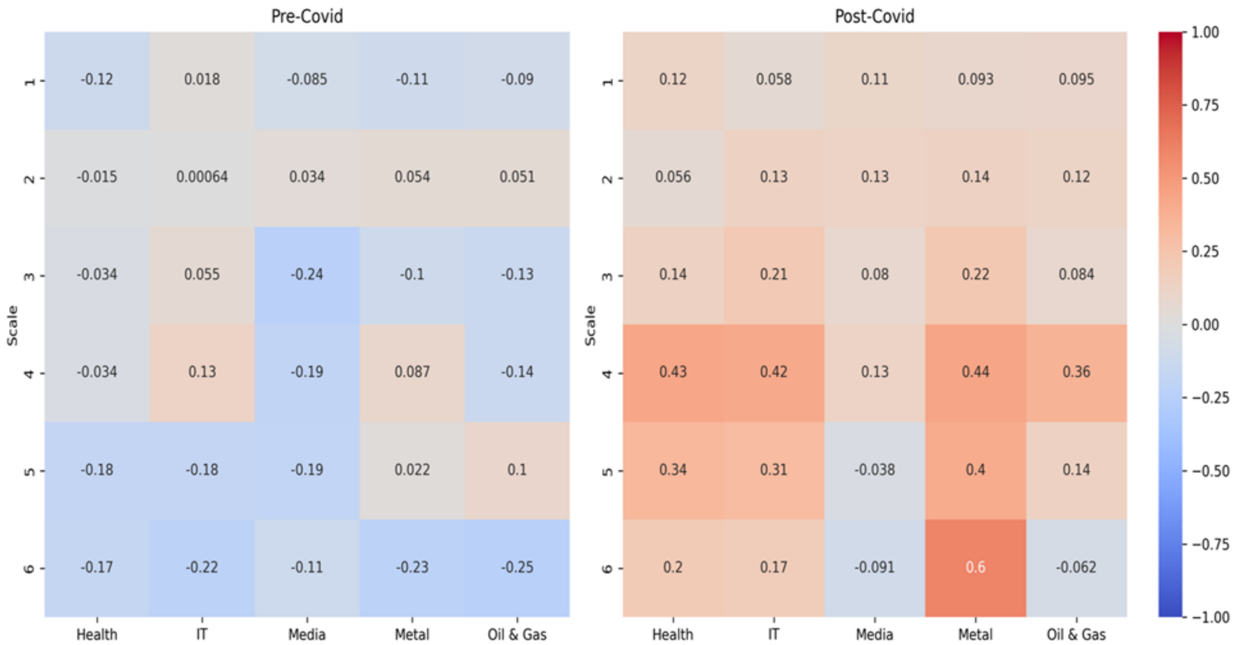
At the smaller scales (1 and 2), representing shorter-term correlations, the coefficients are predominantly close to zero within the range of (-0.10 to 0.10), with no strong directional relationship evident across the asset classes. This suggests that, in the short run, the movements of Bitcoin were largely unaligned with the fluctuations in sectors of Indian financial markets such as Automobiles (Auto), Banking (both Private and Public Sector Undertakings), and Fast-Moving Consumer Goods (FMCG).

Figure 16: Heatmap of scale-based wavelet correlation between Bitcoin and various sectors. Part 1



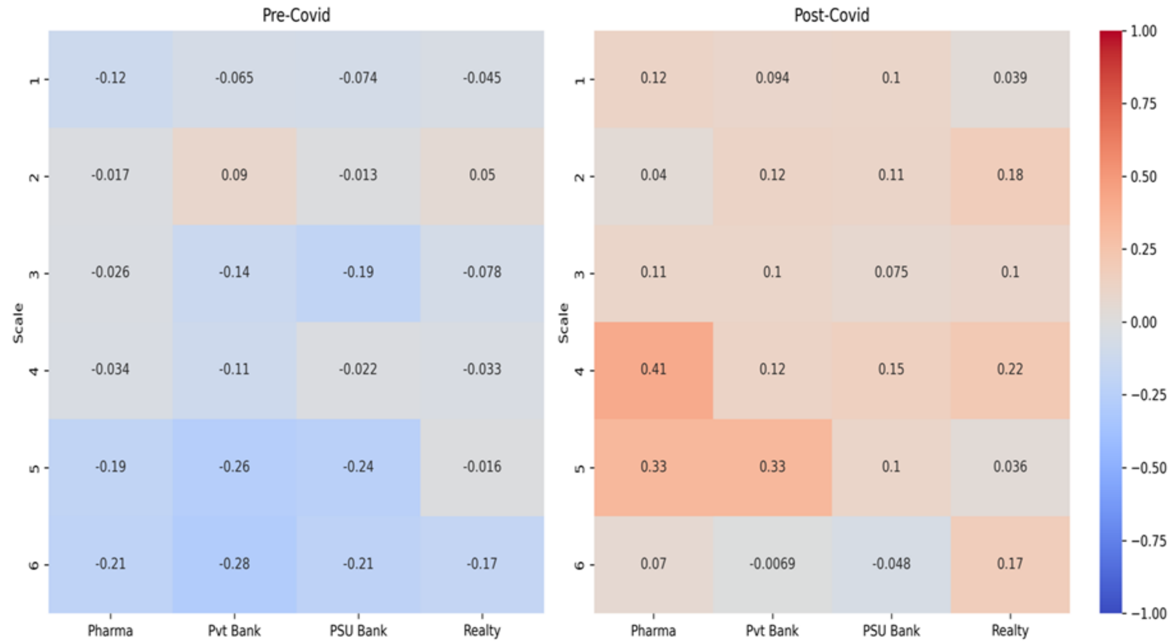
Source: Author's own work.

Figure 17: Heatmap of scale-based wavelet correlation between Bitcoin and various sectors. Part 2



Source: Author's own work.

Figure 18: Heatmap of scale-based wavelet correlation between Bitcoin and various sectors. Part 3



Source: Author's own work.

As we move to intermediate scales (3 and 4), a subtle shift in correlation patterns becomes apparent. The figures suggest a mild negative trend, particularly within the Auto, Financial Services (FS), Media, and FMCG sectors, with the Media sector showing a more pronounced negative correlation of -0.24 at scale 3. This pattern could indicate a cautious market sentiment in these areas, potentially driven by investor skepticism or a search for stability in non-correlated assets.

The negative correlations become more evident at the longer-term scales (5 and 6). Bond and FS sectors at scale 5 show a notable negative correlation of -0.33 and -0.24, respectively, the most pronounced across all scale five and asset classes in the pre-COVID data. This may reflect a distinct inverse response of this sector to the Bitcoin prices during this period. Similarly, the FMCG sector exhibits a substantial negative correlation at scale 6 with a coefficient of -0.30, suggesting a consistent long-term decoupling from the Bitcoin price movements.

The pre-COVID analysis thus presents a picture of the Indian financial market with intricate connections, where different sectors exhibited varying degrees of independence from Bitcoin. The observed negative correlations, especially at longer scales, underline the potential of Bitcoin to act as a hedge against certain sectors, offering avenues for risk mitigation and portfolio diversification. These findings provide a critical baseline for understanding market behavior before the global crisis, setting the stage for a stark contrast with the post-pandemic financial environment. The results of the study are also consistent with previous research such as Gil-Alana et al. (2020); Corbet et al. (2018) as well as Mariana et al. (2021), which discovered that adding cryptocurrency to a typical investing portfolio may have benefits for diversification.

Post-COVID Wavelet-Based correlation analysis

In the wake of the COVID-19 pandemic, the wavelet-based correlation analysis reveals a discernible pivot in the relationship dynamics between Bitcoin and the array of analyzed asset classes. The post-COVID period is characterized by a notable trend towards positive correlations, particularly at medium-term scales, which may reflect the market's collective response to the economic recovery and stimulus measures.

The post-COVID heatmaps indicate a significant shift towards moderate positive correlations across most sectors at scale 4. This scale likely captures the medium-term market adjustments and investor sentiment as economies began to stabilize and adapt to the new normal. The health sector displayed a significant moderate positive shift with a correlation coefficient of 0.43, possibly due to the increased focus on healthcare during the pandemic. Similarly, at this scale, the Information Technology (IT) and Metals sectors also showed moderate positive correlations of 0.42 and 0.44, respectively. This could indicate the reliance on technology for remote working arrangements and the rise in metal prices due to supply chain disruptions.

Interestingly, on a scale of 6, which may reflect the long-term structural market changes induced by the pandemic, the real estate sector shows a positive correlation of 0.17. This is a noteworthy divergence from its pre-COVID negative correlation, suggesting a change in investor perception of the sector's resilience or potential for growth in a post-pandemic world. The Pharmaceuticals (Pharma) sector also presents a notable positive correlation at scales 4 and 5, with coefficients of 0.41 and 0.33, highlighting its critical role during the pandemic and potential for continued growth.

However, not all sectors experienced a shift to positive correlations. The Automobile (Auto) sector presents a contrasting trend with a notably moderate negative correlation at scale six post-COVID (-0.31). This could reflect the ongoing challenges the sector faced, such as supply chain issues, changing consumer preferences, and the global semiconductor shortage.

The post-COVID correlation patterns underscore a transformation in the interconnectedness of asset classes, with the heatmaps suggesting a realignment of investment strategies and risk profiles. The observed positive correlations imply that investors may need to reconsider traditional diversification approaches, as the market's behavior in response to the pandemic has altered the historical correlation structures. The results highlight the importance of temporal and sectoral considerations in post-pandemic financial analysis and portfolio management.

Similar results were found in recent studies such as Conlon and McGee (2020); Jana and Sahu (2023); Li and Miu (2023); Rijanto (2023). The heightened anxiety in financial markets and the herding behavior during the pandemic contributed to this relationship (Ghorbel et al., 2023; Susana et al., 2020; Youssef & Waked, 2022).

To summarize, the study concludes that Bitcoin can be utilized in India as a hedge against traditional assets in the pre-pandemic period. However, in the post-pandemic period, Bitcoin does not have the same hedging or safe haven properties it used to have in the long-term portfolios, as the findings showed a rise of low to moderate positive correlation with the majority of sectors in Indian markets. However, Bitcoin can diversify the sectoral portfolios for investors, except for the auto sector in the post-pandemic period.

Conclusion

The study used the daily closing value data of Bitcoin, major sectoral market, and bond market indices to examine the relationship between these variables in India's pre- and post-covid period. The study employed the MODWT approach of the wavelet analysis to uncover this relationship across various scales.

During the pre-COVID period, the correlations were predominantly negative, especially at longer-term scales, suggesting a degree of counter-movement between Bitcoin prices and various sectors. This behavior indicated a possible hedging characteristic of these sectors against the primary asset class.

Conversely, in the post-COVID era, the correlation turned markedly positive at mid to long-term scales for many sectors, with the Health, Information Technology (IT), and Metals sectors illustrating a robust positive correlation, particularly at scale 4. This shift is indicative of the crucial role these sectors played during the pandemic and their perceived growth trajectory in its aftermath. It also reflects the broader market optimism and the rally of investments towards sectors that have shown resilience or are expected to benefit in a post-pandemic economy.

The stark shift from negative to positive correlations in the post-COVID heatmaps is emblematic of a broader market realignment. For example, the Health sector's movement from a non-significant correlation pre-COVID to a noticeable moderate strong positive correlation post-COVID suggests a reevaluation of its stability and central role during the health crisis. Meanwhile, the persistent negative correlation in the Automobile sector post-COVID, especially at the longest scale, could signify deeper structural issues that the pandemic may have exacerbated.

The comparative analysis suggests that historical correlation patterns that investors relied upon for pre-COVID diversification and risk management strategies may no longer hold true in the post-pandemic financial landscape. The new correlation structures observed post-COVID could necessitate rethinking asset allocation strategies, as the changed correlations reflect the market's structural adaptations to the economic realities introduced by the pandemic.

This study highlights the need for investors and policymakers to consider the temporal shifts in market correlations when making decisions. The clear difference between the pre- and post-COVID correlation structures underscores the pandemic's lasting impact on market dynamics and the importance of agile and responsive investment strategies in such structural market shifts. Therefore, Bitcoin may have hedging and safe haven properties for investors during a crisis, but no such ability has been found during non-crisis periods such as the COVID-19 pandemic. However, further testing may require fully designating the cryptocurrency as a safe haven and hedge against normal and downturn market periods using various econometrics techniques in the future and with a panel of emerging markets. Further, return and volatility spillover can also be tested for both crisis and non-crisis periods.

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