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ARTICLE

On the determinants of Bitcoin returns and volatility contagion between oil, gold and stocks: Evidence using wavelet coherence and DCC-GARCH approaches

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Abstract

This study examines the key determinants of Bitcoin's price dynamics and its volatility contagion with major financial assets, including Brent oil, gold, USDX (US Dollar Index), EURO-USD, DJIA, and Nikkei-225, using advanced econometric techniques. By employing Wavelet Coherence and multivariate DCC-GARCH models on daily data from January 2010 to October 2022, we uncover critical insights into Bitcoin's interconnectedness with traditional markets. Our Wavelet Coherence analysis reveals that Bitcoin exhibits a leading relationship with Brent crude oil, particularly during crisis periods, while displaying negative correlations with gold, challenging its status as a consistent safe-haven asset. Strong comovements are observed between Bitcoin and currency index pairs (USDX and EURO-USD), whereas Bitcoin and DJIA exhibit an inverse relationship, suggesting diversification potential. The DCC-GARCH results further identify distinct volatility transmission mechanisms: while no short-term spillovers exist between Bitcoin and Brent oil, long-term volatility persistence is significant. Gold confirms its role as a stable hedge, showing minimal volatility clustering. Meanwhile, USDX, EURO-USD, and DJIA exhibit long-term volatility persistence, with Nikkei-225 also demonstrating prolonged volatility effects. These findings provide practical guidance for investors in constructing resilient portfolios by understanding Bitcoin's volatility linkages with traditional assets. This study not only advances empirical knowledge of cryptocurrency markets but also offers actionable insights for risk management and strategic investment decisions.

Keywords: Bitcoin Volatility; Volatility Contagion; Wavelet Coherence; Safe-Haven Assets

JEL classification: G12; G15; C58

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1. Introduction

The growing public attention to digital currencies in recent years has propelled them into academic, financial, and public policy discussions. The issue, according to academics, is caused by the contentious characteristics of digital currencies that challenge the definition of money. As a product of IT conception, the digital currency definition can be confusing; it is described as a protocol, platform, currency or mode of payment (Athey et al., 2016). Since its creation in 2009, Bitcoin has garnered the most attention among digital currencies (Nakamoto & Bit, 2008). It functions as a peer-to-peer electronic cash system that enables transactions over the internet without intermediation of the financial system. Digital currency is also known as cryptocurrency, termed in such a way because of its attribute of utilizing encryption frameworks that manage the making of coins and exchanges.

During the past twenty years, the financial sector has encountered rapid improvements in regulation, development, and financial services, which have produced a dynamic and interconnected financial environment on a worldwide scale. Additionally, it exhibits volatility and instability, which may be understood in light of the financial markets' deregulation, which has facilitated the flow of capital and led to the dismantling of established boundaries within the financial services sectors. Additionally, they backed the financial institutions' globalization as well as the IT sector's rapid expansion. In light of these developments, the value of digital currencies has emerged due to the variety of peculiarities associated with globalization, the interconnection of financial systems, and the resulting freedom of capital movement.

In recent years cryptocurrency has witnessed a significant increase. The evolution of cryptocurrency prices has garnered the interest of investors and researchers, as well as the attention of the media. The return on investment in Bitcoin has climbed dramatically from early 2020 to the present, by over 150%, and it currently exceeds the returns on investments in gold and many emerging market stock markets. Cryptocurrencies are accepted and used by a wide range of businesses as a means of payment and as a medium of exchange in a vast number of transactions. This demonstrates the value of digital cryptocurrencies as a medium of exchange (Baur et al., 2018; Bowala & Singh, 2022; Yan et al., 2022). It has also demonstrated that cryptocurrencies can be used as a safe haven, an asset for hedging, or to diversify a portfolio (Hussain Shahzad et al., 2020; Dubey, 2022; Yan et al., 2022). These qualities largely depend on how well they match and correlate with other assets. The market for cryptocurrencies is seen as an important development for the portfolio of investors. This financial market creates a new asset class (Corbet et al., 2017). Since then, many studies have been done to determine the price of Bitcoin in relation to a number of different factors. As a result, the GETS (General-to-Specific) model is only occasionally used in research to determine the most significant group of variables.

This nascent asset class is characterized by frequent speculative bubbles and extreme price volatility. Accordingly, it has been found that the fundamental price of Bitcoin could be considered as zero (Cheah & Fry, 2015). Nonetheless, a number of analysts have noted that Bitcoin is extremely volatile and may have spillover volatility onto other cryptocurrencies or conventional assets (Baur et al., 2018; Dyhrberg, 2016; Ji et al., 2021). Many studies are being investigated; Bitcoin returns can be impelled by evident behavioural variables (Bouri et al., 2017; Dias et al., 2022). These characteristics all point to the significance of looking into the factors that influence Bitcoin returns using a variety of techniques. Furthermore, very few scholars are interested in methods that reduce the number of factors determining a cryptocurrency's yield. Therefore, the primary goal of this study is to ensure that this task is completed by using general-specific modelling.

Therefore, identifying the determinants of asset prices has always been one of the most significant questions in finance. The traditional asset pricing theories are established on the notion that equity prices should be governed by the fundamentals for example, earnings. However, behavioural finance literature advances that the prices do not always follow the fundamentals because of investor sentiment trading (Stambaugh et al., 2012). In the case of digital currencies, academia has barely tried to look at the surface with respect to detecting the determinants of their prices. For instance, various researchers assert that Bitcoin has no core value and that its price has relentlessly revealed bubble-like behaviour (Cheah & Fry, 2015). Other studies indicate that the prices of Bitcoin, Ripple, and Ethereum vary across exchanges for weeks (Makarov & Schoar, 2020). Even without academia, the President of the United States of America also tweeted that cryptocurrencies are created out of "thin air".

Our study systematically investigates the determinants of Bitcoin's price volatility and its interconnectedness with key financial markets, including gold, oil, and major equities (represented by the DJIA and Nikkei 225). While existing literature highlights diverse macroeconomic and financial factors influencing Bitcoin's price formation, our work specifically investigates how these markets drive Bitcoin's volatility dynamics relative to the USD, employing gold prices, Brent oil, USDX, and EURO-USD as critical indicators. By analyzing both short- and long-term relationships, this research addresses a gap in understanding Bitcoin's role during market stress, e.g., crises like the COVID-19 pandemic. Our findings offer actionable insights for investors and portfolio managers seeking to optimize risk-adjusted returns, particularly given the growing inclusion of Bitcoins in diversified portfolios. Our study also contributes to debates about cryptocurrencies as potential safe havens, challenging conventional assumptions through empirical evidence. Section 2 presents a comprehensive literature review, grounding the study in existing theories and forming testable hypotheses about volatility transmission. This foundation supports our dual analytical approach, which combines time-series econometrics with market-specific drivers to decode the complex behavior of Bitcoin in global financial systems.

2. Literature Review

The topic of Bitcoin's fundamental value has piqued the interest of a number of authors. The foundation of financial theory is the notion that financial values are objective, meaning that each asset has a basic value based on the likelihood that it will produce income in the future. According to this idea, which maintains that finance should provide a reliable image of the real economy, it is possible to ascertain the fundamental value, or true value, of each asset at any given time. Some researchers observed that the cryptocurrency has no fundamental value (Cheah & Fry, 2015; Treiblmaier, 2022). Chaim & Laurini (2019) showed the existence of a bubble in cryptocurrency. Likewise, Baek & Elbeck (2015) discovered that the return on Bitcoin cannot be explained by its underlying value and that the cryptocurrency is 26 times more volatile than the S&P 500.

Other study by Panagiotidis et al. (2020) and Dubey (2022) empirically investigates the determinants and fundamental value of cryptocurrency. Advocates of the optic of essential value have employed a variety of factors that frequently alienated students by employing different strategies. Financial, technological, and macroeconomic categories relate to these indicators. Numerous studies have suggested a link between the price of Bitcoin and the financial indicators seen in most developed and emerging countries' stock markets. As an illustration, consider the acceptance of the Selection Operator (lasso) and the Least Absolute Shrinkage. It showed a strong relationship between the return on Bitcoin and stock markets in the US (the Dow Jones index) and China (the Shanghai Stock Exchange Composite Index). Additionally, Chen et al. (2021) showed how the returns on Bitcoin are influenced by the most well-known financial markets, including the Dow 30, S&P 500, Nasdaq, FTSE-100, and SSE. According to Kapar and Olmo (2021), the S&P 500 had a positive influence during the period of July 2010 to May 2019 when they used the VECM as an estimation method. However, Klose (2022) came to the conclusion that, after taking into account four factors, there were similarities and divergences between gold and four distinct cryptocurrency types. In this sense, it calculated a GARCH-in-Mean model and found that, for both gold and cryptocurrencies, the liquidity premia are basically negligible.

The primary focus was on the factors that determine cryptocurrency exchange liquidity, despite the volatility premia found in gold and cryptocurrencies. According to Brauneis et al. (2022), the liquidity of the larger financial markets and the liquidity of the Bitcoin-USD are essentially uncorrelated. Panagiotidis et al. (2018) used the same methodology to evaluate indicators of digital currency returns for various quantiles based on a variety of predictors. The most important factors were returns on small company stocks and US government bond indices (Ciner et al., 2022). Bouri et al. (2017) examine Bitcoin's principal purpose as a safe haven over the years 2011–15 using Engle's bivariate Dynamic Conditional Correlation (DCC) model. Along with other conventional financial assets like equities and commodities, they take into account the return of Bitcoin. Ultimately, they came to the conclusion that Bitcoin had a poor correlation with all of the variables. Although it was a useful asset for diversification, investors shouldn't view it as a safe haven. Dubey (2022) reached similar conclusions by demonstrating Bitcoin's potential for diversification. Similarly, Guesmi et al. (2019) looked at Bitcoin's usefulness as a hedging and diversifying asset. They were able to determine that a portfolio that consist on Bitcoin, gold, oil, and stocks had lower risks than a portfolio that only included gold, oil, and stocks by applying the GARCH model to evaluate the asymmetric behaviour of the spillover effect. Their main goal was to investigate any potential characteristics of Bitcoin that would make it a valuable hedging tool.

By the time a price increase accelerates exchange transactions in the near term, there is a case to be made for the quantity theory of money to offer commentary on Bitcoin's long-term behavior. Meanwhile, in the near term, Bitcoin is susceptible to fluctuations. Polasik et al. (2015) found evidence that price rises will result from demand driven by users' transactional demands, but that supply will not statistically significantly affect Bitcoin returns because the latter are more assured due to their adherence to a known mathematical method. Since Bitcoin's price determinants are not very similar to those of other financial assets, Kristoufek (2015) found that there is very little correlation between Bitcoin and other financial assets. According to Li and Wang (2017), the price of Bitcoin is determined less by economic financial factors and more by a distinct collection of factors, including user privacy, attractiveness, energy costs, the popularity of computer programming, and illicit behaviour (Yelowitz & Wilson, 2015).

However, after the financial crisis around the world and the COVID-19 pandemic, by using alternative techniques, Panagiotidis et al. (2019) and Panagiotidis et al. (2020) have also included the uncertainty surrounding economic policy as a factor influencing the return on Bitcoin. While many academics employ uncertainty as one of the explicative variables, some focus only on it. For example, Bouri et al. (2017) demonstrated a negative correlation between the return on cryptocurrency and the Global Economic Policy Uncertainty between March 2011 and October 2016, using the wavelet decomposition method and the quantile in the quantile regression approach.

Furthermore, Demir et al. (2018) validated the outcome and discovered that there was an inverse correlation between the return on Bitcoin and the uncertainty of economic policies, indicating that Bitcoin was intended to be a hedging medium. In addition, there might be additional macroeconomic financial market elements that have an impact on Bitcoin's performance. In the long run, these factors are likely to have a greater influence than technological ones. They came to the conclusion that a few macroeconomic factors, including the US dollar money supply and interest rate (i), had an impact on Bitcoin's return and discovered a strong positive link between the return on Bitcoin and various other variables, such as gold, oil, currency rates, and interest rates. Principal Component Analysis (PCA) and a method known as Factor Augmented Vector Autoregressive are used in this process. Panagiotidis et al. (2019) found that gold, the federal fund effective rate, and the price of oil had a substantial impact on the return of Bitcoin over an eight-year period from 2010-18. Yet, there was a negative correlation between the return on Bitcoin and the European Central Bank's deposit facility rate. More recently, Chen et al. (2021) suggested that short-term fluctuations in the price of Bitcoin were caused by changes in the price of gold and oil. Their findings demonstrated that the Adaptive Network Fuzzy Inference System (ANFIS) could not match the long short-term memory's (LSTM) capacity for predicted outcomes. Kapar and Olmo (2021) note that the price of gold has a negative impact on the return of Bitcoin.

Research on using Bitcoin as a diversification and hedging strategy, or possibly as a safe haven in times of crisis, is lacking (Bouri et al., 2017; Dubey, 2022; Mokni et al., 2022). In spite of Bitcoin's high volatility, Brière et al. (2015) used weekly data for the years 2010–13 to continue their investigation into the relationship between Bitcoin, bonds, stocks, fiat currencies, and alternative investments like commodities. Their findings were consistent with Baur et al. (2015). Their research revealed that traditional asset classes like stocks and bonds have little effect on Bitcoin performance, indicating the need for diversification.

Finally, our study examines Bitcoin's connections with Brent oil, Gold, USDX, EURO-USD, DJIA, and Nikkei-225, grounded in key financial theories. Bitcoin and gold share a safe-haven role, attracting investors during economic uncertainty, whereas the oil prices influence Bitcoin through macroeconomic risk and mining cost channels. The currency index movements (USDX, EURO-USD) impact Bitcoin demand via currency substitution effects, where weaker fiat currencies may drive capital into crypto. Major stock market linkages (DJIA, Nikkei-225) arise from financial contagion and speculative trading behaviours, with correlations strengthening during market stress. Our wavelet coherence approach captures time-frequency dynamics, while DCC-GARCH models volatility spillovers, testing hypotheses rooted in portfolio rebalancing and risk transmission theories. This framework clarifies Bitcoin's dual nature as both a hedge and a risk asset, strengthening the analysis of its interactions with traditional markets. Therefore, we proposed the following hypotheses for this research:

H1: Bitcoin's price is positively impacted by the price of Gold.

In first hypotheses, we will check impact of gold price on Bitcoin prices. We will examine whether the price of Bitcoin is positively correlated with the price of gold or not. Gold has always been a safe haven. So, it will guide the investors to choose carefully right stock for their investments.

H2: The price of Bitcoin is negatively impacted by the price of oil.

The prices of crude oil have witnessed puzzling swings recently especially during COVID-19 pandemic. Whenever there are any global financial crises or any other event occurred then crude oil stocks react quickly to the market. So, we will check the relationship between Bitcoin and crude oil.

H3: The USDX has positively affected the price of the Bitcoin

While checking the drivers of Bitcoin prices, this study will also examine the existence of any positive or negative correlation between USDX (US dollar index) and Bitcoin price returns.

H4: The EURO-USD has negatively affected the price of the Bitcoin

Being a prominent global currency at global stage, EURO-USD has also been included in our analysis. We will consider the EURO in terms of its monetary value in US dollar.

H5: The price of Bitcoin is positively impacted by the DJIA (Dow Jones Industrial Average)

In our proposed fifth hypothesis, we will further investigate any possible relationship between Bitcoin price returns and American Dow Jones Industrial Average index.

H6: The price of Bitcoin is adversely impacted by the Nikkei 225 index

The last hypothesis of our study will examine the any possible impact of Japanese Nikkei 225 index on the Bitcoin. We will check whether Nikkei-225 can be considered as determinant on the Bitcoin price returns along with the nature of relationship between these two stocks.

3. Data and research methods

3.1 Data

The core aim of this study is to examine the interaction between Gold, Brent oil, USDX, EURO-USD, DJIA, Nikkei-225 and Bitcoin. For this research, we have obtained daily data over the period of January 2010 to October 2022. The data has been collected from Yahoo Finance and other different sources/data streams depending upon the availability of data from respective sources. The data period contained different global financial crises period including Chinese stock market crash and COVID-19 pandemic. Our dataset has only a few missing observations, so we removed the affected entries across all variables to maintain consistency. We then calculated the daily log returns for each series using the following formula, where r_t represents the return on asset, ln is the natural logarithm, pt is the current price at time t, and P_{t1} is the previous price at time $t-1$.

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

Table 1. Summary statistics

	Mean	Median	Max.	Min.	Std. Dev.	Skew.	Kurt.	ADF	J-B test
Bitcoin	0.0015	0.0003	0.6402	-0.3686	0.0289	2.83	92.95	-27.70***	1113687.08***
Brent Oil	0.0000	0.0004	0.2525	-0.2828	0.0174	-0.63	98.00	-39.59***	1233668.07***
Gold	0.0000	0.0001	0.0542	-0.0463	0.0045	-0.16	16.78	-32.85***	36197.18***
USDX	0.0000	0.0000	0.0104	-0.0104	0.0018	0.09	1.91	-31.84***	475.49***
EURO-USD	-0.0000	0.0000	0.0131	-0.0104	0.0022	-0.02	1.86	-32.78***	446.56***
DJIA	0.0001	0.0002	0.1065	-0.0964	0.0064	0.05	53.69	-36.26***	370306.42***
Nikkei-225	0.0001	0.0002	0.1202	-0.1092	0.0085	-0.07	38.20	-38.32***	187475.10***

Notes: ***indicates significance at the 1% confidence level.

In Table 1 from the summary statistics, Bitcoin demonstrates a unique risk-return profile, with significantly higher mean (0.15%) and median (0.03%) returns compared to other traditional assets. Its extreme volatility (64% max gain, -37% max loss, and highest standard deviation at 0.0289), along with strong positive skewness (2.83) and massive kurtosis (92.95), highlights its high-risk, high-reward nature and fat-tailed distribution. In contrast, Brent oil shows moderate volatility (25%/-28%) but negative skewness (-0.63) and extreme kurtosis (98), indicating severe downside risks. Gold and currency indexes (USDX, EURO-USD) exhibit stability with near-zero returns and minimal fluctuations, while equities (DJIA, Nikkei) display moderate volatility and occasional extreme moves as kurtosis is over 38. These findings justify analyzing Bitcoin's volatility spillovers with more stable assets, as its outsized swings could impact portfolio diversification during market stress. Additionally, at the 1% level of significance, the Jarque-Bera test rejects normalcy for each series. Additionally, we also apply the Augmented Dickey-Fuller (ADF) test to check for stationarity. The unit root test is significant for each series at the 1%, hence, there is no unit root issue.

From Table 2, the results of the correlation matrix indicate that there is a mild positive correlation among the stock markets ranging from 0.009 to 0.236, suggesting a possible comovement among the markets. These outcomes indicate that the stock market in general moves in the same direction. Regarding the correlation between the commodity market and the stock market, the results show a low to mild positive correlation among the markets, with a few negative correlations. This indicates that, on the whole, the commodity market and the stock market are fairly related and move in the same direction. However, the correlation among the commodity markets shows a high level of positive correlation among the Brent oil, gold and Bitcoin markets. The results suggest a possible strong positive comovement among the commodities, indicating that these markets move in the same direction.

Table 2. Correlation matrix

	Bitcoin	Brent Oil	Gold	USDX	EURO-USD	DJIA	Nikkei-225
Bitcoin	1						
Brent Oil	0.027	1					
Gold	0.021	0.056	1				
USDX	-0.019	-0.020	-0.338	1			
EURO-USD	0.032	0.020	0.298	-0.872	1		
DJIA	0.074	0.159	0.015	-0.092	0.111	1	
Nikkei-225	0.009	-0.021	-0.018	-0.008	0.013	0.236	1

Notes: This table presents Correlation Matrix of selected variables and the results of the correlation matrix indicate a considerable level of correlation among the markets.

In Figure 1 we have present different stocks over time. We have presented several stocks, such as Brent oil, gold, Bitcoins, EURO-USD, USDX, DJIA and Nikkei 225. If we observe Brent oil and gold; both have followed the increasing and decreasing trend over the period of time. Bitcoin followed a different trend. With the start of 2016, the price of Bitcoin started increasing and followed a peak in the first quarter of 2020 and observed a peak. However, other stocks have followed the different trends due to their domestic and global activities. Most of the markets react quickly during the periods of historical crises. Some stocks indicate an increasing trend in their prices. For example, DJIA, USDX and Nikkei-225: all these markets respond more quickly to global events, such as the Chinese stock market crash and the COVID-19 pandemic crises. But most of the time, there was an increase with an increasing trend, which shows the prices of their stocks increase with the passage of time. However, on the other hand, some other stock markets have been very volatile during the sample period. Further, Brent oil and gold both have followed the increasing and decreasing trend over the period of time. Bitcoin followed a different trend. Starting in 2016, the price of Bitcoin began to increase, reaching a peak in the first quarter of 2020.

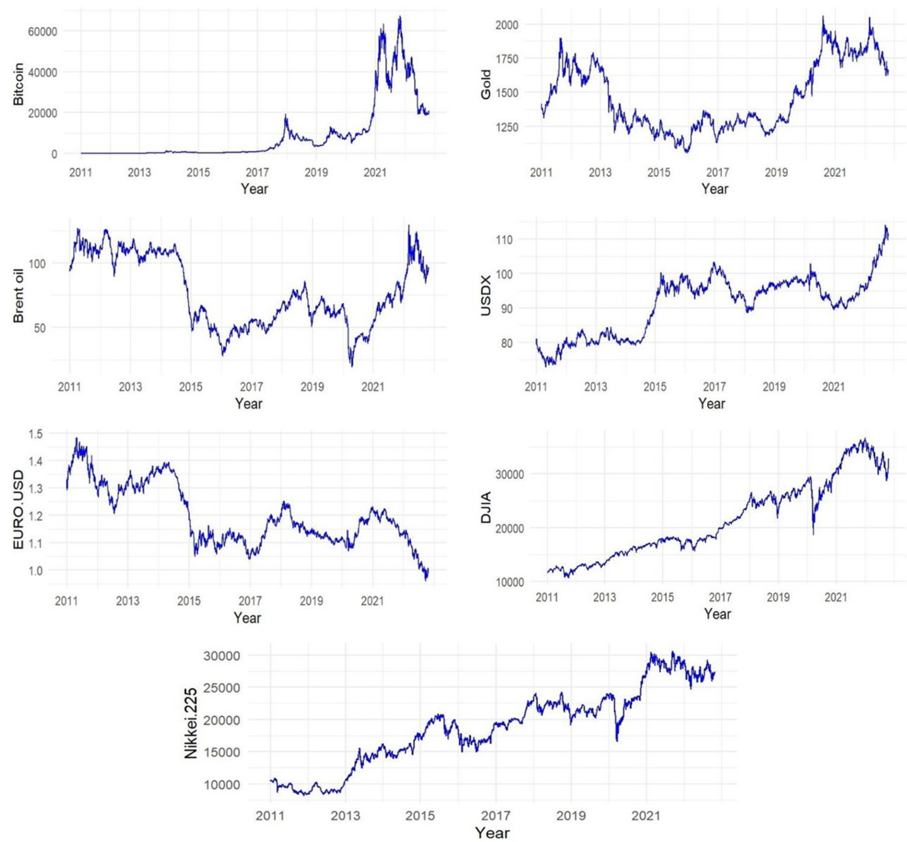

Figure 1. Dynamics of Price Series

Further Figure 2 represents the different stocks return series over the period of time by considering daily data. We have graphically presented the return series of oil, gold, Bitcoin, and four other stocks. Many stock return series have shown high volatility during periods of crises and global events. This volatility was particularly evident during the Chinese stock market crash and the COVID-19 pandemic. EURO-USD and USDX have been found highly volatile.

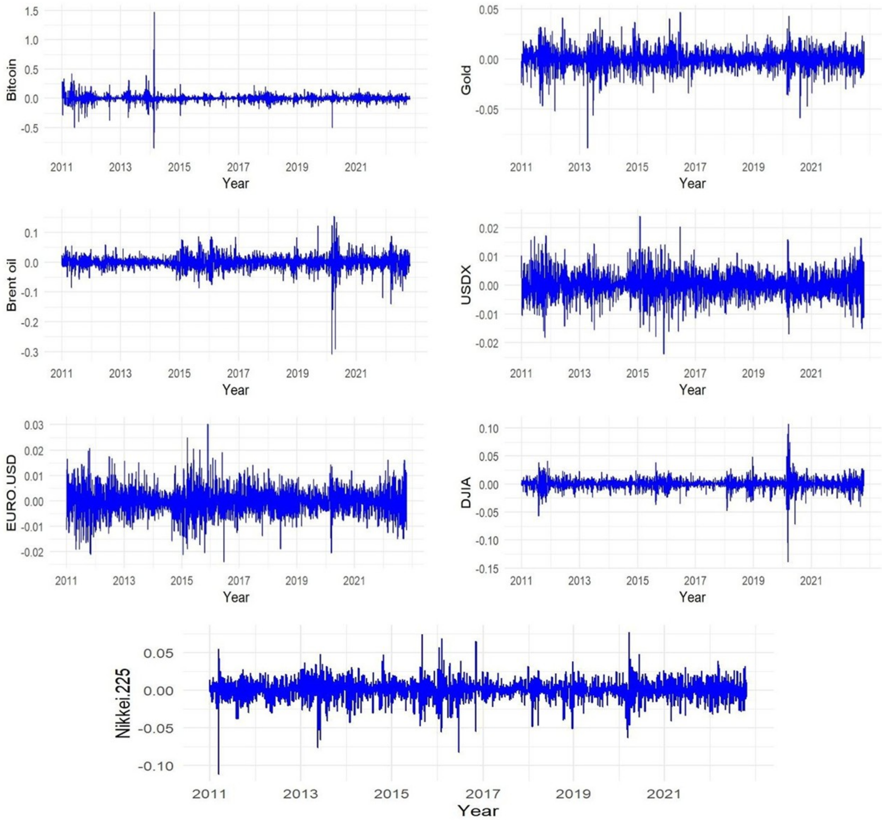

Figure 2. Dynamics of return Series

3.2 Wavelet coherence

A strong tool for data compression, processing, and analysis is wavelet analysis. It can be used to extract important information from various data types, including high-frequency time series in finance and economics that include images. Despite the rapid growth of the wavelet literature, wavelet analysis is still a relatively new idea in the fields of finance and economics. One of the main advantages of wavelets is their simultaneous localization in the time and frequency domains. Wavelets' second main advantage is that they are computationally rapid thanks to the speedy wavelet transform. The ability of wavelets to distinguish between the minute details of a signal is a major advantage. We can show that the cause-and-effect relationship changes based on the timescale by breaking the original time series into different timescales and examining each one separately. Wavelets have their origins in Fourier analysis and filtering techniques. However, this method failed to appropriately address changes that occurred quickly. The wavelet transforms, defined over a broad range of space, could overcome these limitations. Wavelet transformation allows us to characterize signals by frequency, position in time, and length. It can handle sudden changes in a time series.

A wavelet $\Psi(t)$ is a square integrable function with complex values that is produced by functions with the following form:

$$\Psi_{u,s}(t) = \frac{\Psi\left(\frac{t-u}{s}\right)}{\sqrt{s}} \tag{2}$$

using scale s and position u at time t. It is possible to reconstruct any time series from its wavelet transform if the admissibility requirement is met. A wavelet is standardly normalized and has a zero mean so that $\int_{-\infty}^{+\infty} \Psi(t)dt = 0$ and $\int_{-\infty}^{+\infty} |\Psi|^2(t)dt = 1$. A continuous wavelet transform $W_x(u,s)$ is obtained via the projection of a wavelet $\Psi(.)$ on the examined series $x(t)$ so that

$$W_s(u,s) = \int_{-\infty}^{+\infty} \frac{x(t)\Psi^*\left(\frac{t-u}{s}\right) dt}{\sqrt{s}} \tag{3}$$

where $\Psi^*(.)$ as the complex conjugate of $\Psi^*(.)$. Without any information loss, the original series can be recreated using the continuous wavelet transforms at the specified frequencies (Grinsted et al., 2004a; Percival & Walden, 2000). We select the Morlet wavelet among a large set of complex-valued wavelets that support multivariate analysis because it offers a fair trade-off between temporal and frequency localization (Aguiar-Conraria et al., 2008; Grinsted et al., 2004b).

For a bivariate scenario, the continuous wavelet framework can be generalized to analyze the interaction between two series across scales and in time. Next, we generalize a continuous wavelet transform to a cross wavelet transform as

$$W_{xy}(u,s) = W_x(u,s)W_y^*(u,s) \tag{4}$$

Where $W_x(u,s)$ and $W_y(u,s)$ are continuous wavelet transforms of series $x(t)$ and $y(t)$, respectively. Because the cross-wavelet transform is usually complex, the cross-wavelet power $|W_{xy}(u,s)|$ is usually used as a measure of co-movement between the two series.

The cross-wavelet power identifies regions in the time-frequency space where the series have a similar high power. It can be thought of as a covariance localized in the time-frequency space. On the other hand, because the standard covariance is not bounded, its explanation power of is limited.

To address this weakness, the wavelet coherence is introduced as

$$R_{xy}^2(u,s) = \frac{\left| s\left(\frac{1}{s} W_{sy}(u,s)\right)\right|^2}{S\left(\frac{1}{s}|W_s(u,s)|^2\right) S\left(\frac{1}{2}|W_y(u,s)|^2\right)} \tag{5}$$

where S is an operator for smoothing (Grinsted et al., 2004b; Torrence & Webster, 1999). One way to understand the squared wavelet coherence, which is a function of both time and frequency, is as a squared correlation with a range of 0 to 1. The direction of the link is lost because of the previously noted complexity of the wavelets utilized, which leads to the use of squared coherence rather than coherence itself. To do this, a phase difference is presented as

$$\varphi_{xy}(u,s) = \tan^{-1}\left(\frac{\Im\left[s\left(\frac{1}{s} W_{xy}(u,s)\right)\right]}{\Re\left[s\left(\frac{1}{s} W_{xy}(u,s)\right)\right]}\right), \tag{6}$$

where $\Im$ and $\Re$ represent an imaginary and a real part operator, respectively. An arrow is used to graphically depict the phase difference. If the arrow points to the right (left), the series are positively (negatively) correlated, indicating that they are in the in-phase or anti-phase, respectively. If the arrow is pointing up or down, the first series is ahead of the other by (vice versa).

A combination of the two is usually present in the relationship; for instance, if the arrow points northeast, there is a positive correlation and the second series leads the first. It should be emphasized that the interpretation of phase relationships depends partly on certain assumptions about the relationship since a leading relationship in the in-phase could be a trailing relationship in the anti-phase. Please refer to Grinsted et al. (2004b) for a comprehensive explanation.

Partial wavelet coherence has recently been presented as a way to explain the shared effects of two variables on the third (Mihanović et al., 2009; Ng & Chan, 2012). It is defined as

$$RP^2_{y,x_1,x_2} = \frac{\left|R_{yx_1} - R_{yx_2}R^*_{yx_1}\right|^2}{\left(1 - R^2_{yx_2}\right)^2\left(1 - R^2_{x_2x_1}\right)^2} \tag{7}$$

The partial wavelet coherence, which is between 0 and 1, can be thought of as the squared partial correlation between series y(t) and x1(t) after accounting for the influence of x2(t) localized in time and frequency. Readers interested in a more thorough analysis of the partial wavelet coherence are referred to Mihanović et al. (2009) and Ng & Chan, (2012).

3.3 DCC-GARCH model

This study employs the multivariate DCC-GARCH model to ascertain the variables influencing relationships among these stocks. For example, the bivariate DCC-GARCH model specification for two assets, x and y, is as follows:

$$H_t = D_t R_t D_t \tag{8}$$

where the conditional covariance matrix is denoted by $Ht; D_t = diag\{\sqrt{h_t^x}, \sqrt{h_t^y}\}$is the diagonal matrix produced by the following univariate GARCH model that contains the conditional standard deviations for the x and y return series at time t:

$$h_t = c + ae^2_{t-1} + bh_{t-1} \tag{9}$$

where a and b are the parameters that capture the GARCH and ARCH effects, respectively, and c is a constant and ht is the conditional variance.

$R_t = [\rho_{xy,t}]$ is the unconditional correlation matrix of et and a symmetric positive definite matrix. To extract the time-varying correlation estimator, compute the following:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha e \tag{10}$$

$$\rho_{xy,t} = \frac{q_{xy,t}}{\left(\sqrt{q_{x,t}}\sqrt{q_{y,t}}\right)} \tag{11}$$

where $\bar{Q}$ is the standardised residuals unconditional correlation matrix. If 4, then this model is mean-reverting.

4. Results and discussion

4.1 Wavelet coherence results

In Figure 3, we have presented wavelet squared coherency graphs. We are observing interaction among Bitcoin, Brent oil, Gold, USDX, EURO-USD, DJIA and Nikkei-225 to look at any potential changes in these commodities. The Bitcoin pairs plot indicates the least correlated pairs and the significant regions between these pairs during the periods of the financial crisis in 2016 and the COVID-19 crisis, with the Bitcoin plot leading Brent oil. The Bitcoin-Gold pair is out of phase and indicates negative correlations at medium and high frequency bands for 2014, 2016 and late 2020. We observe strong comovement not only between Bitcoin and USDX, but also between Bitcoin and EURO-USD. The wavelet coherence analysis reveals a complex relationship between Bitcoin, DJIA, and Nikkei 225. Blue areas show weak correlation, while red indicates strong comovement, particularly at 64–126 day frequencies. During COVID-19, a prominent red loop emerged, showing heightened correlation. The Bitcoin-DJIA pair exhibited anti-cyclical behaviour, suggesting negative correlation in certain periods. These findings demonstrate that the role of Bitcoin as a portfolio diversifier varies significantly across time horizons and market conditions, with crisis periods particularly altering these dynamics. The results provide valuable insights for risk management and investment strategies.

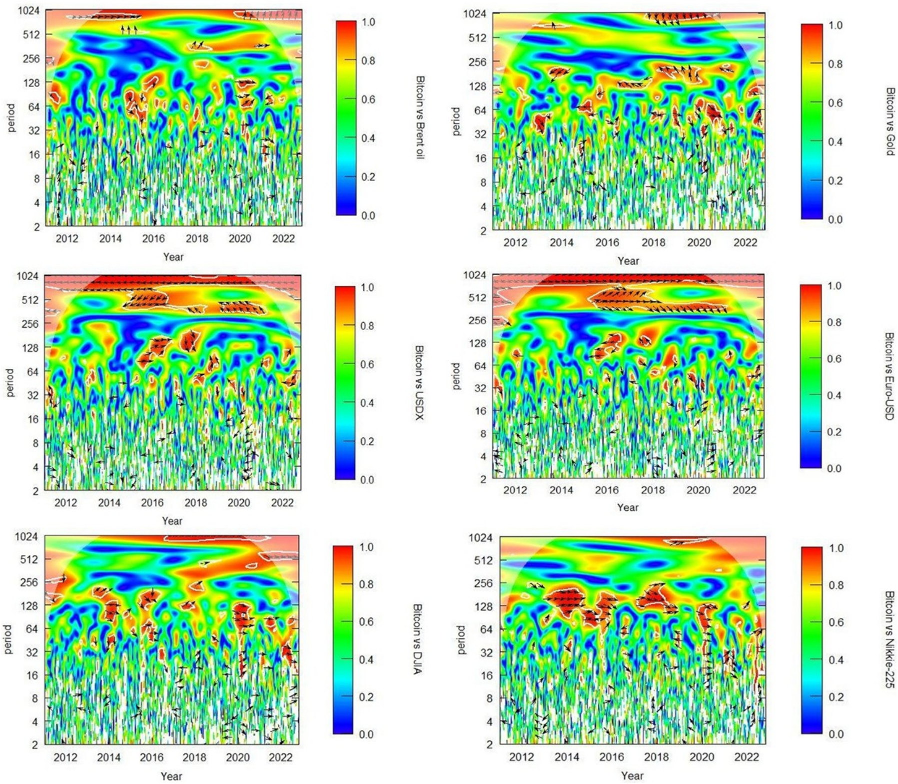

Figure 3. Wavelet coherence between Bitcoin and other stocks

4.2 Estimation of DCC-GARCH model

We have used a multivariate DCC-GARCH model to calculate the numerous macroeconomic and financial determinants of Bitcoin. We have considered multiple stocks such as Brent oil, gold, USDX, EURO-USD, DJIA and Nikkei-225. We provide the dual representation of the outcomes as numerical and graphical in the inspection of the DCC-GARCH model. The DCC's numerical results are likewise not entirely consistent, with Bitcoin showing a stronger correlation with many markets.

In our DCC-GARCH model, μ represents the long-term average return of the asset, while ω demonstrates the baseline level of volatility. The α (ARCH) term measures how quickly volatility reacts to recent market shocks, while β (GARCH) captures the persistence of volatility over time. For dynamic correlations, δ_1 (DCC alpha) reflects the immediate impact of shocks on asset correlations, and δ_2 (DCC beta) governs their long-term stability. The condition $\delta_1 + \delta_2 < 1$ ensures that correlations evolve dynamically over time, confirming the presence of time-varying interdependence between the two indices.

Table 3. Estimation of DCC-GARCH model

	Bitcoin–Brent Oil	Bitcoin–Gold	Bitcoin–USDX	Bitcoin–EURO/USD	Bitcoin–DJIA	Bitcoin–Nikkei-225
w_1	0.000***	0.000	0.000	0.000	0.000**	0.000
w_2	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
α_1	0.302	0.061***	0.038***	0.037***	0.308***	0.450**
α_2	0.166***	0.166***	0.166***	0.166***	0.166***	0.166***
β_1	0.612***	0.919***	0.959***	0.959***	0.632***	0.505**
β_2	0.827***	0.827***	0.827***	0.827***	0.827***	0.827***
δ_1	0.000	0.013***	0.009*	0.003**	0.007*	0.000
δ_2	0.963***	0.979***	0.983***	0.995***	0.991***	0.926***

Notes: ***, **, * indicates the level of significance at 1%, 5% and 10%, respectively. Here we employed return series of Bitcoins crypto currency, Crude oil (Brent oil), Gold spot prices, US dollar Index (USDX), EURO currency to US dollar (EURO-USD), Dow Jones Industrial Average (DJIA) for US and Japan Stock Index (Nikkei-225).

We have presented different macroeconomic and financial determinants of Bitcoin in Table 3 and found that there is no short-term volatility persistent between Bitcoin and Brent oil. However, in the case of long-term Brent oil, it is highly significant, which shows that their long-term volatility persists between Brent oil and Bitcoin. In the case of gold, both short-term and long-term are highly significant. In fact, gold is one of the stable financial assets. It has a tendency to rise in a crisis period. So, it is natural that there is less volatility clustering in the gold movements. We can conclude that gold is still not volatile in the COVID-19 period and thus can be considered a safe haven financial asset. It means that there exists persistent volatility, both in the short term and the long term. Moreover, USDX, EURO-USD and DJIA have long-term volatility persistence, which indicates that the market will remain volatile even if positive news comes out. Like during the COVID-19 pandemic, we can see that volatility is not decreasing but it is slightly coming down slowly and slowly but still the market is volatile. Even if we are having positive information in the market, the volatility of the market is still high. Nikkei-225 does not have any short-term volatility transmission but possesses it in the long run.

Robustness test

Our robustness checks using the framework developed by Baruník and Křehlík (2018) confirm and extend our main findings. In Table 4, the results show the strongest volatility spillovers in the short term (21.08% for 1-4 days), declining to 15.42% (4-10 days) and 5.66% (long-term). This pattern validates our DCC-GARCH and wavelet results, particularly the rapid crisis-period transmission (high δ_1) and gold's dual hedge/safe-haven role. The dominance of short-term spillovers supports behavioural theories of investor overreaction, while the limited long-term connectedness suggests Bitcoin's systemic risk may be overstated in stable markets. These findings provide policymakers with clear evidence that volatility containment measures would be most effective when focused on short-term market stress periods.

Table 4. Estimation of framework developed by Barunik and Křehlík (2018)

	Short-term Spillover (1–4 days)							
	Bitcoin	Brent Oil	Gold	USDX	EURO-USD	DJIA	Nikkei-225	FROM
Bitcoin	98.65	0.16	0.48	0.02	0.09	0.60	0.01	1.35
Brent Oil	0.18	95.50	0.48	0.14	0.08	3.59	0.03	4.50
Gold	0.17	0.51	81.94	9.57	7.48	0.12	0.21	18.06
USDX	0.08	0.21	6.25	51.06	41.01	1.22	0.16	48.94
EURO-USD	0.06	0.08	4.89	41.64	52.22	1.02	0.09	47.78
DJIA	0.59	3.12	0.12	1.29	1.38	85.04	8.46	14.96
Nikkei-225	0.38	1.12	0.16	0.15	0.25	9.91	88.03	11.97
TO	1.46	5.20	12.39	52.80	50.29	16.46	8.96	147.56
Net	0.11	0.70	-5.67	3.86	2.51	1.50	-3.01	TCI=21.08%
	Medium-term Spillover (4–10 days)							
	Bitcoin	Brent Oil	Gold	USDX	EURO-USD	DJIA	Nikkei-225	FROM
Bitcoin	72.65	0.09	0.20	0.02	0.07	0.43	0.01	0.81
Brent Oil	0.10	85.61	0.44	0.12	0.07	3.13	0.02	3.89
Gold	0.12	0.34	64.96	7.41	5.63	0.09	0.12	13.70
USDX	0.04	0.13	4.01	38.20	29.20	0.77	0.16	34.32
EURO-USD	0.03	0.06	3.29	31.09	39.42	0.71	0.08	35.25
DJIA	0.40	2.22	0.08	0.87	0.96	74.39	7.36	11.89
Nikkei-225	0.22	0.86	0.14	0.14	0.21	6.51	77.26	8.07
TO	0.90	3.68	8.17	39.64	36.14	11.64	7.75	107.93
Net	0.09	-0.20	-5.53	5.33	0.89	-0.26	-0.32	TCI=15.42%
	Long-term Spillover (beyond 10 days)							
	Bitcoin	Brent Oil	Gold	USDX	EURO-USD	DJIA	Nikkei-225	FROM
Bitcoin	26.01	0.07	0.27	0.00	0.02	0.17	0.00	0.54
Brent Oil	0.08	9.88	0.04	0.02	0.01	0.46	0.01	0.62
Gold	0.05	0.17	16.99	2.16	1.85	0.04	0.09	4.36
USDX	0.04	0.08	2.24	12.87	11.81	0.45	0.00	14.62
EURO-USD	0.03	0.03	1.60	10.55	12.80	0.31	0.00	12.53
DJIA	0.19	0.90	0.03	0.42	0.42	10.66	1.10	3.06
Nikkei-225	0.17	0.26	0.02	0.01	0.04	3.40	10.76	3.90
TO	0.56	1.52	4.22	13.16	14.15	4.82	1.21	39.63
Net	0.02	0.90	-0.14	-1.46	1.62	1.76	-2.70	TCI=5.66%

Notes: The table presents the spillover effects among network variables using the TVP-VAR-BK method. The "From" column indicates total volatility spillovers received by a market from others, while the "To" row shows spillovers transmitted from one market to the rest. The "NET" row reveals whether a market is a net transmitter (positive value) or net recipient (negative value) of volatility. Results are further decomposed into three horizons: short-term (1-4 days), medium-term (4-10 days), and long-term (>10 days), providing insights into how spillovers evolve across different timeframes.

5. Conclusion and implications

This study examines Bitcoin return drivers and volatility spillovers across oil, gold, and stocks using Wavelet Coherence and DCC-GARCH approaches using daily data. Additionally, we also use the framework of Baruník and Křehlík (2018) to confirm our results.

This study provides groundbreaking insights into Bitcoin's complex market dynamics through an innovative dual-method approach combining Wavelet Coherence and DCC-GARCH analysis of data. Our findings reveal Bitcoin's evolving and nonlinear relationships with traditional assets, challenging conventional market assumptions. The wavelet coherence analysis demonstrates crisis-period leadership of Bitcoin over oil markets during turbulence and the COVID-19 pandemic (Khan et al., 2025), while simultaneously showing unstable correlations with gold that contradict traditional safe-haven narratives. These patterns strongly align with behavioral finance theories, particularly regarding investor herding during volatile periods.

The DCC-GARCH results provide compelling evidence of distinct volatility transmission mechanisms, with gold exhibiting both short-term and long-term persistence, while equities show delayed responses that create strategic portfolio opportunities. The condition confirms the dynamic nature of these correlations, with robustness checks through frequency-domain spillover analysis further validating our findings. Notably, the short-term spillovers during crises versus just long-term connectedness suggest that systemic risk concerns may be overstated during stable periods. We further confirm the robustness of our results by using the Baruník and Křehlík (2018) framework. From a practical perspective, our identification of specific volatility cycles offers investors actionable thresholds for dynamic portfolio rebalancing. Our findings also provide regulators with critical metrics for implementing targeted market safeguards without stifling innovation. The distinct patterns we observe in different market conditions enable more nuanced risk management strategies for both institutional and retail investors.

Furthermore, we identify transformative research directions: developing hybrid machine learning-wavelet models for enhanced regime-switching prediction, expanding analysis to decentralized finance assets to map broader crypto-market dependencies, and incorporating real-time geopolitical risk indicators to refine volatility modeling. Our study not only advances academic understanding of cryptocurrency markets but also establishes a robust methodological framework for analyzing next-generation digital assets. By combining time-frequency decomposition with dynamic correlation modeling, we provide practitioners with powerful new tools to navigate the increasingly complex cryptocurrency landscape.

While our analysis provides valuable insights, it is limited by its focus on a select set of traditional assets. Future research should develop hybrid machine learning-wavelet models to better forecast regime shifts, extend the analysis to decentralized finance (DeFi) assets to map broader crypto-market interdependencies, and integrate real-time geopolitical indicators to refine volatility spillover models.

List of Abbreviations

USDX	U.S. Dollar Index
EURO-USD	EURO to U.S. Dollar
DJIA	Dow Jones Industrial Average
DCC-GARCH	Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity
TVP-VAR-BK	Time-Varying Parameter Vector Autoregression with Baruník-Křehlík

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