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Article

Bitcoin halvings and institutional investors: A wavelet analysis

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Abstract:
As a highly speculative asset, Bitcoin's (BTC) demand is largely driven by agents' perceptions of the asset. This is particularly true for institutions, which have started to leave a more significant footprint in the market, causing changes in transaction flow and price cycles. To assess how halving dynamics have changed the BTC market, wavelet methodology was applied with daily data (from January 2011 to December 2021) on the BTC price and transaction count. Decomposition in scale and frequency indicates that flows were altered by the arrival of new investors, and stronger correlations between prices and transactions were found at lower frequencies (i.e., a longer time horizon).

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Cryptocurrencies, particularly Bitcoin (BTC), have attracted considerable attention in the media, academic research, and economic and political circles, gaining increasing notoriety. Institutional investors, hedge funds, and private equity firms started to invest heavily in Bitcoin in the last few years (Iyer, 2022). With global economic uncertainty as a consequence of the COVID-19 pandemic and the Ukraine war, coupled with the quantitative easing policy promoted by the U.S. Federal Reserve System and the Bank of England (BoE) (Kang et al., 2019),[1] companies started to protect their holdings from expected inflationary effects and profitability losses.

[1] According to Robert Skidelsky, quantitative easing (QE) can be seen as an example of state-created financial instability. Increasing the money supply through QE provides a significant, temporary boost to housing and financial securities, greatly benefiting asset holders. The professor references Keynes's argument in *A Treatise on Money*: during an economic downturn, money is not necessarily hoarded, but it flows from "industrial" to "financial" circulation. When in financial circulation, it is used for "holding and exchanging titles to wealth, including stock exchange and money market transactions". Depression is marked by the transfer of money from industrial to financial circulation, from investment to speculation (Skidelsky, 2021).

Under certain specific circumstances, Bitcoin has proved to be an investment vehicle, an alternative diversifier, and a hedge[2] against or with other assets (Baek and Elbeck, 2015; Bouoiyour et al., 2015; Bouoiyour and Selmi, 2015; Briére et al., 2015; Cheah and Fry, 2015; Dyhrberg, 2016; Bouri et al., 2016; Blau, 2017; Bouri et al., 2017; Demir et al., 2018; Dyhrberg et al., 2018; Kang et al., 2019; Jareño et al., 2020; Bhuiyan et al., 2021).

Speculation and trading algorithms (Gray and Breton, 2020) can efficiently capitalize on potential arbitrage opportunities between different exchanges (Kristoufek, 2015; Tut, 2022), while market dynamics, in the form of dramatic volatility with swings and bubbles, have largely followed Bitcoin's lead. Today, the heightened economic and regulatory environment tend to drive instability, wavering investor confidence, triggering frequent selloffs and increasing market hype (Omane-Adjepong et al., 2019).

While Bitcoin's price dynamics are historically tethered to the halving phenomenon,[3] the emergence of institutional participants has fundamentally shifted market liquidity and flow,[4]. Consequently, the most recent price cycle exhibits deviations from previous patterns. Identifying periods with stronger measures of cross-correlation between price and transaction volumes provides a timeframe in which market players are most active, distinguishing between short- and long-term relationships. Price and transaction volumes in exchanges are a manifestation of how agents value (or undervalue) a specific crypto asset, making them crucial variables for a hypothesis under investigation.

The wavelet methodology targets periodic phenomena in time series in the presence of potential frequency changes across the time domain (Rösch and Schmidbauer, 2018). This is a useful technique for analyzing financial relations. Its ability to work with nonstationary data is particularly advantageous, as most econometric methodology assumes stationarity, which may or may not be apparent in economic data (Crowley, 2007). This study uses continuous wavelet power analysis, wavelet coherence, and phase difference to assess correlations, capturing market dynamics, through time and across scales, of the Bitcoin price series (in USD) and the number of transactions in BTC.

Our present hypothesis is framed by the following research questions: 1) *Did the last BTC price cycle behave differently than the other cycles?* 2) *Is it possible to observe through the co-movements between BTC price and transaction count how institutions are active in the BTC market, through frequency and scale decomposition?* The rationale is that the main crypto environment (Bitcoin) has changed with the arrival of agents with high financial leverage that are capable of leaving specific trails when analyzing price vis-à-vis their impacts on transactions over different time frequencies. This shift points to different dynamics that could influence not only low- to middle-income speculators but also market reaction and volatility.

Wavelet decomposition reveals a multi-scale structure in Bitcoin dynamics: high-frequency components are driven by localized volatility from retail participants, whereas low-frequency scales exhibit persistent trends associated with large-scale speculators. Increased access to crypto

[2] If an asset is negatively correlated with another asset, putting them together significantly decreases portfolio risk. Bouri et al. (2016, p. 2), to better qualify terminology, differentiate between a diversifier, a hedge, and a safe haven: "A diversifier is an asset that has a weak positive correlation with another asset on average. A weak (strong) hedge is an asset that is uncorrelated (negatively correlated) with another asset on average. A weak (strong) safe haven is an asset that is uncorrelated (negatively correlated) with another asset on average during times of stress".

[3] Despite their importance as a key technical element of the Bitcoin network, halvings are not thoroughly studied in academic literature. Economic studies dedicated to Bitcoin are generally focused on market power, supply, demand, production costs, and public interest through mass media (Meynkhard, 2019).

[4] Here we define big players or institutions as companies that own a large sum of Bitcoins.

investment through specialized exchanges, and market capitalization, pushed the price/transaction correlation to a long-term trend (lower frequency).

The remainder of this paper is organized as follows. The first section describes the halving phenomenon and how it affects incentives to mine and transact in the Bitcoin market. The second section reviews the academic literature on wavelet methodology concerning BTC price movement. The third section provides a more detailed explanation on continuous wavelet, wavelet coherence, and phase difference. The final part of the article covers the dataset, interpretation specifics, and results, ending with conclusions.

1. Halving phenomenon

Unlike traditional assets, Bitcoin's production is governed by automated, immutable code, rendering the creation of new supply both predictable and strictly limited. All else being equal, this scarcity should drive price appreciation and protect against currency devaluation one of Bitcoin's main purposes. Because no central authority can change the supply, Bitcoin's circulation remains independent of government monetary policy.[5]

Following the completion of new blocks on the blockchain, the frequency with which they are generated is constant: six blocks per hour. Each BTC block is limited to one megabyte in size and cannot process more than eight transactions per second (Tut, 2022). The number of coins mined by the network is reduced in a geometric progression: for every 210.000 Bitcoins mined, there is a 50% reduction in the BTC reward, corresponding to a four-year cycle.

When Bitcoin was launched, the award for the transaction block was 50 BTC. In one hour, the network produced an output of 300 BTC, or 7,200 BTC per day. Four halving events have happened since Bitcoin's inception: in 2012, 2016, 2020, and 2024. The end of 2012 marked a decline in emissions from 50 to 25 BTC for each new found block, which consequently generated 150 BTC per hour, 3,600 BTC per day, and 1,312,500.00 BTC per year. The market price was at approximately $12 when the halving happened; a year later, the BTC price reached a maximum of $1,150, amounting to a rise of 9,600%.

The second halving event occurred in July 2016, releasing 2,625,000.00 BTC in circulation, which was 12.5% of the maximum issuance of Bitcoin (table 1). At the time of the halving, the BTC price was $670. After nearly a year and a half, in December 2017, the Bitcoin price reached $19,500, a new all-time high, resulting in a 2,910% increase in market value. The third halving event occurred in May 2020, and the block reward was reduced from 12.5 to 6.25 BTC per block. The Bitcoin price was at $8,599 at the time of the halving event. To date, there were two highs: one in May 2021 when the BTC price reached $58,218, and the other towards the end of 2021, when the BTC price reached $65.342, a new high (697%). The last halving occurred in April 2024, when miners reached a total amount of 20,343,750 mined Bitcoins.

Therefore, halving can significantly affect Bitcoin market value, in addition to influencing overall miners' earnings (Meynkhard, 2019; El Mahdy, 2021; Lashkaripour, 2024; Fabus et al., 2024). Analyzing historical data from 2012, 2016, and 2020, Fabus et al. (2024) identify patterns in price movements, focusing on the timing and magnitude of peaks and troughs post-halving.[6]

[5] There are three basic market principles of Bitcoin: 1) limited issuance, 2) mining difficulty, and 3) the halving event (Meynkhard, 2019). In this paper, we will focus on further qualifying the limited Bitcoin issuance and the halving phenomenon.

[6] The study employs technical indicators such as the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) to assess market momentum and potential reversal. Statistical regression is also utilized to explore the relationship between the timing of the halving events and subsequent price movements.

The authors developed a mathematical model that suggests that Bitcoin's price typically reaches a peak approximately 19 months after the halving event and a trough around 31 months post-halving (following the 2024 halving, the next significant price peak will occur in November 2025, with a subsequent trough in November 2026).

Table 1 – *Bitcoin emission*

Year	Block remuneration	Number of mined Bitcoins	Percentage (%) of the number of Bitcoins emitted	Number of mined Bitcoins by cumulative totals
2009	50	10.500.000,00	50,00%	10.500.000,00
2012	25,0	5.250.000,00	25,00%	15.750.000,00
2016	12,50	2.625.000,00	12,50%	18.375.000,00
2020	6,250	1.312.500,00	6,25%	19.687.500,00
2024	3,125	656.250,00	3,13%	20.343.750,00
2028	1,5625	328.125,00	1,56%	20.671.875,00
2032	0,78125	164.062,50	0,7813%	20.835.937,50
2036	0,39063	82.031,25	0,3906%	20.917.968,75
2040	0,195313	41.015,63	0,195313%	20.958.984,38
2044	0,097656	20.507,81	0,097656%	20.979.492,19
2048	0,0488281	10.253,91	0,04882813%	20.989.746,09
2052	0,0244141	5.126,95	0,02441406%	20.994.873,05
2056	0,01220703	2.563,48	0,0122070313%	20.997.436,52
2060	0,00610352	1.281,74	0,0061035156%	20.998.718,26
2064	0,003051758	640,87	0,0030517578%	20.999.359,13
2068	0,001525879	320,43	0,0015258789%	20.999.679,57
2072	0,0007629395	160,22	0,0007629395%	20.999.839,78
2076	0,0003814697	80,11	0,0003814697%	20.999.919,89
2080	0,0001907349	40,05	0,0001907349%	20.999.959,95
...	...	...	...	...
2140	0,0000000058	0,001222360	0,0000000058%	21.000.000,00

Source: Adapted from Meynkhard (2019, p. 8).

Lashkaripour (2024) also offers an empirical analysis of Bitcoin's responses to its halving events in 2012, 2016, and 2020. His research investigates the dual effects of halvings: the reduction in Bitcoin supply, which could potentially boost prices, and the decrease in miners' revenue, which might undermine network security and lower prices.

Contrary to common sense on the subject, the study finds that Bitcoin prices slightly decrease following halving events, and in post-halving periods there is an increase in transaction fees (this rise might be a compensation for the reduced block rewards). As expected, miner revenue declines, impacting the economic incentives for mining activities.

Hypothetically, Bitcoin network participants who used to mine and sell 100 BTC per month begin to produce 50% fewer coins after a halving to offset their production costs, leading to a decrease in the supply of "newly minted" BTC.

With the same level of demand and a halved supply, market reaction could lead to an increase in asset price. Escalating BTC prices are traditionally attributed to supply and demand fundamentals, estimated output volumes, the role of global financial development, equity market indices, exchange transactions, and long-term price behavior (Ciaian et al., 2016; Bouoiyour and Selmi, 2015; Kristoufek, 2015; Bouoiyour et al., 2016; Iyer, 2022).

Initially, many companies and institutional investors began viewing Bitcoin not just as a speculative asset, but as the potential "future of money". This shift gave Bitcoin greater legitimacy, making its perceived value real, which sparked speculation on whether price surges were bubbles or a reaffirmation that it was becoming a more popular "store of value". Bitcoin has largely become a financial asset, in a globally integrated market with a diverse group of holders, who are increasingly looking at its artificial scarcity.

Despite long-term trends in BTC markets, current and prospective traders should bear in mind that prices are mainly driven by the most recent BTC halving and the current global economic environment, with its asset bubbles and short-term trader expectations, making Bitcoin a highly volatile[7] and speculative investment.

2. Review of the academic literature

Wavelet coherence, which monitors temporal relationships over the short, medium, and long run, has been widely used in the financial literature. Crypto-focused wavelet literature has identified co-movement between Bitcoin and its fundamental attributes (Kristoufek, 2015; Phillips and Gorse, 2018), global uncertainty (Bouri et al., 2017), hedging capabilities and informational inefficiencies (Kang et al., 2019; Omane-Adjepong et al., 2019; Qiao et al., 2020; Bhuiyan et al., 2021), and regional markets (Lim and Masih, 2017).

Kristoufek (2015) was one of the first to analyze Bitcoin's main drivers with wavelet coherence analysis. According to the author, if Bitcoin is used for trade, it appreciates in the long run, boosting demand for the asset and motivating users to become miners.[8] The study incorporates important Bitcoin characteristics: 1) fundamental economic drivers (trade exchange ratio, price level, and money supply); 2) technical drivers (hash rate and mining difficulty); 3) public interest and speculation (search engine queries); and 4) the Chinese market influence.

This underscores the importance of the complex interplay of fundamental economic variables across both time and frequency domains to fully understand the multifaceted nature of Bitcoin's price movements. Revisiting and extending Kristoufek's (2015) study, Phillips and Gorse (2018) use wavelet coherence and a generalized supremum augmented Dickey-Fuller bubble test to address online usage factors and market regime.

Bouri et al. (2017), using wavelet-based quantile-in-quantile regressions, examines whether Bitcoin can hedge global uncertainty. Unlike Kristoufek (2015), who does not identify safe-haven properties of Bitcoin, the authors reveal that BTC does hedge against risk when the market is in a bull regime (upper quantiles) but not when it is in a bear regime, where BTC returns are negatively impacted by uncertainty.

[7] Interestingly enough, in its quarterly report, Coinbase, a platform for buying and selling cryptocurrencies, explicitly discloses an extensive number of risk factors involved in its trading activities, reaffirming the highly erratic nature of this market: "[…] there is no assurance that any supported crypto asset will maintain its value or that there will be meaningful levels of trading activities. In the event that the price of crypto assets or the demand for crypto assets declines, our business, operating results, and financial condition would be adversely affected" (Coinbase, 2022, p. 57).
[8] However, this effect vanishes over time, as specialized mining hardware components drive hash rates and mining difficulty even higher.

Employing wavelet covariance and correlation, using daily prices from July 2014 to November 2019, to analyze BTC and several representative asset classes,[9] Bhuiyan et al. (2021) find that, in most circumstances, there is a neutral dependence (with a notable exception for gold prices). This outcome implies that the Bitcoin market is relatively isolated from the global financial system; nonetheless, it shares important features with gold.

Kang et al. (2019), who are also interested in diversification properties of gold futures vis-à-vis Bitcoin prices, aim to reveal whether the bubble patterns in gold future prices could be used to hedge against overall market and downside risk in the Bitcoin market. There is evidence of volatility persistence, causality, and phase differences between Bitcoin and gold futures. Contagion increased during the European sovereign debt crises of 2010-2013.

Using wavelet coherence, Qiao et al. (2020) analyze relationships across returns, volatility, and risk in a time-frequency domain. Among representative cryptocurrencies, hedging effects are considered in different investment horizons. Results indicate that time and scale are important determinants of the co-movement between returns, whether in correlation or phase difference. Bitcoin has a closer relationship with newly issued cryptos because they are not stable enough to withstand external influences. However, across different investment periods, risk reduction is possible, with positive correlations between BTC and other cryptos.

With a multivariate GARCH DCC (MGARCH-DCC) and wavelet tools, Lim and Masih (2017) conduct an exploratory study on whether Bitcoin can be used as a portfolio optimization strategy for Islamic fund managers. Collecting daily closing prices from 1 January 2013 to 2 January 2017, and a holding period of 8-16 days, correlations are negative for all indices, indicating that investors should look into BTC as a short-to medium-term investment diversifier.

Omane-Adjepong et al. (2019), employing ARFIMA-FIGARCH class models under the Gaussian and Student's t-distributions with a modified log-periodogram method, explore the persistence of the eight largest cryptocurrency markets, using daily data from August 2015 to March 2018. Market (in)efficiencies are examined using derived and filtered conditional market returns across short-, medium-, and long-run trading horizons through Maximal Overlap Discrete Wavelet Transform (MODWT). The authors find that informational efficiency and volatility persistence are highly sensitive to time-scale and regime shifts.

For empirical purposes, it would be more effective to have a transform with an adaptive basis. The Empirical Mode Decomposition (EMD), performed by Bouoiyour et al. (2016) on daily time series related to the Bitcoin Price Index (BPI) from December 2010 to June 2015, explains the time-frequency evolution of multi-component signals, showing that BTC seems to be largely explained by long-run factors.

Employing causal wavelet analysis over the period from 2014 to 2024, Alvarez-Ramirez et al. (2025), introduce a method that ensures that only past information influences present price dynamics. The complex Morlet wavelet application captures time-frequency characteristics of Bitcoin's price movements, allowing for a detailed examination of market complexity across different time scales. Their analysis reveals that periods of high wavelet power correspond with bearish market phases that precede significant price peaks, which indicate increased market complexity during downturns. The study also estimates the characteristic time scale of the decaying memory, suggesting that Bitcoin's price dynamics are influenced by long-term memory effects.

[9] Gold, the U.S. Dollar Index, oil, the Dow Jones Commodity Index, the S&P Global 100 index, and the EuroMTS 7 -10 Year Government Bond Index (EMTX 7 - 10Y).

Celeste et al. (2020) investigates the complex price behaviors of three major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) using fractal geometry and wavelet analysis. To examine the presence of long memory, fractal characteristics, and dynamic interdependences in the daily return series of BTC, ETH, and XRP from 2016 to 2017, the authors use a combination of Rescaled Range (R/S) analysis and various wavelet-based techniques, including Continuous Wavelet Transform (CWT), Cross Wavelet Transform (XWT), and Wavelet Coherence (WTC). Bitcoin exhibits evidence of long-term memory, and its return series trends toward a random walk, suggesting increasing market maturity and alignment with the Efficient Market Hypothesis (EMH).[10]

Phiri (2022) integrates continuous complex wavelet transforms with the traditional Dickey-Fuller test, examining the presence of random walk behavior in Bitcoin's daily returns from 19 July 2010 to 3 March 2022. The study adapts the conventional Dickey-Fuller test into a time-frequency framework using continuous complex wavelet transforms. This enables the detection of nonstationary behavior in Bitcoin returns across various time scales. Segmenting the data into subsamples based on the halving events, Phiri observes that each successive halving event correlates with a progressive decline in market efficiency. This trend may reflect increasing speculative behavior and Bitcoin market maturation challenges following these events.

Che et al. (2023), using an agent model with time-varying aggregate risk aversion, illustrate how shifts in investor risk preferences can lead to a synchronized movement between crypto and equity markets, especially as institutional involvement grows. Some of their main findings are highly pertinent to our study: 1) They identify a single underlying component termed "the crypto factor" that accounts for approximately 80% of the variation in cryptocurrency prices; 2) Correlation between the crypto factor and global equity markets, particularly the U.S. stock market, has intensified over time (this trend coincides with the growing participation of institutional investors in crypto markets); and 3) U.S. Federal Reserve tightening has also negatively affected the crypto factor via the risk-taking channel (showing that it is highly susceptible to broader financial conditions).

Although Bitcoin does behave as a bubble (high-frequency component) prone to speculative attacks, long-term fundamentals (low-frequency component) are likely to be major contributors of price variation. Therefore, price dynamic scholars should be highly aware of the properties of the identified data. Since our main objective is to recognize patterns of price dynamics vis-à-vis their impacts on transactions over the short and the long term, the motivation behind the next section is to comprehend wavelet methodology and the underlying data-generating process.

3. Methodology

Most time series techniques interpret data in the short and the long run but do not explain precisely how long the long run is or how short the short run is (Bhuiyan et al., 2021). Specific economic phenomena are better addressed at different time scales, while variable decomposition may reveal correlations that are not visible at the aggregate level: "[…] economic processes are the result of the actions of several agents, who have different-term objectives. Therefore, economic time series are a combination of components operating on different frequencies" (Aguiar-Conraria and Soares, 2011, p. 1).

[10] Other important findings include the time-varying co-movements between the crypto assets, which indicate that shocks in one market can influence others. These co-movements are more pronounced during periods of market stress or significant price movements.

Ignoring time and frequency dependence between variables may lead to erroneous conclusions. A more realistic approach is to separate different time scales and analyze relationships among variables at each level (Gallegatti and Semmler, 2014; Ramsey, 2014).

By definition, wavelets are a parameter-preserving, multi-resolution decomposition with a finite number of oscillations. They are ideally suited to approximating variables across scales: they can be “stretched” or “squeezed” to mimic the series under investigation. Choosing the appropriate degree and nature of the oscillation within the supports of the wavelet is key. Elementary functions (father ⍰ and mother wavelets ⍰), being well localized in both time and scale, provide a decomposition on a “scale-by-scale” as well as a frequency basis (Crowley, 2007; Gallegatti and Semmler, 2014; Ramsey, 2014).

A father wavelet ⍰(⍰) integrates to 1, and a mother wavelet ⍰(⍰) integrates to 0. The father wavelet essentially represents the smooth trend (low-frequency) part of the signal, whereas mother wavelets represent the detailed (high-frequency) parts. The amount of stretching of the wavelet is known as “dilation”. Mother wavelets are compressed in the time domain to generate cycles to fit actual data (Crowley, 2007; Ramsey, 2014). Generated from father and mother wavelets through scaling and translation, the approximating functions $\phi_{j,k}\,(t)$ and $\psi_{j,k}\,(t)$ are as follows:

$$\phi_{J,k}(t) = 2^{\frac{-J}{2}}\,\phi\left(\frac{t-2^{J}k}{2^{J}}\right) \qquad (1)$$

and

$$\psi_{J,k}(t) = 2^{\frac{-J}{2}}\psi\left(\frac{t-2^{J}k}{2^{J}}\right) \qquad (2)$$

Here, j indexes scale so that 2^{j} is a measure of the scale (or width of the functions), and k indexes translation so that $2^{j}k$ is the translation parameter. Thus, wavelets take the following functional form:

$$\psi(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \qquad (3)$$

The u parameter specifies location; the scale parameter s refers to the width of the wavelet, which indicates how stretched or dilated it is while maintaining its wavelike shape. The ${}^{1}/_{\sqrt{s}}$ term ensures that the norm of Ψ is equal to one.[11] As the wavelet widens, a broad support yields large-scale information, whereas a small support wavelet yields small-scale information. Conversely, low scales allow for the analysis of (higher-frequency) short-term dynamics of the time series under consideration, whereas high scales allow for the analysis of (lower-frequency) long-term dynamics. Lastly, if a wavelet is shifted, this is referred to as translation or shift of u (Ramsey, 2014; Phillips and Gorse, 2018).

A wavelet is, therefore, a complex-valued, square-integrable function that is rapidly decaying (Kristoufek, 2015). Applying a wavelet continuously leads to a complex-valued transform of the

[11] A normalization factor is used to ensure that wavelet transforms are comparable across scales and time series (Lim and Masih, 2017, p. 8).

time series at hand, which is information-preserving considering a careful selection of time and frequency resolution parameters. The continuous wavelet transform (CWT) of a given time series x is:

$$W_x(u,s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \bar{\psi}\left(\frac{t-u}{s}\right) dt, \tag{4}$$

Here, s is again the scaling factor that controls the width of the wavelet, and u is a translation parameter controlling the location of the wavelet. The bar over psi ⍰ denotes complex conjugate. When the wavelet ⍰(⍰) is a complex-valued function, the wavelet transforms $W_x\ (u,s)$ are also complex-valued, returning information about amplitude and phase difference. A complex wavelet is therefore almost mandatory when studying the oscillatory behavior of parameters (Torrence and Compo, 1998; Aguiar-Conraria et al., 2014).

Assume that the wavelet (equation 1) has been normalized so that $\int_{-\infty}^{\infty} |\psi(t)|^2\, dt = 1$. This normalization, $|\psi(t)|,^2$ defines a probability density function with its mean and standard deviation called, respectively, the center, μ_ψ and the radius, σ_ψ, of the wavelet. They are measures of localization and spread of the wavelet. The interval $[\mu_\psi - \sigma_\psi, \mu_\psi + \sigma_\psi]$ is set where $\psi(t)$ attains its "most significant" values.

The rectangle $H_\psi = [\mu_\psi - \sigma_\psi, \mu_\psi + \sigma_\psi] \times [\mu_{\grave{\psi}} - \sigma_{\grave{\psi}}, \mu_{\grave{\psi}} + \sigma_{\grave{\psi}}]$ is called the Heisenberg box or window for the function ψ. The function ψ is localized around the point $(\mu_\psi, \mu_{\grave{\psi}})$ of the time-frequency plane, with uncertainty given by $\sigma_\psi \sigma_{\grave{\psi}}$. The Heisenberg principle establishes that uncertainty is bounded below by $1/_2$ (Aguiar-Conraria and Soares, 2011; Aguiar-Conraria et al., 2014).

The Morlet wavelet achieves this lower bound, where uncertainty attains the minimum possible value while time and frequency radii are equal $\sigma_\psi = \sigma_{\grave{\psi}} = \frac{1}{\sqrt{2}}$. Mathematically, the Morlet wavelet builds on a Gaussian-windowed sinusoid that keeps its shape during frequency shifts. Thus, it provides a reasonable separation of contributions from different frequency bands without excessive loss of time resolution (Rösch and Schmidbauer, 2018). The "mother" Morlet wavelet is described as follows:

$$\psi_{\omega_0}(t) = \pi^{\frac{-1}{4}} e^{i\omega_o t} e^{\frac{-t^2}{2}} \tag{5}$$

ω_0: localization parameter

Strictly speaking, $\psi_{\omega_0}\ (t)$ is not a true wavelet; however, for sufficiently large ω_0 $(e.g.\ \omega_o > 5)$ and practical purposes, it can be considered as such. This is the most common choice for the angular frequency ω_0, or rotation rate in radians per time unit, $\omega_0 = 6$. This choice facilitates the conversion from scales to frequencies, $f \cong 1/_S$, making the Morlet wavelet approximately analytic (Aguiar-Conraria and Soares, 2011; Aguiar-Conraria et al., 2014; Rösch and Schmidbauer, 2018).

The set of scales s determines wavelet coverage of the series in the frequency domain. The scale value is a fractional power of 2:

$$S_{min}\ 2^{j.d_j}, j = 0\,, \dots, J. \tag{6}$$

One revolution is equal to $2\pi\ radians$; therefore, the period (or inverse frequency) measured in time units equals $2\ {}^{\pi}/_{6}$. Inverse frequency, or the Fourier factor, is used to convert scales into periods:

$$\lambda(S) = \frac{2\pi}{\omega_{\psi}} S \tag{7}$$

The minimum (maximum) scale is fixed by choosing the minimum (maximum) period of interest through a conversion factor of ${}^{6}/_{2\pi}$. This gives consistent results for sinusoidal waves of known frequency. The relationship between scale and the Fourier frequency, expressed in cycles per unit time, is:

$$f(s) = \frac{\omega\psi}{s} \tag{8}$$

The local amplitude of any periodic component of the time series under investigation, as well as how it evolves over time, can be retrieved from the modulus of its wavelet transform:

$$Apml\ (u,s) = {}^{1}\!\Big/_{s^{\frac{1}{2}}} . [Wave\ (u,s)] \tag{9}$$

where: $Wave = equation$ (3).

The modulus produces “biased” wavelet amplitudes in the sense that high-frequency (short-period) phenomena tend to be underestimated.

The square of the amplitude is the time-frequency wavelet energy density, also known as the wavelet power spectrum:

$$Power(u,s) = \frac{1}{s}[Wave\ (u,s)]^2 \tag{10}$$

What is expected is that the value at each time and scale corresponds to the series variance, with a proportionality factor $\frac{1}{s}$ in this rectified version of the wavelet power.

To compare the frequency contents of two time series and to draw conclusions about their synchronicity at certain periods, the cross-wavelet analysis provides the appropriate tools. The continuous wavelet transform is generalized to a cross-wavelet transform, as:

$$W_{xy}(u,s) = \frac{1}{s} W_x(u,s) W_y * (u,s) \tag{11}$$

where $W_x\ (u,s)$ and $W_y(u,s)$ are continuous wavelet transforms of series $x(t)$ and $y(t)$.

While the wavelet power spectrum is depicted as the local variance of a time series, the cross-wavelet power of two time series depicts the local covariance in the time-frequency space. Cross-wavelet power $\left|W_{xy}\ (u,s)\right|$ is usually used as a measure of co-movement between two series, as it uncovers regions in the time-frequency space where the series have common high power.

With some limitations, wavelet coherency can remedy this, as it measures the cross-correlation between two time series as a function of frequency. Formally and geometrically, coherency is analogous to the classical correlation; it requires the smoothing of both the cross-wavelet spectrum and the normalization of the individual power spectra. Wavelet coherency is given by the formula:

$$Coherence = \frac{|sWave.xy|^2}{sPower.x.sPower.y} \tag{12}$$

or

$$R_{xy}^2(u,s) = \frac{\left|s\left(\frac{1}{s}W_{xy}(u,s)\right)\right|^2}{s\left(\frac{1}{s}|W_x(u,s)|^2\right)s\left(\frac{1}{s}\left|W_y(u,s)\right|^2\right)} \tag{13}$$

where s is the smoothing operator.

Smoothing is necessary because, otherwise, coherency would have modulus one at all scales and times. It is important to emphasize that there is no general agreement in the literature on the direction of smoothing (scale or time) or the amount of smoothing required to obtain an appropriate measure of coherence without losing information.[12]

Based on equation (13), wavelet coherence is the ratio of the cross-wavelet power to the product of the individual wavelet power, comparable to the squared correlation coefficient. The squared wavelet coherence ranges between 0 and 1, and it can be interpreted as the correlation coefficient around each moment in time and for each frequency.

The direction of the relationship between the variables is lost due to the use of the squared coherence and the complexity of the wavelets (Kristoufek, 2015; Phillips and Gorse, 2018). To solve this, phase difference is introduced, separating the transform into its real and imaginary parts, providing both local amplitude and instantaneous phase information of the periodic process. An important condition for investigating coherency between time series is as follows:

$$\varphi_{xy}(u,s) = tan^{-1}\left(\frac{\Im\left[s\left(\frac{1}{s}W_{xy}(u,s)\right)\right]}{\Re\left[s\left(\frac{1}{s}W_{xy}(u,s)\right)\right]}\right) \tag{14}$$

where $\Im$ and $\Re$ represent an imaginary and a real operator.

The angle φ_{xy} is called the phase difference (phase lead of x over y). In this case, $\varphi_{xy} = \varphi_x - \varphi_y$ estimates the difference of individual phases, justifying its name. This relation holds after $\varphi_x - \varphi_y$ is converted to an angle in the interval $[-\pi, \pi]$. If the absolute value is less than $\pi/2$, it indicates that the two series move in phase. If the absolute value is greater than $\pi/2$, they move anti-phase. If $\varphi_{xy} \in (0, \frac{\pi}{2})$, then the series move in phase but time series x leads y; if $\varphi_{xy} \in (\frac{-\pi}{2}, 0)$ then it is y that is leading. For an anti-phase relation of $\pi, -\pi$ when $\varphi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$, then y is leading; if $\varphi_{xy} \in \left(-\pi, \frac{\pi}{2}\right)$, x is leading (Aguiar-Conraria and Soares, 2011; Aguiar-Conraria et al, 2014).

Disaggregating the assumed relationship between the BTC price (in USD) and transactions allows us to recognize patterns of price dynamics and their impact on transactions across different frequencies. The phase-difference approach provides information on the direction of co-movements, as well as potential causal relationships between transactions and the Bitcoin price. The variables, dataset and specificities of the wavelet analysis are detailed in the next section.

[12] The R package used in our study, "WaveletComp", provides three directional options and a variety of filtering windows over time and scale, which have a tunable width to choose from (Rösch and Schimidbauer, 2018)

4. Data and set results

By placing both time and frequency as relevant measures to understand the forces behind Bitcoin price action, wavelet coherence not only identifies correlation but also shows the evolution of the relationship in time and across scales. It can shed more light on the co-movement between prices and transactions, compared to conventional analysis (Kang et al., 2019)

To evaluate in detail the consequences of the three past Bitcoin halvings, two variables were chosen: 1) the Bitcoin closing price in U.S. dollars, estimated in a natural logarithm, and 2) the total amount of transactions (in BTC), which was converted to a natural logarithm through EViews 10.[13] As explained by Phillips and Gorse (2018), raw financial time series can be multi-modal, as they are likely to cluster around psychological support and resistance levels. Converting these series into logarithms produces unimodal distributions that are closer to a normal distribution.

Daily data was taken from Glassnode,[14] the specific time frame was 1 January 2011, to 11 December 2021. Simulations were performed using the WaveletComp 1.1 R package.[15] The time frame was divided into three phases:

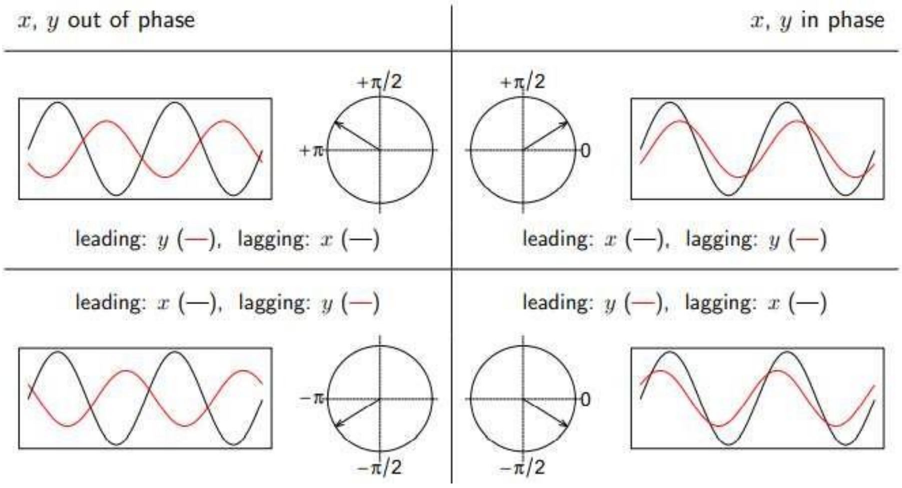
1) Phase one: from 1 January 2011 to 31 December 2014, which includes the first halving in November 2012 (block reward halved to 25 BTC).
2) Phase two: from 1 January 2015 to 31 December 2018, which corresponds to the second halving, in July 2016 (block reward halved to 12.5 BTC).
3) Phase three: from 1 January 2019 to 11 December 2021, which includes the third halving in May 2020 (block reward halved to 6.25 BTC). This phase comprises the data available at the time of writing.

Before we begin the data analysis, it is important to clarify some specific interpretations. Wavelet coherence shows regions where time series covary in time and across frequencies. The vertical axis shows frequency (with a corresponding time scale in days), while the horizontal axis shows time in years. Warmer colors (yellow, orange, and red) represent regions where the two time series are highly correlated, while cooler colors (green, light blue, and blue) show a weaker relationship between them. The arrows on the coherence wavelet plot represent the direction of the lead-lag relationship. This is the synchronization in terms of an instantaneous or local phase advance of the periodic component of (x_t) to the correspondent component of (y_t), or the phase difference of x over y. Figure 1 illustrates the range of possible phase differences (displayed as arrows) and their interpretation, while table 2 clarifies the comprehension of our variables in the wavelet context.

Arrows that point to the right show that variables are in phase, indicating a positive correlation. Arrows that point to the left show that the variables are out of phase, indicating a negative correlation. When two series are in phase, they move in the same direction; when they are out of phase, they move in the opposite direction. If the arrows point to the right/up or left/down, this indicates that the first variable (the log of Bitcoin) is leading and the second variable (the log of transaction count) is lagging. If the arrow points to the right/down or left/up, the second variable (the log of transaction count) is leading and the first (the log of Bitcoin) is lagging.

[13] EViews (Econometric Views) 10 is a Windows-based statistical software package used for econometric analysis, forecasting, and time-series modeling.
[14] Glassnode is a blockchain data and intelligence provider that generates on-chain metrics tools for institutional and retail crypto investors through Glassnode Studio web site and Application Programming Interface (API).
[15] WaveletComp 1.1 is an open-source package for the R programming language designed specifically for the continuous wavelet analysis of univariate and bivariate time series.

Figure 1 – *Phase differences*



Source: Rösch and Schmidbauer (2018, p. 7).

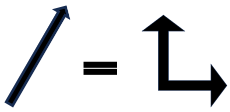
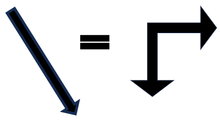
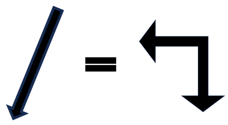
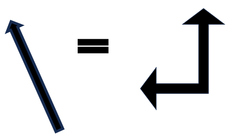
Kristoufek (2015) emphasizes that the interpretation of phase difference is partially dependent on specific expectations that rest upon the variables being analyzed. A leading relationship in phase can easily become a lagging one in anti-phase. High-power areas between white contour lines indicate joint periodicity and significance, for which the null hypothesis of a white-noise process is rejected at a default significance level of 10%. The white shaded area shows the cone of influence (COI). In wavelet analysis, it is standard to use a COI to represent areas subject to border distortions. As with other types of transforms, the continuous wavelet transform (CWT), when applied to a finite-length time series, suffers from edge effects. This is because values of the transform at the beginning and at the end of the time series are incorrectly computed. They involve missing values of the series that are artificially prescribed; consequently, this area of the time-frequency plane should be interpreted carefully (Aguiar-Conraria and Soares, 2011).[16]

The wavelet coherence output for the first phase (from 1 January 2011 to 31 December 2014) is displayed below (figure 2a). Looking closely at 2011 (on the horizontal axis), the Bitcoin price and transaction count roughly display the same overall trend, at the 64- to 128-day frequency. Arrows point to the northeast, indicating that the variables are in phase, and the Bitcoin price leads the relationship while the transaction count lags. Sharp price increases began in May and consolidated in June (9 June 2011), when Bitcoin reached its all-time high.

With Bitcoin's price starting to peak, agents who were more familiar with the inner workings of the system became interested. This sharp price increase led to a downtrend that caused Bitcoin to vary between $15 and $2.19, marking a very volatile second semester, with the price ending 2011 at $4.72. Transactions also dropped, but not at the same rate. A more intense spectrum was observed at the 128- to 256-day period, following the trend that year (fire sales due to price slumps).

[16] In addition to correlation and phase difference, short-, medium-, and long-term effects will be defined: the short term refers to the 2-4 and 4-8 period bands; the medium term refers to the 8-16 and 16-32 daily bands; and the long term refers to the 32-64, 64-128, and 128-256 frequencies.

Table 2 – *Wavelet analysis, arrow interpretation*
Variables: Bitcoin price and number of transactions in Bitcoin

Arrow Direction	**Variable Interpretation**	**Arrow Direction**	**Variable Interpretation**
	Positive correlation (phase) without lag, of the BTC price in log (lnbtc), and the number of transactions in BTC in log (lntranscount).		Positive correlation between the leading variable BTC price (lnbtc) and the lagging variable number of transactions in BTC (lntranscount).
	Negative correlation (anti-phase) without lag, of the BTC price in log (lnbtc), and the number of transactions in BTC in log (lntranscount).		Positive correlation between the number of transactions in BTC (lntranscount) and the BTC price with lag.
	Lag of the BTC price in log (lnbtc), and the number of transactions in BTC in log (lntranscount), But with no apparent correlation.		Negative correlation between the leading variable BTC price (lnbtc), and the lagging variable (lntranscount).
	Lag of the number of transactions in BTC in log (lntranscount), to the BTC price in log (lnbtc). However, it is not possible to infer correlation.		Negative correlation between the leading variable number of transactions in BTC (lntranscount) and the lagging BTC price (lnbtc).

Source: Author's elaboration based on Rösch and Schmidbauer (2018).

In 2012, the phase difference was pronounced between the short and the medium term. Agents bought Bitcoins in a timid movement as relationships changed and arrows started pointing up, and the number of transactions started lagging behind toward the halving event in November 2012. Both variables alternated between leading and lagging relationships, but they were always in phase. The yellow line that traverses all years at the 128-day mark (four-month frequency) shows an increasingly stronger correlation in the long run between price and quantity cycles over time.

As 2013 began, Bitcoin witnessed an upward price trend. Wavelet coherence showed a statistically significant correlation between price and number of transactions, which was compatible with the sharp price growth that started in April 2013. At the end of the year, the BTC price reached a value five times its initial value, reaching an all-time high in November 2013.

Although Bitcoin USD prices declined in 2014 (starting the year at $753.40 and ending it at $320.00), a linear growth trend in the number of transactions was still evident. At lower frequencies (128-, 256-, and 365-day periods) warmer colors (yellow and orange) appeared, emphasizing *hodling*[17] characteristics of crypto investors in a bear market.

A comprehensive look at this four-year cycle (2011-2014) shows a stronger correlation between transactions and Bitcoin price action at higher frequencies (short to medium term). In contrast, at the 64- to 128-day lower frequencies (long term), there is a weaker (but growing) relationship between price and quantity. The only exception is at the end of 2013, which can be attributed to the halving event.

Phase two (from 1 January 2015 to 31 December 2018), as shown in figure 2b, displays warmer colors (yellow and orange) above the 128-day period. A stronger correlation between these variables at increasingly lower frequencies (long term), a tendency that carried over from the last cycle, can be attributed to crypto exchanges.

Although crypto exchanges have existed since the beginning of Bitcoin,[18] these virtual platforms gained greater importance during the second phase.[19] Bitcoin prices ranged between $172.20 (on January 14, 2015) and $463.12 (on December 17, 2015). Wavelet coherence levels at the 128- to 256-day frequency (vertical axis), showed that there was a positive correlation (in phase) but without lag. Throughout 2016, there was very little statistical significance between the transaction count and the BTC price. The only exception was at the 16- to 32-day frequency in 2016. Halving occurred at the beginning of July 2016 and, a month before, prices increased ($767.45, 19 June 2016). Both variables were in phase, and the BTC price led the relationship, while transactions lagged.

Prices decreased in the second semester but climbed again at the end of the year ($967.74 on 31 December 2016). Nevertheless, the actual all-time high occurred in December 2017, when the price reached $19,179.66. Bitcoin started 2017 at $995.93 and experienced a slow and continuous upward climb until September. A steeper climb marked the final months of the year before the price peaked in December. Wavelet coherence levels showed a high correlation (red and orange colors) at the 64- to 256-day frequency. Both variables were positively correlated (in phase), with the transaction count leading the relationship while the BTC price lagged. Political and policy events, including the U.S. presidential election, combined with the impact of the Bitcoin halving, increased market volatility in 2017 (Qiao et al., 2020).

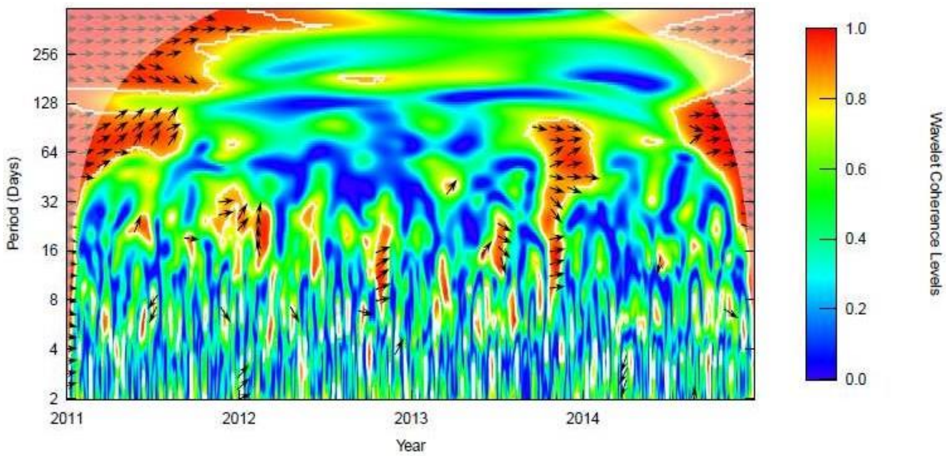
[17] The term was originally typed as HODL, a misspelling of the English word "hold" in a post in the Bitcointalk forum. In December 2013, there was a huge fall in the Bitcoin price, and an investor named GameKyuubi posted "I AM HODLING". After rambling about his poor trading skills, he concluded that the best course of action was "to hold". This clear investment strategy became a byword for a specific approach to crypto investment (Frankenfield and Mansa, 2022).

[18] To my knowledge, the oldest crypto exchanges or institutionalized spaces for exchanging cryptos for other currencies, cryptos, or services are Mt Gox (2010), Bitstamp (2011), Kraken (2011), and the Silk Road (2011). Mt. Gox, which was launched in July 2010, was one of the world's leading exchanges before filing for bankruptcy in 2014 due to 850,000 missing (stolen) Bitcoins. The Silk Road anonymous marketplace was founded in 2011 by Ross Ulbricht on the deep web. Financial transactions linked to illegal and criminal activities led to its shutdown in 2013 by U.S. FBI officials.

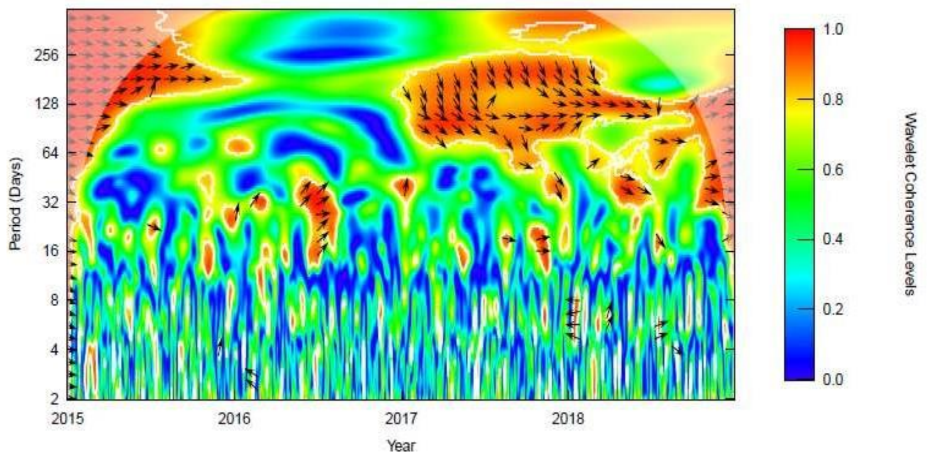
[19] The biggest crypto exchanges in existence today, ordered chronologically by their founding date, are: Bitstamp (2011), Kraken (2011), Local Bitcoin (2012), Coinbase (2012), Coincheck (2012), Bitfinex (2012), Houbi (2013), Bitflyer (2014), Gemini (2014), KuCoin (2013, but officially launched as an exchange in 2017), Crypto.com (2016), Binance (2017), Gate.io (2017), Bybit (2018), and FTX (2019).

Figure 2 – *Wavelet coherence: first, second, and third phase (from January 1, 2011, to December 11, 2021). Variables: Log of BTC in USD and transaction count*

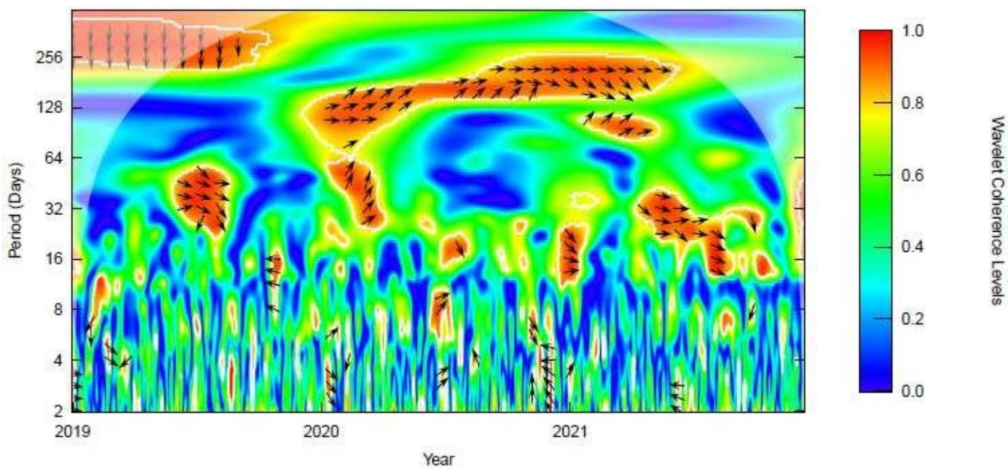
(2a)



(2b)



(2c)



These related trends continued into 2018, with high BTC prices and a large number of transactions in January. Coherence levels were intense between the 32- to 128-day frequency at the beginning of 2018, with both variables remaining in phase (continuing the 2017 trend). Transactions moved precipitously, leading to a phase difference as the Bitcoin price declined at a slower pace. Looking at the four-year cycle (2015-2018), the BTC price, although still correlated, started lagging behind the number of transactions. The all-time high of the second halving was much more anticipated by investors, who started building positions in BTC at the 64-day frequency. Transactions were also more volatile, leading to price changes. This indicates that more exchanges were providing access to investors, which generated more market movement.

The wavelet coherence for the third and final phase (from 1 January 2019 to 11 December 2021) began to depict warmer colors at the 32-day frequency, showing a positive correlation with Bitcoin's price lagging. Prices peaked in July ($12,560.62) and stayed between this and the $10,070.39 mark until September, before going on a downward slope. Positive correlations turned into a clear BTC price leadership in 2020, the year of the first wave of COVID-19 and the third halving. Shutdowns and the inevitable economic slump due to social distancing increased uncertainty and accelerated fears about the global economy, causing investors to turn to cryptocurrencies as a risky investment option.

Market players, closely observant of price movements, took advantage of the price drop that Bitcoin experienced at the beginning of the year, seizing the opportunity to build positions in anticipation of the halving in May. Phase difference was observed from the 32-day frequency and beyond. The arrows started directing a clear leadership of the BTC price, which then turned into a distinctive positive correlation (at the 64- to 128-day frequency), after which leadership alternated between the BTC price and transactions.

The price started at $6,985.65 in January and reached a new high of $28.988,64 in December 2020. A favorable year for Bitcoin investors was 2021, as the price remained above $29,783.00. Two price peaks were reached that year: in April 2021 ($63,603.70) and in November 2021 ($67,589.00).

It is important to keep in mind that just showing diverging relationships between different frequencies does not answer the important question of what effectively drives these periodic movements. Over the last 10 years, considering both the number of transactions and the price, the first, second, and third phases were marked by in-phase relationships. When measured in days, 128- to 256-day frequencies, which are long-term horizons for short-term investors, were most relevant in the second and third phases. The long term is expected to play a significant role, considering the relationship between the Bitcoin price and its supply (Bouoiyour et al., 2016). Since asset supply is known in advance, price dynamics can be easily incorporated into the expectations of BTC users and investors (Kristoufek, 2015).

The all-time high after the first halving in November 2012 occurred exactly a year later, in November 2013, when the BTC price reached $1,134.39. After the second halving in July 2016, a year and a half later, Bitcoin's price reached $19.179,00 in December 2017. After the third halving in May 2020, BTC's maximum price was in November 2021, surpassing the 65K mark. Prediction theories (such as the Stock-to-Flow Model[20]) expect that the BTC price will surpass the 100k mark by 2024.

[20] The Stock-to-Flow Model treats Bitcoin as being comparable to commodities (such as gold, silver, and platinum). Due to their relative scarcity and retention of value over long periods, they are known as "stores of value". Bitcoin requires a lot of electricity and computing effort to augment its supply. Stock-to-Flow (SF) ratios are used to evaluate the current stock of commodities against the flow of new production (SF = stock/flow). A higher ratio indicates that the commodity is increasingly scarce and therefore more valuable. Theory suggests that it is possible to project where prices may go;

Alternating leading and lagging relationships (phase difference) between the BTC price and the number of transactions depend on the halving event, the overall political environment, and systemic downturns. This reinforces the notion that speculative markets are driven by anticipation, expectations, and self-fulfilling prophecies – defined as predictions or expectations that come true simply because agents believe and anticipate that they will happen, causing the agent's behavior to align and fulfil that belief, or consequences to conform to the initial belief.

In defining a self-fulfilling prophecy, Merton (1948) quotes W.I. Thomas: "If men define situations as real, they are real in their consequences" (as cited in Merton, 1948, p. 193). The underlying explanation is that agents respond not only to the objective features of a situation but also to the meaning that this situation has for them. Once they have assigned meaning, their behavior and consequences are determined by that particular interpretation: "Public definitions of a situation (prophecies or predictions) become an integral part of the situation and thus affect subsequent developments" (Merton, 1948, p. 195).

The most interesting self-fulfilling prophecies are those that involve more complex social processes, such as financial markets and investment bubbles. If investors believe that an investment will generate large returns, they will invest. This is where the "greater-fool theory" comes into play: the idea that, during a market bubble, one can make money by buying overvalued assets and selling them for a profit later, because there will always be someone who is willing to pay a higher price (Bogan, 2025).

As more agents invest, the asset becomes more valuable, possibly enabling price manipulation and Ponzi schemes that provide initial investors with generous promised returns. This process eventually becomes unsustainable and leads to financial failure. Nevertheless, while Ponzi schemes are abundant in unregulated and relatively new investment types like cryptocurrencies, the point here is not the schemes themselves but rather how self-fulfilling prophecies show that economic agents can be "caught in a web of their own making" (Biggs, 2013, p. 766).

Bitcoin itself is algorithmically determined, but agents are the ones who allocate value to the asset. If speculators share conventions, common beliefs, proxies, and crypto market prognostications, prophecies will come to pass, reinforcing demand for the asset. Overall, scarcity is not enough to create price value; there needs to be demand (Prasad, 2021), even if it is a speculative one. As Bitcoin's market value goes up, transactions will oscillate at both lower and higher frequencies.

The blockchain technology that underlies Bitcoin's functioning is an important factor that may boost investors' confidence and demand, as a valuable tool for many practical real-world applications.[21] Another example is the association of member companies and private initiatives that created one of the largest cryptocurrencies by valuation, second only to Bitcoin.[22] The Enterprise Ethereum Alliance, launched in February 2017, is a blockchain-based decentralized

this calculation is based on the Bitcoin mining schedule and the projection that BTC will have a low-price elasticity supply. Halving events become important for BTC prices and the SF ratio as they cause the supply growth rate to be stepped down in a staggered fashion (PlanB, 2019).

[21] Smart-contract-based tokens, decentralized finance (DeFi), intellectual property rights, authentication of digital asset ownership, marketing, and supply management (collecting sales, industry trends, and product information data in the context of supply chain logistics) are some of the expected industry uses. Therefore, blockchain usability goes beyond the creation of Bitcoin, providing solutions for both individuals and businesses (El Mahdy, 2021; Tut, 2022).

[22] The founding members of Enterprise Ethereum Alliance (EEA) include Accenture, Santander, BlockApps, BNY Mellon, CME Group, ConsenSys, IC3, Intel, J.P. Morgan, Microsoft, and Nuco. The members of the EEA represent a variety of businesses from every region of the world, including technology, banking, government, healthcare, energy, pharmaceuticals, marketing, and insurance (Frankenfield, 2022).

software platform[23] that enables smart contracts and allows users to create and deploy their distributed applications.[24]

5. Conclusions

Most crypto-focused wavelet literature concentrates on Bitcoin's fundamental attributes, global uncertainty, hedging capabilities, informational inefficiencies, and regional markets. Our study uses a well-known methodology in a novel way: to specifically address how halvings affect the relationship between price and quantity in the Bitcoin market.

Using daily data from 1 January 2011, to 11 December 2021, the Bitcoin price in USD and the transaction count were decomposed on a scale-by-scale basis (in different frequency bands) using wavelet coherency analysis. Cycles and transient dynamics between the time series revealed a growing presence of institutions that articulate market entries and exits, which influences overall market sentiment (i.e., at lower frequencies, higher timescales).

Through speculation, co-movements between BTC transactions and prices are consistent with upcoming halving events. In recent years, large-scale operators have started accumulating positions in BTC in anticipation of a valuation increase. With its limited supply, Bitcoin is, by definition, a scarce asset, which could be considered a speculative tool for portfolio diversification.

Wavelet coherence analysis of the first phase showed strong correlations at the 8- to 64-day frequency (short term) before converting to a stronger correlation at the 64- to 256-day frequency (long term) in the last two cycles. Since supply is curtailed, the long term plays a significant role, as dynamics are incorporated into price expectations.

However, prediction models (like the Stock-to-Flow Model, whose basic hypothesis is that scarcity drives value) can create their own measure of self-fulfilling prophecies. In market psychology, conventions could eventually feed into these theories, as market bubbles rely on the greater-fool theory (Bogan, 2025): any price, no matter how high, can be justified, since another buyer is willing to pay an even higher price: "Bitcoin is worth exactly as much as users are willing to pay for it" (Wiseman, 2016, p. 424). This notion amplifies the volatility problem, as rogue entities can manipulate crypto market pricing (Ankier, 2020).

In the third and final phase, BTC price and transactions gained a stronger correlation in the medium to long term. There was a change in dynamics, including increasing investor access through crypto-exchanges – a trend that started in the second phase – and with more "big players" in the game, as well as prevailing economic uncertainty due to the COVID-19 pandemic. Rapidly increasing prices highly incentivized the "hodling" of BTC.

Addressing the questions set forth in the introduction, it is possible to infer that, although the technical attributes of the halving dynamics cannot change due to their algorithmic nature, a change in market dynamics is observable when comparing the last two BTC price cycles. As a main contribution to the debate, this study confirms that co-movements between the BTC price and the transaction count do identify a measure of institutional activity in the market. The arrival of these market makers has altered flows, resulting in stronger correlations at lower frequencies (64- to 256-day frequencies) between price and quantity, as revealed by the wavelet coherence analysis.

[23] https://entethalliance.org/

[24] Crypto researcher Loi Luu in 2017 explained that, through ETH, one could easily build an app to facilitate cross-border money remittances at a cost of a fraction of the current charges, which could ultimately benefit senders and receivers. Micropayments and insurance are other possible areas enabled by ETH and blockchain technology, allowing people to make very small payments (a fraction of a cent), and to claim insurance without worrying that the service provider will not honor its promise (Mavadiya, 2017).

Increased investor access through crypto exchanges in the second phase and market entries in the last phase, motivated by global economic crises and the pandemic, increased market capitalization, which strengthened the price-transaction correlation.

This study provides a nuanced picture of the Bitcoin market's evolution. By using a novel wavelet approach, we not only confirm the impact of halving events but also provide specific evidence that institutional investors are fundamentally reshaping market dynamics. Our findings of robust long-term correlations offer a significant contribution to the debate on Bitcoin's maturation, suggesting that its market is increasingly driven by factors beyond pure speculation.

Future researches on Bitcoin prices should address its correlation to broader measures, such as global liquidity. Given Bitcoin's recent bear market and global monetary tightening, empirical tests should be performed to understand if prices have a floor compared to the post-halving market price, despite their higher volatility compared to other assets.

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