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DYNAMIC INTERACTION BETWEEN BITCOIN AND DEVELOPED STOCK MARKETS: EVIDENCE FROM THE DCC-GARCH MODEL WITH WAVELET COHERENCE APPROACH

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ABSTRACT

This study examines the volatility spillover and time–frequency connectedness between Bitcoin (BTC) and major developed stock markets, namely Nasdaq (USA), ASX200 (Australia), CAC40 (France), DAX (Germany), Nikkei 225 (Japan), FTSE 100 (UK), TSX (Canada), Hang Seng (Hong Kong), and Straits Times (Singapore), using the DCC-GARCH model and wavelet coherence techniques. Daily data ranging from April 01, 2015, to March 31, 2025, are collected from the Refinitiv database. The DCC-GARCH results indicate limited evidence of short-run volatility spillovers between Bitcoin and several developed stock markets, while statistically significant long-run spillovers emerge for selected market pairs, suggesting horizon-dependent interdependence. In particular, the Bitcoin–Nasdaq and Bitcoin–Nikkei 225 pairs exhibit both short- and long-run volatility transmission, implying stronger information linkages across investment horizons. The wavelet coherence analysis reveals that co-movement between Bitcoin and developed stock markets is time- and scale-dependent. During relatively tranquil periods, coherence remains weak at high frequencies, indicating potential diversification benefits in the short run. However, during periods of financial stress, statistically significant medium- and long-term coherence emerges within regions inside the Cone of Influence, reflecting temporary increases in market integration and reduced diversification potential. Overall, the findings suggest that Bitcoin's diversification properties are not uniform across time or investment horizons. The results provide conditional insights for investors and policymakers regarding risk management and portfolio allocation, while emphasizing the importance of accounting for time–frequency dynamics and crisis regimes.

Keywords: *Bitcoin, Developed Stock Markets, Nasdaq, DCC GARCH, Portfolio Diversification*

1. INTRODUCTION

Due to enhanced globalization and the widening of financial markets, global markets are now highly interconnected, which increases the risk of volatility transmissions (Alamaren et al., 2024; Manahov and Li, 2025). Global financial crisis (2008-09) transformed the investment avenues options in the evolving global financial landscape and led to the birth of Bitcoin in the year 2008 (Oben, Seraj, & Zihni Eyüpoğlu, 2025). The world has witnessed numerous rises and falls in the stock market since the recession (Kadiri et al., 2026). Covid-19 pandemic, Russia-Ukraine war, Israel-Iran war, and great geopolitical uncertainty have attracted the attention of academicians, portfolio managers, regulators, and policymakers in the search for new investment avenues that will act as a better safe haven in the condition of market distress compared to gold. Geopolitical conflicts and tariff wars are reshaping the connectedness of the stock market (Agrawal et al., 2025). The adoption of cryptocurrency by multinational companies such as Wikipedia, Expedia, Microsoft, Dell, and AliExpress has opened the door for investors to diversify their money in a safe and secret manner (Abbasi et al., 2021). The global crypto market cap is $3.21T in which Bitcoin has emerged as a rapidly growing crypto asset class having market capitalisation of $1.87T with dominance is 56.95% from (CoinMarketCap,2026 as 06.01.2026).

Cryptocurrencies attract investor capital and attention to optimize their portfolios for wealth preservation (Ballis et al., 2025). The cryptocurrency adoption rate is higher in developed economies than in developing economies Elhag and Alshehri (2023) as referenced in Alomari and Abdullah (2023). Bitcoin (BTC) which is the proxy for cryptocurrency has become the most widely traded digital asset and is increasingly incorporating into mainboard financial systems of the world (Hunady et al., 2025). Its high volatility (Dwyer, 2015) and blockchain technology have prompted rigorous research into its price dynamics, risk characteristics, and interlinkages with traditional financial markets. Understanding these interactions is crucial because financial integration across asset classes influences portfolio diversification, systemic risk, and the transmission of economic shocks.

Thus, it is necessary to measure the interrelationships between Bitcoin and other major world indices so that global investors can make better-informed portfolio investment decisions. Given the scarcity of literature on the linkages of cryptocurrency markets with other stock markets, there is a visible gap in the literature on the interlinkages of Bitcoin with major developed stock markets, and it seems to be an unexplored area of research.

Modelling stock market volatility is a widely attractive issue in the literature (Gungor and Gungor, 2024). The main research question focused on understanding how volatility spillovers and connectedness between Bitcoin and developed stock markets influence decisions regarding various diversification opportunities and investment strategies for investors and policymakers. Therefore, an empirical examination of volatility in the variables mentioned in this study will help policymakers, regulators, academicians, financial analysts, and logical investors. Focusing on the lack of simultaneous studies on the volatility spillover and connectedness between Bitcoin with Nasdaq, ASX200, CAC40, DAX, Nikkei 225, FTSE 100, TSX, Hang Seng, and Straits Times, appears to be a novel area of research.

The benchmark indices covered in this study are major developed economies across different regions of the world, reflecting diverse economic structures and regulatory environments. The Nasdaq and TSX are from North America, CAC 40, DAX, and FTSE 100 are from Europe, and ASX200, Nikkei 225, Hang Seng, and Straits Times belong to the Asia-Pacific region.

Furthermore, the study covers the daily log return data of Bitcoin (BTC), serving as a proxy for cryptocurrency, and stock markets of major developed economies, including Nasdaq (USA), ASX200 (Australia), CAC40 (France), DAX (Germany), Nikkei 225 (Japan), FTSE100 (UK), TSX (Canada), Hang Seng (Hong Kong), and Straits Times (Singapore). The data span from 1st April 2015 to 31st March 2025, expressed in USD terms, and are sourced from the Refinitiv database to ensure consistency.

The inclusion of a diverse set of equity markets in this study covering Australia (ASX 200), Europe (CAC 40 and DAX), the United Kingdom (FTSE 100), North America (Nasdaq and

TSX), and Asia-Pacific (HSI, Nikkei 225, and Straits Times) represents diverse regional economies with varying levels of market advancement, liquidity, and investor behaviour. These markets are closely monitored indicators of economic health and are highly interconnected through globalization, capital flows, and investor sentiment. By analysing these pairwise relationships, this study identifies potential transmission channels of volatility and informs global portfolio management and risk mitigation strategies.

The main problem with examining the relationship between BTC and global stock markets is the nonlinear and time-varying nature of the data. Simple correlation analysis cannot capture co-movement patterns at different time scales or frequencies, resulting in incomplete or misleading conclusions. BTC is known for its high volatility, which requires more advanced methods to capture short-term and long-term trends. Here, we introduce the wavelet coherence analysis (Kang et al., 2019; Sharif et al., 2020; Goodell and Goutte, 2021), a method to analyse the co-movement between two time series in both the time and frequency domains simultaneously. To examine the changing relationship between Bitcoin & Stock indices over time and across different investment horizons to provide deeper insight into market independence.

Wavelet coherence analysis has the advantage of allowing a multi-scale examination of the data, which can be valuable for investors in short-term trading dynamics and long-term strategic asset allocation.

Wavelet coherence analysis (Kang et al., 2019; Sharif et al., 2020; Goodell and Goutte, 2021) offers several advantages over traditional econometric methods. First, it accommodates non-stationary data, a common feature of financial time series, without requiring pre-filtering or transformation. Second, it identifies both localized and persistent relationships, distinguishing between temporary contagion effects and structural co-movements. Third, it enables a multi-scale examination of data, which is particularly useful for investors and policymakers seeking insights into short-term trading dynamics and long-term strategic asset allocation.

This study is further motivated by the growing interest of institutional investors in crypto currencies. While retail investors have historically dominated Bitcoin trading, institutional participation has increased significantly, driven by regulatory clarity, the emergence of cryptocurrency derivatives, and recognition of Bitcoin as a potential diversification tool. Understanding the co-movement between Bitcoin and major stock indices is crucial for institutional investors who aim to optimize risk-adjusted returns while managing exposure to multiple asset classes. Additionally, policymakers are increasingly concerned about the systemic implications of cryptocurrency market integration, particularly regarding financial stability, regulatory oversight, and contagion risk during periods of extreme market stress.

The remainder of this paper is organized as follows. The next section presents a literature review of the relevant studies. The third and fourth sections are devoted to the methodology and empirical analysis, respectively. Finally, Section 5 presents the concluding remarks and future scope.

2. REVIEW OF LITERATURE

Global financial markets have become unpredictable, volatile, and erratic due to geopolitical crises (Ha, 2023). This situation urges investors, portfolio managers, and academics to explore alternative strategies for safeguarding their investments, particularly in equities, during uncertain periods. The dawn of cryptocurrencies is one of the most significant innovations that have impacted the financial ecosystem in the last decade. Cryptocurrencies are now a popular asset class in global financial markets (Sehgal and Singh, 2024). Many earlier studies have examined the potential of cryptocurrencies in equity markets. These studies focused on how cryptocurrency and equity markets interact (Bouri et al., 2021; Attarzadeh and Balcilar, 2022;

Jana and Sahu, 2025; Bejaoui et al., 2023). Cryptocurrencies are a form of digital or virtual currency that uses cryptography and blockchain technology for financial transactions (Swan 2017; Mastilo et al., 2025). Caferra and Vidal-Tomás (2021) explored the interlinkages of cryptocurrencies (BTC and Ethereum) with the S&P500 and Euro Stoxx benchmark indices during the COVID-19 pandemic using the wavelet coherence method. They collected daily data for the period 1/11/2019 – 01/06/2020 from Yahoo Finance. The objective was to observe whether cryptocurrencies could be used as a hedge during the pandemic, and concluded that cryptocurrencies do not reduce financial risk during a crisis. Sami and Abdallah (2020) investigated the impact of cryptocurrency on the Middle East and North Africa (MENA) region stock market and found significant relationship between the cryptocurrency market and the stock market performance in the MENA region. Yen and Ha (2024) assessed the Interlinkages of cryptocurrency with the USA stock markets and found cryptocurrencies could explain the volatility of the US stock markets during the pandemic. Wang et al. (2022) examined the the risk contagion effect between the cryptocurrency and the U.S. stock markets in an innovative way. Using the time-varying SJC-Copula-GARCH model, we find dynamic correlations between the two types of financial markets. Kyriazis and Corbet (2025) discussed the dynamic interaction between the S&P 500, gold, and ten cryptocurrencies and found that traditional assets such as the S&P 500 and gold can be used as effective hedging instruments against the volatility of cryptocurrencies. Jiang et al. (2021) documented co-movement of cryptocurrencies with S&P 500, Shanghai Composite index and Nikkei 225, the USA, China and Japan during the pandemic and can be diversifiers during the normal time. Nam (2023) demonstrated that cryptocurrency exerts a positive influence on the USA stock market. The present study is novel in the sense that it analyses a new dataset and the techniques used for data analysis are also new. To date, no comparative study has investigated BTC and Gold with developed stock markets for diversification benefits in long and short periods.

Based on the literature review, the authors propose the following hypothesis which is tested using DCC GARCH methos

H_1: *There exists a volatility spillover between BTC to ASX200 in the short and long run.*

H_2: *There exists a volatility spillover between BTC to DAX in the short and long run.*

H_3: *There exists a volatility spillover between BTC to CAC40 in the short and long run.*

H_4: *There exists a volatility spillover between BTC to FTSE 100 in the short and long run.*

H_5: *There exists a volatility spillover between BTC to HSI in the short and long run.*

H_6: *there exists a volatility spillover between BTC to Nasdaq in the short and long run.*

H_7: *There exists a volatility spillover between BTC to Nikkei 225 in the short and long run.*

H_8: *There exists a volatility spillover between BTC to Straits Times in the short and long run.*

H_9: *There exists a volatility spillover between BTC to TSX in the short and long run.*

2. 1. OBJECTIVES OF THE STUDY

i. To assess volatility spillover between BTC and Nasdaq, ASX200, CAC40, DAX, Nikkei 225, FTSE 100, TSX, Hang Seng and Straits Times in the short and long run

ii. To identify the time frequency connectedness relationship among BTC, Nasdaq, ASX200, CAC40 DAX, Nikkei 225, FTSE 100, TSX, Hang Seng and Straits Times

3. METHODOLOGY

This study collected daily data on BTC, ASX200, CAC 40, DAX, FTSE 100, HSI, Nasdaq, Nikkei 225, Straits Times, and TSX from the Refinitiv database. To maintain consistency across markets, all return series are synchronized by retaining only common trading days across Bitcoin and the respective stock market indices. Since Bitcoin trades continuously, its return series is aligned with stock market trading days by removing Bitcoin observations corresponding to equity market holidays.

To ensure stationarity and comparability across markets, all price series are converted into logarithmic returns. Returns are computed as the first difference of the natural logarithm of closing prices:

$$R_t = \ln (P_t) - \ln (P_{t-1}) \quad (1)$$

This study uses the DCC-GARCH model and wavelet coherence approach to measure how these markets are connected.

3. 1. GARCH MODEL

One of the unique contributions to financial econometrics was made by Engle (1982), who devised a stochastic approach to autoregressive conditional heteroscedasticity (ARCH) for measuring the conditional mean and variance. Later, Bollerslev (1987) developed an advanced ARCH model in the form of GARCH, known as generalized autoregressive conditional heteroscedasticity.

The GARCH models have been proven successful in analysing the volatility of an asset (Nordstrom, 2021). Dynamic volatility is well-known to spread across interconnected assets and markets (Soni, Nandan & Chatnani, 2023). This study employs the DCC-GARCH model developed by Engle and Sheppard (2001).

3. 2. TIME –VARYING CONDITIONAL CORRELATION MODEL

It is commonly known as the dynamic conditional correlation model (DCC-GARCH). "It is a non-linear combination of univariate GARCH models and can be formulated as follows:"

$$H_t = D_t R_t D_t \quad (2)$$

The conditional standard deviation matrix is represented as

$$D_t = Diag\,(h^{½}_{11t}, \ldots, h^{½}_{NNt}) \quad (3)$$

Or in matrix form

$$D_t = \begin{bmatrix} \sqrt{h_{11t}} & 0 & \ldots & 0 \\ 0 & \sqrt{h_{22t}} & \ldots & \ldots \\ \ldots & \ldots & \ldots & 0 \\ 0 & \ldots & 0 & \sqrt{h_{NNt}} \end{bmatrix} \quad (4)$$

Each element h_{iit} can be articulated in a univariate GARCH form as outlined below

$$h_{it} = \alpha_{i0} + \sum_{q=1}^{Q} \alpha_{iq} + \epsilon^2_{\{i,t-q\}} + \sum_{p=1}^{p} B_{ip} h_{i,t-p} \quad (5)$$

"The univariate GARCH model can take different orders and the simple first order GARCH (1,1) model is usually used.

The Matrix Rt represents the correlation matrix of standard errors u_t and the conditional correlation matrix R_t takes the form of a symmetric matrix as follows

$$\begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \cdots & \rho_{1n,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \cdots & \rho_{2n,t} \\ \rho_{13,t} & \rho_{13,t} & 1 & \cdots & \cdots \\ \cdots & \cdots & \cdots & 1 & \rho_{n-1,n,t} \\ \rho_{1n,t} & \rho_{2n,t} & \cdots & \rho_{n-1,n,t} & 1 \end{bmatrix} \quad (6)$$

Two fundamental requirements need to be met in order to create the conditional correlation matrix Rt:

1. Since the covariance matrix Ht is positive definite, Rt also needs to be positive definite.
2. The conditional correlation matrix Rt's members must all be less than or equal to 1.

To verify that the two conditions are satisfied in the conditional correlation matrix, it can be split as:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (7)$$

Where

$Q_t = q_{itj}$ denotes an N X N symmetric positive definite matrix and stated as

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u`_{t-1} + \beta Q_{t-1} \quad (8)$$

Where,

$\bar{Q} = cov(u_t u`_t)$ is an N X N unconditional covariance matrix

Where $u_t = \frac{\epsilon_{it}}{\sqrt{h_{iit}}}$ is the standard error where α, β are the non-negative parameter scalars so that $\alpha + \beta < 1$ to secure that the covariance is positive.

$Q_t^{*-1} = Diag\,(q_{11t}^{1/2}, \ldots, q_{NNt}^{1/2})$ also guarantee a diagonal matrix with the square root elements of the principal diagonal matrix is Q_t

For the DCC-GARCH model, volatility spillovers are considered present if the estimated conditional correlations or spillover parameters are statistically significant at the 5% level.

3. 3. WAVELET COHERENCE

Wavelet Coherence is a normalized measure of the relationship between two time series in both time and frequency domains. It is defined as:

$$R_{xy}^2(s,\tau) = \frac{|S(s^{-1}W_{xy}(s,\tau))|^2}{S(s^{-1}|W_x(s,\tau)|^2) \cdot S(s^{-1}|W_y(s,\tau)|^2)} \quad (9)$$

where:

S(·) is known as smoothing operator from both time and scale,

$Rxy^2(s,\tau)$ is the squared wavelet coherence, taking values between 0 (no coherence) and 1 (perfect coherence).

The smoothing operator ensures that the coherence is a localized measure that considers both time and frequency. A value close to 1 indicates strong coherence at that particular time and frequency.

3. 4. PHASE DIFFERENCE

x(t) and y(t) are known as phase difference between the two-time series is given by the argument of the cross wavelet transform:

$$\phi_{xy}(s,\tau) = \arg(W_{xy}(s,\tau)) \quad (10)$$

The phase difference helps in interpreting the time lag between the two-time series. If $\phi_{xy}(s,\tau) = 0$, the series move in phase, while $\phi_{xy}(s,\tau) = \pi$ reveals that they navigate in opposite directions.

For the wavelet coherence analysis, co-movement is considered statistically significant only when coherence values exceed the 5% critical threshold

3. 5. INTERPRETATION OF WAVELET COHERENCE PLOTS

The Wavelet Coherence plot displays the squared coherence $R_{xy}^2(s,\tau)$ across time (horizontal axis) and frequency or scale (vertical axis). Regions with high coherence (close to 1) are highlighted, and the phase arrows indicate the lead-lag relationship:

- Right Arrows represents: In-phase movement.
- Left Arrows represents: Anti-phase (opposite) movement.
- Arrows pointing upwards: x(t) and y(t).
- Arrows pointing downwards: y(t) leads x(t).

4. DATA ANALYSIS AND FINDINGS

The results are divided into three sections. The first section deals with the Descriptive Statistics, followed by the DCC GARCH model and wavelet coherence approach**.** The movement of prices and return series of BTC and Nasdaq, ASX200, CAC40, DAX, Nikkei 225, FTSE 100, TSX, Hang Seng, and Straits Times for the period April 01, 2015, to March 31, 2025, are shown in Figure 1. The measures of central tendency, Mean, Median, Kurtosis, Skewness, Standard Deviation, are presented in Table 1. Furthermore, the values of the ARCH LM and ADF tests, which are prerequisites for running the DCC-GARCH, are also available in Table 1.

All markets, BTC, Nasdaq, ASX200, CAC40, DAX, Nikkei 225, FTSE 100, TSX, Hang Seng, and Straits Times, have provided positive returns. According to the Kurtosis and Skewness values, returns do not follow a normal distribution. The HSI (Hong Kong) shows a positively skewed distribution, and other markets follow negatively skewed distributions.

BTC, Nasdaq, ASX200, CAC40, DAX, Nikkei 225, FTSE 100, TSX, Hang Seng and Straits Times have a Kurtosis value >3, which indicates a leptokurtic characteristic of all the markets, inferring that the series could have exceptionally high or low returns (Yadav, Sharma & Bhardwaj, 2023). The p-value of the Jarque–Bera test indicates that all returns do not follow a normal distribution. The authors also verified the existence of the ARCH effect in all daily series, which validates the application of the DCC-GARCH for all markets (Rastogi, Kanoujiya& Doifode, 2024). The ADF test given by Dickey and Fuller (1979) was executed to test the stationarity of the time series. The return series were stationary. The movements of Nasdaq, ASX200, CAC40, DAX, Nikkei 225, FTSE 100, TSX, Hang Seng, and Straits Times are shown in figure 1, along with their corresponding log returns. All-time series witness volatility clustering. This confirms that the error term or residual is conditional heteroscedastic and that the GARCH and ARCH models can be adequately applied to capture their characteristics (Kumar, Singh & Kumar, 2022). All variables exhibit varying return patterns.

Table 1. Descriptive Statistics

	ASX200	BTC	CAC40	DAX	FTSE100	HSI	Nasdaq	Nikkei 225	Straits Times	TSX
Mean	0.000081	0.002411	0.000175	0.000199	0.000001	0.000009	0.000575	0.000169	0.000038	0.000176
Median	0.000575	0.002128	0.000540	0.000586	0.000465	0.000217	0.001062	0.000515	0.000112	0.000688
Maximum	0.068800	0.223171	0.086701	0.110283	0.104600	0.088078	0.089346	0.096464	0.064918	0.115500
Minimum	--0.115746	-0.317282	--0.138459	-0.138024	-0.134738	-0.099964	-0.131491	-0.116036	-0.083319	-0.142591
Std. deviation.	-0.012543	0.041560	0.012956	0.013177	0.011968	0.013949	0.013588	0.013090	0.009372	0.012301
Skewness	-1.137085	-0.290248	-0.741120	-0.506608	-1.100992	0.023077	-0.638892	-0.277776	-0.431416	-1.292056
Kurtosis	13.40051	8.224464	14.21887	13.79657	18.53373	6.556195	11.00596	9.973117	10.81266	26.52927
Jarque-Bera	11499.54	2803.497	12992.75	11930.74	24973.50	1283.311	6668.672	4964.661	6268.320	56847.54
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.197559	5.871622	0.425373	0.484767	0.003917	0.023624	1.400844	0.410783	0.093337	0.427575
Sum Sq. Dev.	0.382915	4.204094	0.408568	0.422616	0.348621	0.473563	0.449376	0.417089	0.213795	0.368288
ARCH LM Test (P value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF test (p value)	0.0001	0.0000	0.0002	0.0004	0.0001	0.0001	0.0000	0.0002	0.0004	0.0001
Observations	2435	2435	2435	2435	2435	2435	2435	2435	2435	2435

Source: Author's own analysis, LR indicates log return, *indicates significance at 5%.

4. 1. DCC-GARCH MODEL

The important parameters for the best model fitting in DCC, that is, α1, β1, α2, β2, θ1, and θ2 coefficients for each possible pair, are given in Table 2. Parameters α1 and α2 measure the short-term volatility impact due to new shocks in the system, while β1 and β2 indicate the presence of long-term volatility contagion. Further, θ1 and θ2 show the correlation dynamics between these different developed market indices. The α value portrays the coefficient of GARCH, while the β value shows the coefficient of GARCH, which is crucial in determining volatility based on the conditional variance of previous days. The data shown in Table 3 indicate that the values of α and β of all the variables BTC-Nasdaq, BTC- ASX200, BTC- CAC 40, BTC-DAX, BTC-Nikkei 225, BTC-FTSE 100, BTC-TSX, BTC-HSI and BTC-Straits Times illustrate that a significant persistence of volatility can be forecasted with the help of residual and historical volatility. The coefficients DCC α and DCC β, also known as spillover parameters, are symbolized as θ1 and θ2 Immediate diversification opportunities can be identified by investors with short-term analysis. Long-term analyses help investors gain insights into persistent market linkages. This dual focus offers a complete picture of market dynamics, which is important for both tactical and strategic decision-making (Agrawal et al. 2025).

The results of the DCC-GARCH analysis demonstrate that the coefficients of DCC α, which is a sum of estimates, represented as θ1 and the pairs of BTC-Nasdaq, BTC- ASX200, BTC-CAC 40, BTC- DAX, BTC- Nikkei 225, BTC- FTSE 100, BTC- TSX, BTC- HSI, and BTC-Straits Times are positive, revealing the existence of a consistent level of volatility spillover between the markets. However, the p-values for DCC α between BTC- ASX200, BTC- CAC 40, BTC- DAX,BTC- FTSE 100, BTC- TSX, BTC- HSI, and BTC- Straits Times are not statistically significant, meaning that there may be no relevant relationship and that the observed spillover is just the result of chance (Sainath et al. 2023) and in the short run there is no spill over between BTC- ASX200, BTC- CAC 40, BTC- DAX, BTC- FTSE 100, BTC- TSX, BTC- HSI, and BTC- Straits Times.

Additionally, the probability values for DCC β (θ2) must be significant, inferring that there may be a chance of time variation and asymmetrical influence in the pairwise volatility spillover effects between BTC-Nasdaq, BTC- ASX200, BTC- CAC 40, BTC- DAX, BTC- Nikkei 225, BTC- FTSE 100, BTC- TSX, BTC- HSI, and BTC- Straits Times, showing their interconnectedness in the long run. This implies that there are reduced diversification benefits for ASX200, CAC 40, DAX, FTSE 100, HSI, Nasdaq, Nikkei 225, Straits Times, and TSX.

Hence, we accept our research hypotheses as H1, H2, H3, H4, H5, H6, H7, H8, and H9, which is the persistence of volatility spillover between BTC-Nasdaq, BTC- ASX200, BTC- CAC 40, BTC- DAX, BTC- Nikkei 225, BTC- FTSE 100, BTC- TSX, BTC- HSI, and BTC- Straits Time in the long run.

The value of (α+β) will always be equal to 1. The fact that β is greater than α suggests that previous shocks had a greater influence on the current variances (Hung, 2020).

When long-term volatility persists, regulators easily come up with plans and implement a strong monetary policy to address it. However, in the short term, this is not the case, since policymakers lack the time to respond to such volatility (Yadav et al. 2021). The study shows that there are immediate diversification opportunities among ASX200, CAC 40, DAX, FTSE 100, HSI, Straits Times, and TSX, indicating that there is no transfer of information in the short run. The short- and long-run spillover exists only in the case of BTC-Nasdaq and BTC-Nikkei 225, indicating no diversification opportunity in the short- and long-run because of the transfer of information.

In conclusion, a persistent level of volatility spillover between all the pairs of BTC-Nasdaq, BTC- ASX200, BTC- CAC 40, BTC- DAX, BTC- Nikkei 225, BTC- FTSE 100, BTC- TSX, BTC- HSI, and BTC- Straits Time is witnessed. The significant β DCC estimates statistically demonstrate that the long-term volatility spillover effects may be asymmetric.

Table 2. The Estimates of Bivariate DCC-GARCH between Bitcoin with ASX200, CAC 40, DAX, FTSE 100, HSI, Nasdaq, Nikkei 225, Straits Times and TSX

Instrument Pair	Conditional Correlation Coefficients								Optimal Portfolio Weights (MPT)	
	α_1	β_1	α_2,	β_2,	θ_1 (DCC α)	θ_2 (DCC β)	Log-Likelihood	Observation	Weight 1 Bitcoin	Weight 2 Indices
BTC- Nasdaq	0.094006* (0.000268)	0.872984* (0.0000)	0.135771* (0.00000)	0.840931 (0.0000) *	0.023385** (0.020303)	0.969868 (0.0000) *	12392.01	2514	0.102	0.898
BTC- ASX200	0.101199* (0.000018)	0.871742* (0.00000)	0.079323** (0.017536)	0.902507* (0.0000)	0.002230 (0.429887)	0.989378* (0.0000)	12689.76	2530	0.082	0.918
BTC- CAC 40	0.087945* (0.000127)	0.883872* (0.0000)	0.146568* (0.000000)	0.821617* (0.000000)	0.019943 (0.445728)	0.949258* (0.0000)	12626.93	2560	0.082	0.918
BTC- DAX	0.086046* (0.000178)	0.886807* (0.000000)	0.104939* (0.000347)	0.867991* (0.0000)	0.010230 (0.716247)	0.978607* (0.000000)	12413.49	2536	0.088	0.912
BTC- Nikkei 225	0.095296* (0.001213)	0.866211* (0.000000)	0.145090* (0.000000)	0.778485* (0.000000)	0.00656 ** (0.037861)	0.983943* (0.00000)	11754.53	2441	0.072	0.928
BTC- FTSE 100	0.090921* (0.000116)	0.880598* (0.00000)	0.123684* (0.00000)	0.840048* (0.00000)	0.015178 (0.226816)	0.966538* (0.00000)	12719.84	2525	0.068	0.932
BTC- TSX	0.089882 * (0.000036)	0.885314* (0.000000)	0.12241* (0.000384)	0.858583* (0.00000)	0.013917 (0.234105)	0.818993* (0.00000)	12825.18	2505	0.07	0.93
BTC- HSI	0.087032* (0.000123)	0.882410* (0.00000)	0.075792* (0.00000)	0.907486* (0.00000)	0.020738 (0.288576)	0.786443* (0.007146)	11669.83	2458	0.102	0.898
BTC- Straits Times	0.090090* (0.000255)	0.880419 * (0.00000)	0.108877* (0.00000)	0.825641* (0.00000)	0.004899 (0.506607)	0.961011* (0.00000)	13162.78	2525	0.036	0.964

Source: Author's own work

Model fitting parameters -

i. β_1 and β_2 must be significant
ii. All the parameters $\alpha_1, \alpha_2, \beta_1, \beta_2, \theta_1$ and θ_2 must have +ve value
iii. $\alpha_1 + \beta_1 <= 1$ and $\alpha_2 + \beta_2$ must be $<= 1$
iv. $\theta_1 + \theta_2 <$ or = 1 ,* and ** denotes the significance levelat 1% and 5% respectively.

Weights of 1 and 2 shows proportions of the portfolio those are allotted to the Bitcoin and corresponding indices in order to achieve optimal portfolio allocation, and weight 1+ weight 2 = 1

4. 2. WAVELET COHERENCE APPROACH

The complex Morlet wavelet is employed to conduct the wavelet coherence analysis. The Morlet wavelet is widely used in financial and economic time-series analysis because it provides an optimal balance between time localization and frequency resolution, making it particularly suitable for examining dynamic co-movements and lead–lag relationships across different investment horizons.

The Morlet wavelet is defined as a complex exponential modulated by a Gaussian window. The central frequency is set (ω_0) equal to 6, which satisfies the admissibility condition and ensures an appropriate trade-off between time and frequency domains. This allows for reliable identification of both short-term (high-frequency) and long-term (low-frequency) dependencies between Bitcoin and developed stock market returns.

The wavelet coherence is computed based on the squared absolute value of the smoothed cross-wavelet spectrum, normalized by the product of the individual wavelet power spectra. Statistical significance is assessed using Monte Carlo simulations against a red-noise null hypothesis, and the 5% significance level is indicated by the thick black contour in the wavelet coherence plots.

The wavelet coherence analysis is performed over multiple time scales to capture relationships across different investment horizons. In line with standard practice, the scale parameter is inversely related to frequency, where: Lower scales (4–16) correspond to high-frequency, short-term dynamics (approximately daily to bi-weekly horizons), relevant for short-term traders and speculative behavior. Medium scales (16–64) represent medium-term investment horizons (monthly to quarterly), reflecting portfolio rebalancing and macroeconomic adjustments. Higher scales (64–256) capture low-frequency, long-term dynamics (semi-annual to multi-year horizons), relevant for long-term investors and structural market integration.

Thus, the scale dimension allows us to distinguish between short-run market interactions and long-run co-movements driven by macroeconomic and global financial conditions.

To assess whether observed wavelet coherence values are statistically meaningful, Monte Carlo simulations are employed. 1,000 Monte Carlo simulations are generated to construct the empirical distribution of wavelet coherence under the null hypothesis. The 5% significance level is used as the threshold for statistical significance. Regions where coherence exceeds this threshold are enclosed by a thick white contour in the wavelet coherence plots.

Only coherence within these statistically significant regions is interpreted in the empirical analysis.

The Cone of Influence (COI) identifies regions in the wavelet coherence plot where edge effects become important due to the finite length of the time series. Outside the COI, wavelet estimates are affected by zero-padding and boundary distortions. Therefore, results outside the COI are not considered reliable and are excluded from interpretation. In the figures, the COI is shown by a curved boundary, and all substantive inferences are restricted to areas inside the COI and within statistically significant contours. This ensures that conclusions are based only on robust and reliable time–frequency information.

Phase arrows indicate the direction of co-movement and lead–lag relationships between Bitcoin and stock market returns. The interpretation follows a consistent and correct rule set:

- Rightward arrows (→): Variables are in phase, moving in the same direction (positive correlation).
- Leftward arrows (←): Variables are anti-phase, moving in opposite directions (negative correlation).
- Right and upward arrows (↗): Variables are in phase, and Bitcoin leads the stock market index.

- Right and downward arrows (↘): Variables are in phase, and Bitcoin lags the stock market index.
- Left and upward arrows (↖): Variables are anti-phase, and Bitcoin leads.
- Left and downward arrows (↙): Variables are anti-phase, and Bitcoin lags.

Lead–lag interpretations are made only within statistically significant regions inside the COI, ensuring methodological rigor.

4. 2. 1. BITCOIN V/S NASDAQ

The graph shows the wavelet coherence between BTC and Nasdaq returns for FY 2015 to 2025. In early 2020, a significant red region was observed at a time scale of 64–128 days and at a time scale of 4–64 days during the first quarter of 2022. This suggests a strong co-movement (in phase) between Bitcoin and Nasdaq at small- and medium-term scales, possibly linked to the global market disruption caused by the COVID-19 pandemic. Large portions of the graph are blue, indicating periods in which the Bitcoin and Nasdaq returns were largely independent. This aligns with the general understanding that Bitcoin operates differently from traditional financial assets most of the time, but sometimes shows correlated behavior during market turbulence. Refer figure 1.1

4. 2. 2. BITCOIN V/S NIKKEI 225

A large and continuous red region appears around 2019–2023, especially in the long-term periods (≈ 256 and 64), indicating sustained high coherence between Bitcoin and Nikkei 225. Smaller red patches were observed from 2017 to 2018 and from the second quarter of 2019 to the first quarter of 2021. This suggests that during these periods, Bitcoin and Nikkei 225 co-moved strongly, especially in medium and long cycles, possibly reflecting macroeconomic events such as global market instability and the pandemic's impact. Significant portions of the graph remain blue, indicating periods in which Bitcoin and Nikkei225 behaved independently. In particular, the periods before 2018 and after 2023 showed reduced coherence. Refer figure 1.2

4. 2. 3. BITCOIN V/S ASX200

The strongest coherence appears around 2019–2023, especially in the long-term periods (~256), as shown by the large red patches. This suggests that Bitcoin and ASX200 co-moved strongly during this period, likely due to market-wide events such as the COVID-19 pandemic. Smaller coherence patches were visible during 2017–2018, and significant co-movement was ultimately observed from the second quarter of 2019 to the first quarter of 2021. Further in 256 days frequency second quarter of 2019 to the first quarter of the second quarter of 2022, most of the graph remains blue, indicating that Bitcoin and ASX200 returns are largely independent outside of significant economic events. Refer figure 1.3

4. 2. 4. BITCOIN V/S TSX

The figure shows the wavelet coherence analysis between Bitcoin and the Toronto Stock Exchange Index (TSX). Bitcoin and TSX do not move closely together in the short term. During 2016–2019, very weak coherence was observed, but during 2020–2023, stronger and more persistent coherence was observed, coinciding with the COVID-19 shock and global monetary easing. Both Bitcoin and equity markets were driven by liquidity conditions, showing common long-term trends**.** Refer figure 1.4

4. 2. 5. BITCOIN V/S CAC 40

A blue region with very few small scattered red patches was observed for (periods < 16). This indicates a weak short-run relationship between Bitcoin and the CAC40. This suggests that Bitcoin and French equities do not co-move consistently daily or weekly. Some red/yellow patches were observed, especially during 2020 at a frequency of 64 days and again during 2022–2023. These periods correspond to financial stress (crypto boom–bust the 2017, COVID-19 crash of 2020). This suggests that during crisis episodes, correlations temporarily strengthen medium-term coherence (periods ~64). Some arrows point right/upward, especially in the long-term red areas. This implies that Bitcoin often leads the CAC40 in long horizons. They suggest that Bitcoin may serve as an early indicator of global risk sentiment, with stock markets (CAC40) adjusting afterward. Refer figure 1.5

4. 2. 6. BITCOIN V/S DAX

The image mostly showed blue with scattered small red spots. Suggests a weak short-run connection between Bitcoin and DAX. Daily fluctuations remain largely independent of short-term coherence (periods < 16). Stronger red patches were observed from the second quarter of 2019 to the second quarter of 2020. This suggests that Bitcoin and DAX co-moved more during the financial stress periods.

Some arrows point right and upward in the long-term red zones. This implies that Bitcoin tends to lead the DAX in the long horizons. This suggests that Bitcoin acts as a forward-looking signal for European equity markets. Refer figure 1.6

4. 2. 7. BITCOIN V/S HANG SENG

The skin was predominantly blue with scattered small red patches. This indicates weak short-, medium-, and long-term correlations between Bitcoin and Hang Seng. This suggests that daily and weekly fluctuations remain largely independent. No lead-lag relationship (direction of influence) is observed between Bitcoin and Hang Seng. Refer figure 1.7

4. 2. 8. BITCOIN V/S FTSE 100

The strongest coherence appears around 2019–2023, especially at long-term periods (~256), shown by large red patches. Suggests that Bitcoin and ASX200 co-moved strongly during this period, likely due to market-wide events such as the COVID-19 pandemic. Smaller coherence patches are visible during 2017–2018 and ultimately significant co-movement was observed in the second quarter of 2019 to the first quarter of 2021. Further, in 256 days frequency, the second quarter of 2019 to the first quarter of the second quarter of 2022. Most of the graph remains blue elsewhere, indicating that Bitcoin and FTSE100 returns are largely independent outside significant economic events. Refer figure 1.8

4. 2. 9. BITCOIN V/S STRAITS TIMES

Figure 9 shows the wavelet coherence analysis between Bitcoin and Straits Times (Singapore). Mostly blue with scattered red patches are seen, which indicates a weak short-term correlation between Bitcoin and STI for 4-16 days frequency. Hence, Day-to-day movements are not aligned or correlated, known as short-term coherence (periods < 16). A noticeable red band from 2018 to 2023 (bottom region) indicates persistent long-term integration between Bitcoin and the STI. In the long-term red band (2020–2023), most arrows point rightward and slightly upwards. This means that Bitcoin leads the STI in the long run, that is, Bitcoin shocks often precede Singapore's market movements. This resembles the lead–lag pattern observed in Western indices such as DAX and FTSE100. Long-term coherence (periods ~256). Refer figure 1.9

Figure.1 Wavelet Coherence OF BTC WITH Nasdaq, Nikkei 225, ASX200, TSX, CAC40, DAX, Hang Seng, FTSE100 and Straits Times

Figure 1.1. Wavelet Coherence Analysis Between Bitcoin and Nasdaq

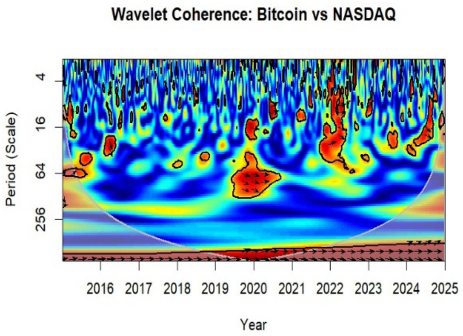


Figure 1.2. Wavelet Coherence Analysis Between Bitcoin and Nikkei 225

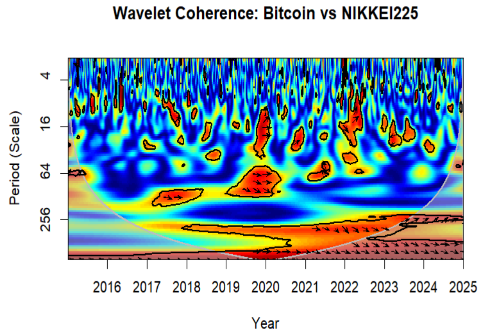


Figure 1.3. Wavelet Coherence Analysis Between Bitcoin and ASX200

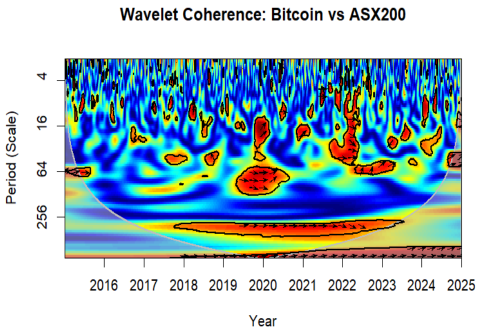


Figure 1.4. Wavelet Coherence Analysis Between Bitcoin and TSX

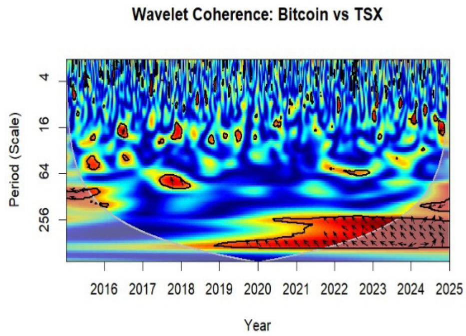


Figure 1.5. Wavelet Coherence Analysis Between Bitcoin and CAC 40

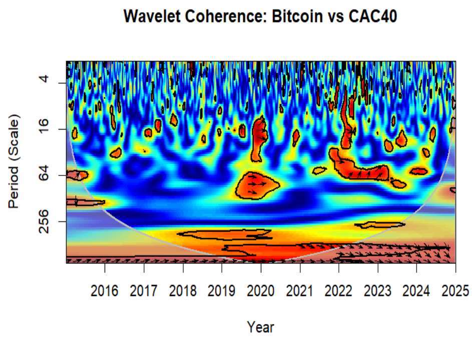


Figure 1.6. Wavelet Coherence Analysis Between Bitcoin and DAX

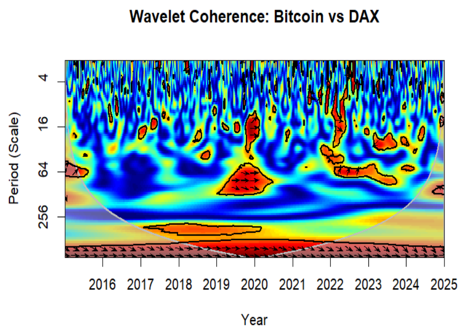


Figure 1.7. Wavelet Coherence Analysis Between Bitcoin and Hang Seng

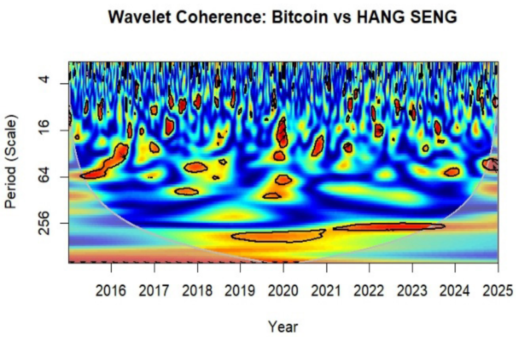


Figure 1.8. Wavelet Coherence Analysis Between Bitcoin and FTSE100

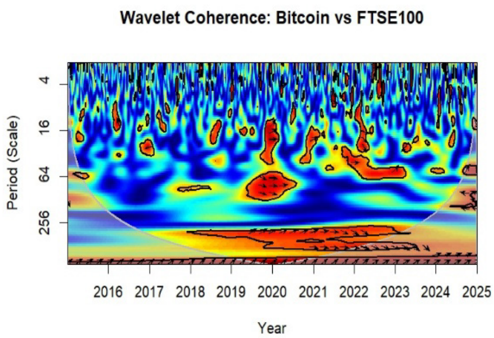
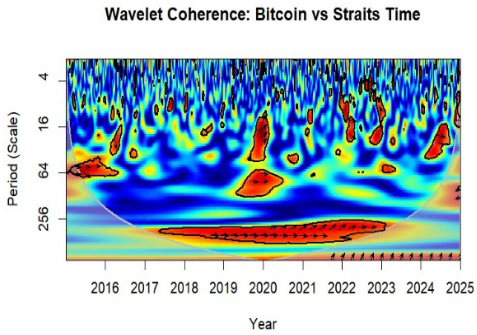


Figure 1.9 Wavelet Coherence Analysis Between Bitcoin and Straits Times



Source: The authors

5. CONCLUSION

This study aims to assess the dynamic interrelationships of Bitcoin with the major developed stock markets of the world using DCC GARCH and wavelet coherence techniques in the time and frequency domains.

The results of the DCC GRACH model conclude that no spillover exists between BTC and ASX200, BTC and CAC 40, BTC and DAX, BTC and FTSE 100, BTC and TSX, BTC and HSI, and BTC and Straits Times in the short run. Additionally, there are statistical findings that record a considerable connection in the long run, which infers the possibility of time-varying volatility spillover effects among all the markets. Furthermore, the authors find diversification opportunities among ASX200, CAC 40, DAX, FTSE100, TSX, HSI, and Straits Times because, in the short run, there is no evidence of information being transferred in the financial market.

The results of this study provide a new perspective on the existing literature. To the best of the authors' knowledge, this is the first study in which the combination of the daily log return of BTC and Nasdaq, ASX200, CAC40, DAX, Nikkei 225, FTSE 100, TSX, Hang Seng, and Straits Times are applied for the financial year (2015-2025). The relationship between Bitcoin-Nasdaq & Bitcoin- Nikkei 225 exhibit a short and long run spillover indicating the movement of information in short and long run both, hence no diversification opportunity exists.

The results indicate that short-run (high-frequency) coherence between Bitcoin and developed stock markets is generally weak and intermittent, even during periods of heightened market volatility. This suggests limited short-term integration and implies that Bitcoin's immediate price dynamics are largely driven by idiosyncratic factors rather than contemporaneous movements in equity markets.

In contrast, medium- and long-run coherence strengthens during the COVID-19 crisis and the 2022 market stress period. At these lower frequencies, statistically significant co-movements emerge within the Cone of Influence, indicating that Bitcoin and developed stock markets tend to respond more synchronously to common macroeconomic shocks and systemic risk factors over longer investment horizons. Importantly, this increase in coherence is episodic rather than persistent, weakening again during relatively tranquil periods.

The findings suggest that Bitcoin's diversification properties are time- and scale-dependent. While Bitcoin may offer diversification benefits in the short run, these benefits appear to diminish at medium- and long-term horizons during crisis episodes, when market integration temporarily intensifies. However, the absence of consistently high coherence across all periods and scales indicates that Bitcoin does not behave as a fully integrated asset with developed equity markets.

The wavelet coherence results indicate periods of statistically significant in-phase co-movement between Bitcoin and selected developed stock markets—namely Nasdaq, Nikkei 225, ASX200, CAC40, DAX, FTSE100, and TSX—primarily at medium-term scales (approximately 16–64 days) during the pandemic period and within regions inside the Cone of Influence. This pattern suggests a temporary increase in co-movement during crisis conditions, which may reduce short- to medium-term diversification potential during such periods.

In contrast, during relatively tranquil market conditions, coherence between Bitcoin and developed stock markets remains weak or intermittent at higher frequencies, indicating that diversification benefits may exist in the short run under normal financial circumstances. Overall, the results suggest that Bitcoin's diversification properties are time- and scale-dependent, weakening during periods of systemic stress while remaining more pronounced outside crisis episodes.

Limitations and Future Research Directions

Despite its contributions, this study has several limitations. First, wavelet-based results are inherently scale-dependent, and alternative scale-band definitions may yield variations in the magnitude of coherence. Second, interpretations are constrained by the Cone of Influence, which limits inference near the sample boundaries. Third, the analysis relies on return series and does not explicitly incorporate macroeconomic or policy variables that may further explain the observed co-movements.

Future research could extend the analysis by integrating macro-financial indicators, applying alternative time–frequency techniques such as quantile coherency or time-varying parameter models, and exploring emerging or frontier markets to assess whether similar patterns hold across different market structures. Future research should explore the relationship between different cryptocurrencies, such as Ethereum, Dogecoin, Ripple, Binance, and Tether, and gold, silver, and emerging stock markets.

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Conflict of interest

No conflict of Interest.

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