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Beyond the Buzz: A Measured Look at Bitcoin's Viability as Money

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Abstract: This paper examines Bitcoin's viability as money through the lens of its risk profile, with a particular focus on its store of value function. We employ a suite of wavelet techniques, including Wavelet Transform (WT), Wavelet Transform Coherence (WTC), Multiple Wavelet Coherence (MWC), and Partial Wavelet Coherence (PWC), to decompose the risk structure of Bitcoin and analyze its relationship with various systematic risk factors. Our dataset spans from 13 August 2015 to 29 June 2024, and includes Bitcoin, major commodities, global and US equities, Shari'ah-compliant equities, Ethereum, and the Secured Overnight Financing Rate (SOFR). We find that Bitcoin's risk profile is increasingly aligned with traditional financial assets, indicating growing market integration. While Bitcoin exhibits high volatility, a significant portion of this volatility can be attributed to systematic rather than idiosyncratic factors. This suggests that Bitcoin's risk may be more diversifiable than previously thought. Our findings have important implications for monetary policy and financial regulation, challenging the notion that Bitcoin's volatility precludes its use as money and suggesting that regulatory approaches should consider Bitcoin's evolving risk characteristics and increasing integration with broader financial markets.

Keywords: Bitcoin; cryptocurrency; monetary policy; systematic risk; wavelet analysis; store of value; financial integration; market efficiency

JEL Classification: E42; G12; G15; C58; F31

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1. Introduction

Background of the Study

The emergence of Bitcoin has sparked considerable debate in the financial literature regarding its classification as money. While Nakamoto (2008) envisioned Bitcoin as a peer-to-peer electronic cash system, academic discourse has largely focused on whether it satisfies the traditional threefold test of money: medium of exchange, unit of account, and store of value (Kubát, 2015; Yermack, 2015).

The recent literature has challenged this framework. Hazlett and Luther (2020) argue that the medium of exchange function should be the primary criterion for defining money, with unit of account and store of value as desirable but not essential features. This perspective aligns with earlier economic thought (Menger, 1892) and opens new avenues for analyzing Bitcoin's monetary properties.

Empirical studies on Bitcoin's financial characteristics have yielded mixed results. Cheah and Fry (2015) estimated Bitcoin's fundamental value at zero, while Dyhrberg (2016a) positioned Bitcoin between gold and the US dollar on a spectrum of financial assets. These

conflicting findings underscore the complexity of categorizing Bitcoin within traditional financial frameworks.

The adoption of Bitcoin as legal tender by El Salvador in 2021 (Alvarez et al., 2023) has further complicated academic discourse, highlighting the potential divergence between theoretical classifications and practical applications of monetary policy.

This paper contributes to the literature by examining the viability of Bitcoin as money through the lens of information risk, building on the Efficient Market Hypothesis (Fama, 1970) and subsequent work on market microstructure (Amihud & Mendelson, 1986; Easley et al., 2002). We posit that the suitability of Bitcoin as a store of value—and by extension, its viability as money—can be assessed by comparing its information risk profile to that of established financial assets.

Our analysis employs a suite of wavelet techniques, including Wavelet Transform (WT), Wavelet Transform Coherence (WTC), Multiple Wavelet Coherence (MWC), and Partial Wavelet Coherence (PWC), to decompose Bitcoin's risk structure and examine its relationship with various systematic risk factors. This approach allows for a multidimensional analysis of Bitcoin's risk profile across different time scales and frequencies.

We address five key questions:

1. What is the nature of Bitcoin's volatility across different time scales?
2. To what extent is Bitcoin's information risk explained by systematic factors?
3. Is Bitcoin's risk exposure becoming increasingly systematic over time?
4. How does Bitcoin's price movement relate to a combination of systematic risk factors?
5. Do Bitcoin's systematic risk exposures persist when controlling for other risk sources?

Our dataset spans from 13 August 2015 to 29 June 2024, and includes daily price data for Bitcoin, commodities (S&P GSCI Commodity Spot index), gold, oil, global equities (Dow Jones Global Index), US equities (S&P 500), Sharia-compliant equities, Ethereum's Ether, the US Dollar Index (DXY), and the Secured Overnight Financing Rate (SOFR).

Our findings suggest that Bitcoin's risk profile is increasingly aligned with traditional financial assets, indicating growing market integration. While Bitcoin exhibits high volatility, a significant portion of this volatility can be attributed to systematic rather than idiosyncratic factors. This finding implies that Bitcoin's risk may be more diversifiable than previously thought, potentially enhancing its viability as a store of value.

These results have important implications for monetary policy and financial regulation. They challenge the notion that Bitcoin's volatility precludes its use as money and suggest that regulatory approaches should consider Bitcoin's evolving risk characteristics and increasing integration with broader financial markets.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature. Section 3 describes our data and methodology. Section 4 presents our empirical results and analysis. Section 5 concludes and discusses policy implications.

2. Literature Review

2.1. Bitcoin's Risk Profile and Market Integration

The literature on Bitcoin's risk profile and its integration with traditional financial markets has evolved significantly since its inception. Early studies, such as Dyhrberg (2016b) and Bouri et al. (2017b), suggested Bitcoin's potential as a hedge against traditional assets. However, these findings may be outdated given recent market developments.

More recent research has focused on Bitcoin's fundamentals and price dynamics. Maiti (2022) and Kubal and Kristoufek (2022) explored the relationship between Bitcoin prices and network characteristics, finding evidence of fundamental value. White et al. (2020) argue that Bitcoin's behavior resembles that of a technology-based

product or emerging asset class, challenging the applicability of existing currency and security regulations.

The influence of sentiment on Bitcoin prices has been a subject of substantial research. Akyildirim et al. (2021) and Aysan et al. (2024) demonstrate the significant impact of sentiment on cryptocurrency returns and price jumps. Polat et al. (2022) and Gaies et al. (2023) further emphasize the role of sentiment, particularly in the context of the COVID-19 pandemic.

2.2. Systematic vs. Idiosyncratic Risk

The debate over Bitcoin's systematic and idiosyncratic risk components is central to understanding its role in financial markets. Drawing parallels with commodity markets, Deaton and Laroque (1992) and Silvennoinen and Thorp (2013) highlight the importance of both fundamental factors and financialization trends in price dynamics.

Asset pricing models, particularly those building on the Capital Asset Pricing Model (CAPM), emphasize the importance of systematic risk (beta) over idiosyncratic risk in determining expected returns (Fama & French, 1992, 2004). This framework provides a lens through which to analyze Bitcoin's risk profile.

Recent studies have examined Bitcoin's relationship with traditional financial markets. Choi and Shin (2022) find evidence of inflation-hedging properties but reject safe-haven qualities. Chemkha et al. (2021) demonstrate Bitcoin's effectiveness in reducing portfolio risk, while Jia et al. (2024) observe stronger overreaction to developed stock markets compared to emerging markets.

2.3. Monetary Policy and Global Market Factors

The influence of US monetary policy on global financial markets is well-documented (Bjørnland & Leitemo, 2009; Georgiadis, 2016). This study employs the Secured Overnight Financing Rate (SOFR) as a proxy for monetary policy and short-term funding conditions markets (Schrimpf & Sushko, 2019).

Global equity markets, represented by indices such as the Dow Jones Global Index and S&P 500, serve as important sources of systematic risk. Liu and Serletis (2019) and Hung (2022) document significant spillover effects from these markets to cryptocurrencies.

The inclusion of Shari'ah-compliant equities in our analysis is motivated by their unique risk characteristics and potential similarities to ESG investing (Mustafida & Fauziah, 2021; Asutay et al., 2022). Further, Disli et al. (2021) found evidence of comovement between Bitcoin and the Dow Jones Islamic Market World Index post COVID-19, indicating that Islamic equities can be a source of systematic risk relevant to Bitcoin.

2.4. Commodity Markets and Bitcoin

The relationship between Bitcoin and commodity markets remains an area of active research. Gronwald (2019) and Bouri et al. (2018) identify similarities between Bitcoin and scarce commodities like gold, while also noting unique characteristics of digital currencies.

The financialization of commodity markets, characterized by increased involvement of financial investors and the development of derivative products, has led to greater market integration and correlation with financial assets (Ding et al., 2021; Silvennoinen & Thorp, 2013). This trend may have implications for Bitcoin's market behavior.

Our analysis incorporates the S&P Goldman Sachs Commodity Index (GSCI), as well as specific attention to oil and gold markets. These commodities are chosen for their global economic significance and potential safe-haven properties (Kilian, 2014; Baur & McDermott, 2016).

2.5. Cryptocurrency Market Dynamics

Within the cryptocurrency ecosystem, Bitcoin's relationship with other digital assets, particularly Ethereum, provides insights into market-wide dynamics. Factors such as regulatory news, technological developments, and market sentiment play crucial roles in price movements (Aysan et al., 2023).

The cryptocurrency market exhibits significant endogenous risk, characterized by leveraged trading and derivative use (Alexander et al., 2023). Pennec et al. (2021) and Feinstein and Werbach (2021) highlight concerns about market manipulation and inadequate regulation in this context.

2.6. Wavelet Analysis in Bitcoin Research

Wavelets are small, localized wave-like oscillations with finite duration. Wavelet analysis has long been used in analyzing time series generally (Grinsted et al., 2004) and financial time series in particular (Celeste et al., 2020) to examine the behavior of time series in both the time and frequency spaces. Details of the wavelet analysis methods we used in this paper are presented in the Section 3.2.

Wavelet analysis has emerged as a valuable tool for examining the price dynamics of Bitcoin across different time scales. Notable studies include Kang et al. (2019), who investigated Bitcoin's relationship with gold, and Kristoufek (2015), who applied early wavelet analysis to Bitcoin.

More recent applications include Goodell and Goutte (2021), who examined Bitcoin's safe-haven properties during the COVID-19 pandemic, and Shehzad et al. (2021), who compared Bitcoin to gold using wavelet techniques. Bouri et al. (2017a) and Celeste et al. (2020) provide comprehensive timeseries analyses of Bitcoin's market behavior and maturation process.

While these studies have yielded valuable insights, limitations in data range and depth of analysis highlight the need for updated research incorporating more recent market developments and a more comprehensive set of financial variables.

3. Data and Methodology

3.1. Data

Our study employs daily price data spanning from 13 August 2015 to 29 June 2024. This period is chosen to ensure a sufficiently wide range and data availability across all variables, particularly Ethereum (ETH). We analyze ten variables (see Table 1): Bitcoin (BTC), S&P GSCI Commodity Index (COM), Gold (GLD), Oil (OIL), Dow Jones Global Index (GLO), Dow Jones Islamic Market World Index (ISL), S&P 500 Index (SPX), Ethereum (ETH), Secured Overnight Financing Rate (SOFR), and US Dollar Index (DXY). All variables except SOFR are expressed as natural logarithmic returns multiplied by 100. SOFR is presented as a percentage.

Table 2 presents summary statistics for these variables. Bitcoin exhibits high mean returns (0.234%) and volatility (SD = 4.185%), with significant negative skewness (−0.375) and excess kurtosis (5.059). Ethereum shows even higher mean returns (0.322%) and volatility (SD = 6.564%). Traditional assets display lower returns and volatility, with the S&P 500 showing a mean return of 0.042% and standard deviation of 1.131%. The SOFR exhibits unique characteristics with extreme skewness (12.742) and kurtosis (251.225), reflecting its nature as an interest rate benchmark.

Table 1. Description of variables.

Variable	Description	Source
BTC	Bitcoin in USD	Thomson Reuters DataStream
COM	S&P GSCI (Goldman Sachs Commodity Index)	www.spglobal.com
GLD	Gold Bullion LBM USD/t oz	World Gold Council
OIL	Europe Brent Spot Price FOB USD/Bbl	Thomson Reuters DataStream
GLO	Dow Jones Global Index	www.spglobal.com
ISL	Dow Jones Islamic Market World Index	www.spglobal.com
SPX	S&P US 500 Index	Thomson Reuters DataStream
ETH	Ethereum's Ether in USD	Thomson Reuters DataStream
SOFR	Secure Overnight Financing Rate	Thomson Reuters DataStream
DXY	USD Strength Index	Thomson Reuters DataStream

Notes: Bitcoin (BTC), S&P GSCI commodity index (COM), gold (GLD), oil (OIL), Dow Jones global index (GLO), Dow Jones Islamic market world index (ISL), S&P 500 Index (SPX), Ethereum (ETH), secured overnight financing rate (SOFR), and US dollar index (DXY). The data used for this research were retrieved from the sources presented next to each series. Some services required a paid subscription.

Table 2. Descriptive statistics.

Variable	Mean	SD	Median	Trimmed	Mad	Min	Max	Range	Skew	Kurtosis	SE
BTC	0.234	4.185	0.224	0.283	2.669	−30.931	21.542	52.474	−0.375	5.059	0.087
COM	0.020	1.402	0.095	0.057	1.046	−12.523	7.683	20.206	−0.830	8.657	0.029
OIL	0.026	3.176	0.131	0.082	1.811	−64.370	41.202	105.572	−2.889	95.023	0.066
GLD	0.032	0.877	0.000	0.029	0.656	−5.262	5.137	10.399	−0.073	3.677	0.018
GLO	0.027	0.920	0.060	0.053	0.600	−9.969	7.964	17.933	−1.204	17.599	0.019
ISL	0.037	0.982	0.062	0.064	0.638	−9.639	7.916	17.555	−0.810	12.558	0.020
SPX	0.042	1.131	0.051	0.076	0.664	−12.765	8.968	21.734	−0.866	16.703	0.024
ETH	0.322	6.564	0.048	0.236	4.080	−58.056	50.575	108.631	0.011	8.506	0.136
DXY	0.004	0.419	0.000	0.006	0.351	−2.401	2.031	4.432	−0.166	2.168	0.009
SOFR	1.013	0.204	1.000	1.000	0.006	0.185	6.000	5.815	12.742	251.225	0.004

Notes: Bitcoin (BTC), S&P GSCI commodity index (COM), oil (OIL), gold (GLD), Dow Jones global index (GLO), Dow Jones Islamic market world index (ISL), S&P 500 index (SPX), Ethereum (ETH), US dollar index (DXY), and secured overnight financing rate (SOFR). SD is standard deviation, trimmed is trimmed mean and mad is mean absolute deviation.

Table 3 presents a correlation matrix based on the Pearson correlation coefficient. BTC and ETH show strong correlation (0.56), while both exhibit moderate correlation with equity indices. SOFR displays weak correlations with other variables, while DXY shows negative correlations with most assets, particularly gold (−0.37).

Table 3. Correlation matrix.

	BTC	COM	OIL	GLD	GLO	ISL	SPX	ETH	DXY	SOFR
BTC	1.00	0.1 *** (0.001)	0.07 *** (0.001)	0.09 *** (0.001)	0.22 *** (0.001)	0.23 *** (0.001)	0.22 *** (0.001)	0.55 *** (0.001)	−0.09 *** (0.001)	−0.01 (0.796)
COM	0.1 *** (0.001)	1.00	0.73 *** (0.001)	0.12 *** (0.001)	0.37 *** (0.001)	0.33 *** (0.001)	0.32 *** (0.001)	0.07 *** (0.001)	−0.1 *** (0.001)	0.07 ** (0.001)
OIL	0.07 *** (0.001)	0.73 *** (0.001)	1.00	0.08 *** (0.001)	0.3 *** (0.001)	0.26 *** (0.001)	0.25 *** (0.001)	0.06 ** (0.007)	−0.04 * (0.045)	0.08 *** (0.001)
GLD	0.09 *** (0.001)	0.12 *** (0.001)	0.08 *** (0.001)	1.00	0.13 *** (0.001)	0.13 *** (0.001)	0.07 ** (0.001)	0.1 *** (0.001)	−0.33 *** (0.001)	0.01 (0.746)
GLO	0.22 *** (0.001)	0.37 *** (0.001)	0.3 *** (0.001)	0.13 *** (0.001)	1.00	0.97 *** (0.001)	0.92 *** (0.001)	0.21 *** (0.001)	−0.24 *** (0.001)	0.04 (0.066)

Table 3. *Cont.*

	BTC	COM	OIL	GLD	GLO	ISL	SPX	ETH	DXY	SOFR
ISL	0.23 *** (0.001)	0.33 *** (0.001)	0.26 *** (0.001)	0.13 *** (0.001)	0.97 *** (0.001)	1.00	0.94 *** (0.001)	0.22 *** (0.001)	−0.21 *** (0.001)	0.04 * (0.038)
SPX	0.22 *** (0.001)	0.32 *** (0.001)	0.25 *** (0.001)	0.07 ** (0.001)	0.92 *** (0.001)	0.94 *** (0.001)	1.00	0.21 *** (0.001)	−0.12 *** (0.001)	0.04 * (0.044)
ETH	0.55 *** (0.001)	0.07 *** (0.001)	0.06 ** (0.007)	0.1 *** (0.001)	0.21 *** (0.001)	0.22 *** (0.001)	0.21 *** (0.001)	1.00	−0.08 *** (0.001)	0 (0.889)
DXY	−0.09 *** (0.001)	−0.1 *** (0.001)	−0.04 * (0.045)	−0.33 *** (0.001)	−0.24 *** (0.001)	−0.21 *** (0.001)	−0.12 *** (0.001)	−0.08 *** (0.000)	1.00	−0.01 (0.725)
SOFR	−0.01 (0.796)	0.07 ** (0.001)	0.08 *** (0.001)	0.01 (0.746)	0.04 (0.066)	0.04 * (0.038)	0.04 * (0.044)	0 (0.889)	−0.01 (0.725)	1.00

Notes: This table presents the pairwise Pearson correlation coefficients between variables along with their respective p-values. This table presents the pairwise Pearson correlation coefficients between the daily log returns of financial variables. Each cell contains the correlation coefficient, significance stars (denoting statistical significance), and the p-value in parentheses. Statistical significance levels are indicated as follows: $p < 0.05$ (*), $p < 0.01$ (**), and $p < 0.001$ (***). The high significance levels observed may be attributed to the large sample size and the inherent properties of financial time series data. The p-values for the diagonal values representing perfect correlations between the same variables have been omitted for clarity, as they are not informative.

3.2. Methodology

We employ a suite of wavelet analysis techniques to examine Bitcoin's risk profile and its relationship with systematic risk factors. Answering the first question in this paper on the nature of Bitcoin's risk, we present in Figure 1 a plotted Generalized Autoregressive Conditional Heteroskedasticity (GARCH) modeling of BTC to be contrasted with a plotted pure projection of BTC, followed by a WT heatmap in Figure 2.

Standardized BTC is plotted in this paper to present a raw projection of BTC volatility, to be complimented by GARCH and WT plotting. We next present the time-varying conditional volatility of Bitcoin as estimated by a GARCH(1,1) model (Bollerslev, 1986). Unlike a pure projection of volatility, a GARCH model captures the persistence of volatility, where high volatility periods tend to persist over time before reverting to lower volatility states. After significant peaks, volatility gradually decreases but remains elevated compared to other periods. The combination of pure volatility, GARCH, and WT provides an objective yet comprehensive understanding of Bitcoin's risk profile.

Specifically, this paper utilizes a specific number of tools relating to wavelet analysis.

We first employ WT: a mathematical technique used to decompose a time series into different frequency components, allowing the analysis of each component with a resolution matched to its scale. The Continuous Wavelet Transform (CWT) is the foundation of the wavelet transform, involving the integration of the original time series with a mother wavelet, a scaling factor, a translation factor, and the complex conjugate of the mother wavelet. The mother wavelet is a prototype function that is localized in both time and frequency, serving as the basis for generating wavelets at different scales and positions. The scaling factor controls the dilation or compression of the wavelet, with smaller values corresponding to higher frequencies (narrower wavelets) while larger values correspond to lower frequencies (wider wavelets). The mother wavelet utilized in this study is the Morlet wavelet, and the ceiling of the scaling factor is 6, in line with the choice of other financial time series wavelet analysis studies (Smolo et al., 2024). The translation factor shifts the wavelet along the time axis, with part of the wavelet transform being calculated for each section, allowing the analysis of different sections of the time series. The complex conjugate ensures that the transform captures the signal's amplitude and phase

information. The detailed mathematical explanation and prototyping are presented by Torrence and Compo (1998).

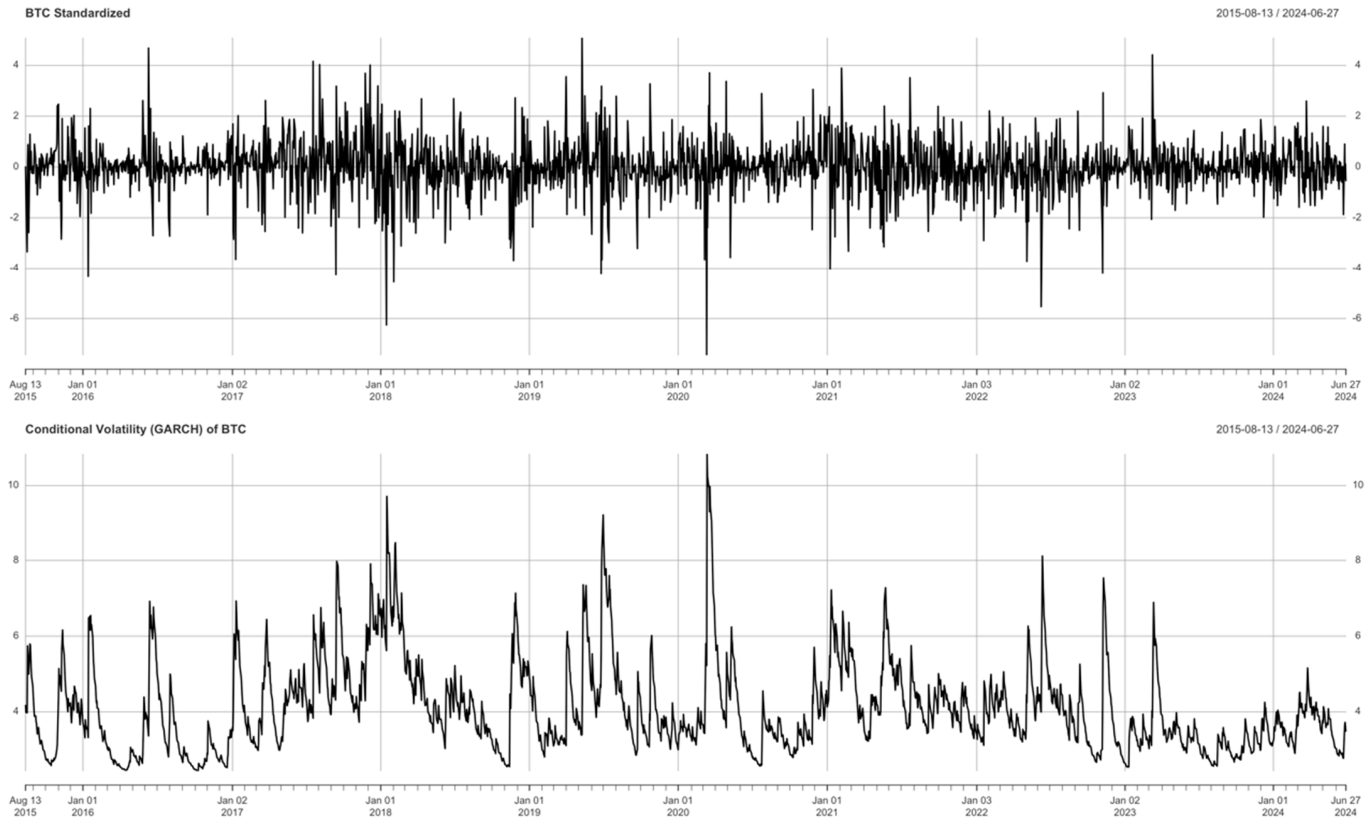


Figure 1. Standardized BTC is plotted in the upper part. The vertical axis of the top graph shows the daily returns, ranging from approximately −6 to 4 standard deviation units. A GARCH (1,1) plot of BTC is projected in the lower part. The ARMA specification for the GARCH model was based on a search for the best combination of AR (autoregressive) and MA (moving average) terms with the lowest information criterion based on AICc (corrected Akaike Information Criterion). The horizontal axis represents the time period, while the vertical axis represents the conditional volatility, ranging from approximately 2 to 10.

The second wavelet method we utilize is WTC, which can reveal co-movement patterns between time series in both time and frequency domains. The approach uses a bivariate model based on CWT that allows for multiple localizations. Instead of a traditional correlation analysis, WTC provides a more detailed understanding of the relationship between variables over different time scales: it allows for an analysis of how the relationship between Bitcoin and other assets varies across the short-, medium-, and long-term.

WTC provides numerous benefits when analyzing time-series data. First, it allows for the detection of both synchronous and lagged relationships between variables by examining their coherence at different time scales. Second, it can capture non-linear relationships that may not be captured by traditional correlation analysis. Third, WTC can add flexibility as a nonparametric method. Fourth, it adds a time–frequency analysis component, providing insights into the dynamic nature of the relationship between variables.

The results of WTC are presented in the form of color spectrum figures indicating the degree of correlation between two vectors. A solid significant correlation is seen in the warmer (red) region, whereas the colder (blue) denotes the weak connection between them. The x-axis represents the time stamp (observation), while the y-axis shows the scale (frequency) dimension. The outer region of the significant area (cone of influence) shows an insignificant correlation between the variables. Arrows on the WTC plots indicate the phase of quadruple areas: right,

left, up, and down. The horizontal position of arrows or zero phase difference (left or right) indicates that the time series (x and y) move together, i.e., none is leader or follower. Right directional arrows denote the 'in-phase' area, where x and y are positively correlated; on the other hand, left directional arrows point to 'anti-phase', where x and y are negatively correlated. Arrows directing 'right-up' denote y as a leader, whereas the arrows pointing 'right-down' define x as a leader. Conversely, 'left-up' positioned arrows indicate y as a follower, whereas left-down arrows identify x as a follower.

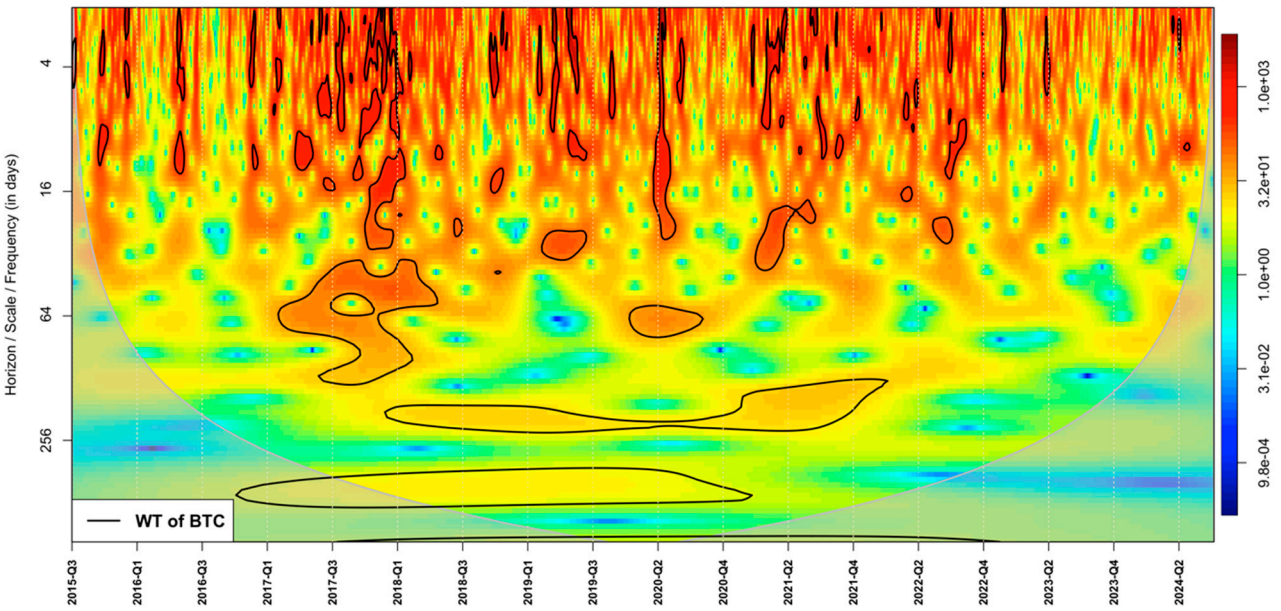


Figure 2. Power spectrum of a wavelet transform of BTC. The color scale on the right indicates the power of the wavelet transform, with warmer colors (reds and yellows) representing higher power, indicating a higher magnitude of volatility, and cooler colors (blues and greens) representing lower power, indicating a lower magnitude of volatility. The significance spots shown in black contour lines in the WT plot indicate regions of statistically significant power at the 5% significance level. These areas highlight periods and scales where the volatility is significantly different from the background noise. The significance contours are based on an AR(1) model of the returns of Bitcoin, which is a common reference for determining statistical significance in wavelet analysis. The AR(1) model helps in identifying whether the observed power is greater than what would be expected from a simple autoregressive process, thus confirming the presence of significant volatility pulses.

The third method we utilize is MWC, as initially proposed by Mihanović et al. (2009) and Oygur and Unal (2021). MWC extends the concept of WTC to more than two time series, allowing for the analysis of the joint behavior and interactions among multiple time series. MWC measures the degree of coherence among multiple time series, providing a comprehensive view of their interrelationships in the time–frequency domain. It can identify common patterns and shared dynamics among a set of time series, which is particularly useful for understanding systemic relationships and group dynamics. In MWC, the combined effect of x1 and x2 on y is computed by considering their individual coherences with y and adjusting for their mutual coherence. Further, MWC accounts for the canceling effect of such a combined effect: if parts of x1 cancel parts of x2, their combined effect will show a weaker impulse to the extent that such an effect took place. Therefore, an MWC heatmap will not show elevated coherence and significance contours unless all the time series do, in fact, move coherently. An extension of MWC is the Vector Wavelet Coherence For Multiple Time Series presented by Oygur and Unal (2021), making it possible to calculate wavelet coherence for any number of time series.

The fourth method we employ is PWC, which can enhance the findings of wavelet coherence by controlling for the effect of a third variable (Wu et al., 2020). As shown in Table 3 above, not only is Bitcoin correlated with several of the variables above, but also a third variable can be correlated with Bitcoin and the compared variable. Partial Wavelet Coherence can be a suitable tool to decompose such signals.

Combining PWC with MWC offers a more comprehensive analysis of multiple time series interactions. MWC provides an overall measure of combined influence, while PWC helps dissect individual contributions and control for confounding effects. This approach enhances the understanding of complex relationships in time series data.

An analysis answering the research questions, and the hypothesis testing conducted in this paper is presented as follows. The first question we address is as follows: How volatile is Bitcoin? A preliminary estimate of Bitcoin volatility provides a solid basis for addressing further questions. Therefore, this paper characterizes Bitcoin's volatility through a combination of descriptive statistics, a GARCH model, and a power spectrum of a wavelet transform of Bitcoin's returns. Each method sheds light on different facets of Bitcoin's volatility, providing a comprehensive view. Descriptive statistics offer a quick summary of return characteristics, the GARCH model captures the time dynamics and persistence of volatility, and the wavelet transform provides an in-depth multi-scale analysis. Since this question is answered by analysis and data, this question does not involve hypothesis testing.

The second question is as follows: Is Bitcoin's information risk explainable by systematic risk? To answer this question, this paper will test Bitcoin for coherence with sources of systematic risk through WTC analysis. The null hypothesis in this sense is that Bitcoin shows no coherence with isolated sources of systematic risk in the short-, medium-, and long run. If not, then the systematic risks explain part of Bitcoin's information risk. Hypothesis testing for the method used in this paper (wavelet analysis) is conducted via a Monte Carlo simulation, as shown in Grinsted et al. (2004). As such, the null hypothesis will be rejected with significance spots (contours) in the WTC heat maps of the concerned assets in the short-, medium-, and long run.

The third question we address is as follows: Is Bitcoin's risk becoming increasingly systematic? The null hypothesis in this sense is that Bitcoin's risk exposure to isolated systematic factors does not change. As such, the assumption that Bitcoin's risk is eternally the same will be tested. If the hypothesis is rejected, this will further support the argument that Bitcoin has become increasingly financialized and, as such, mainstream. A mainstream asset that is widely accepted by mainstream investors is closer to the influence of systematic risk and, therefore, exhibits less information risk to the extent that beta can explain a large part of its risk. The hypothesis for this question will not be tested for SOFR since SOFR (the interest-free rate) is expected to always be a cause of spillover to BTC, and their coherence is not expected to have a trend over time.

The fourth question is the following: Does Bitcoin move coherently with a combination of systematic risk factors? The null hypothesis here is that Bitcoin shows no coherence with a combination of systematic risk sources. Adding to the benefit of comparing Bitcoin to individual risk factors through WTC, it is as consistent to test the coherence of Bitcoin with a combination of systematic risk factors. This is because financial assets are not isolated from the influence of such combinations of factors. The method chosen for such analysis is MWC, which is an extension of standard WTC that analyzes the relationship between one time series and multiple other time series. While WTC considers the relationship between a duality of time series (A and B), MWC examines how one time series (A) is influenced by the combined effects of other time series (B and C together). The heatmaps of MWC can show an elevated power spectrum compared to WTC and PWC due to the combined

effect of multiple time series on coherence. Alternatively, if B and C have movements that cancel each other out (e.g., B moves up while C moves down by the same magnitude), their combined effect on A would be minimal or null. This means that the combined influence of B and C on A is weak or nonexistent during these periods.

The fifth question is the following: Do systematic risks persist if other sources of risk are isolated? The null hypothesis here is that Bitcoin shows no coherence with isolated sources of systematic risk if another source of systemic risk is controlled for. The method used to tackle this question is PWC. The null hypothesis is rejected by significance spots. For a PWC analysis between A, B, and C, PWC provides a method to control for the influence of time series C.

4. Results and Discussion

4.1. Bitcoin Volatility Characteristics

We begin by examining Bitcoin's volatility profile using descriptive statistics, GARCH modeling, and wavelet transform analysis. Figure 1 presents the standardized returns and conditional volatility from a GARCH(1,1) model. The results indicate significant volatility clustering, with notable spikes corresponding to major market events such as the 2017–2018 cryptocurrency bubble and the 2020 COVID-19 market crash.

Figure 2 displays the wavelet power spectrum of Bitcoin returns. This multi-scale analysis reveals the following:

1. Short-term (1–30 days): Frequent, intense volatility spikes, particularly evident in Q4 2017, Q1 2018, and Q1 2020.
2. Medium-term (30–180 days): Less frequent but sustained periods of elevated volatility, notably in late 2017 to early 2018 and early 2020.
3. Long-term (>180 days): Broader regions of high volatility, reflecting prolonged market trends from 2017 to early 2018 and from 2020 onwards.

We note a few observations based on the analysis above. First, describing Bitcoin as inferior based on a higher volatility profile departs from objective analysis. An information approach to risk does not attribute normative values to risk, rating higher risks as inferior or otherwise. What matters is how much we can understand and predict the risk based on the information provided (Easley et al., 2002). Second, while arguments revolving around Bitcoin's excessive risk profile can imply that such risk is mostly idiosyncratic and stochastic, the risk representation above encompasses idiosyncratic and systematic risk that can, to a large extent, be analyzed. The next sections will expand on the systematic part.

4.2. Coherence with Systematic Risk Factors

In this section, we utilize WTC to answer the second and third questions of this paper: Is Bitcoin's information risk explainable by systematic risk? A WTC heatmap graph is a powerful tool for analyzing the relationship between two time series across different time scales by providing a visual representation of the coherence between the series, indicating periods and frequencies where they are in sync or out of sync. The WTC analysis below will be presented with timescales ranging from short-term (up to 30 days), to medium-term (30 to 180 days), to long-term (over 180 days). This categorization was based on Disli et al. (2021), given the shorter time horizon for crypt investors.

The WTC heatmaps are plotted and discussed below. The scale on the right side of the heatmaps indicates the coherence values, normalized to range from 0 to 1. Low coherence is represented by blue, indicating a weak or no relationship between the two time series at that particular time and scale. High coherence is represented by red, indicating a strong relationship between the two time series at that particular time and scale. Black contour lines outline regions where the coherence is statistically significant at a certain confidence

level, such as 5%. These regions indicate where the observed coherence is unlikely to be due to random chance. Significance testing is conducted via a Monte Carlo simulation. Arrows within the heatmap indicate the phase relationship between the two time series. Right-pointing arrows mean the series are in-phase (moving together), left-pointing arrows mean the series are anti-phase (moving in opposite directions), upward arrows mean the first series is leading the second series, and downward arrows mean the second series is leading the first series. The length and direction of the arrows provide insight into the lead–lag relationship and phase differences between the series. The cone of influence is represented by a lighter shaded area or an overlay at the edges of the plot. It indicates the region where edge effects may distort the results due to the finite length of the time series. Data outside this cone should be interpreted with caution.

4.2.1. Commodities

Figure 3 presents the WTC between Bitcoin and the S&P GSCI Commodity Index. We observe the following:

1. Increasing coherence post-2017, particularly in the medium-term.
2. Significant coherence during the COVID-19 crisis period (Q3 2019 to Q4 2020).
3. Emerging long-term coherence in the 256–512-day frequency band since 2017.

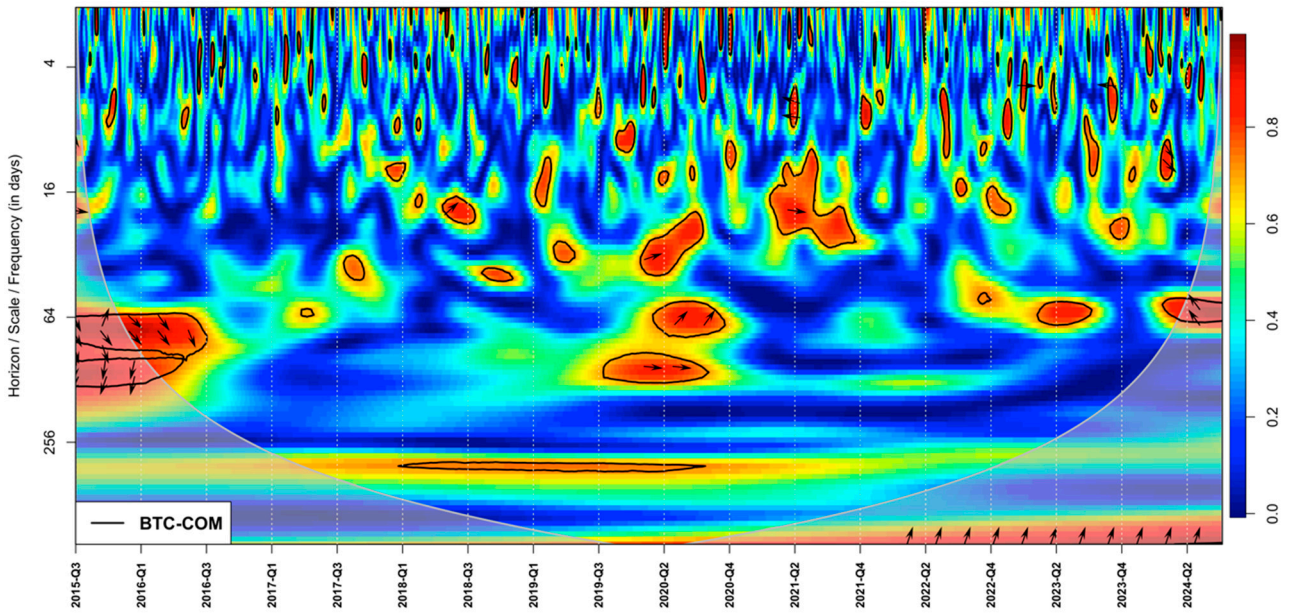


Figure 3. A WTC heatmap of BTC–COM (traded commodities).

Overall, commodities and Bitcoin show several clusters of coherence, implying similar responses to economic events that took place during such periods, which is in line with the findings of Gronwald (2019) and Bouri et al. (2018). As such, and given the existence of significance spots across the time horizon, the first null hypothesis of this paper is rejected for traded commodities. The results also show vast areas of less coherence, which can be attributed to the variety of factors influencing the price of each commodity included in the index. The trend of increasing coherence post-2019 also implies the second hypothesis of this paper is rejected for traded commodities.

The WTC between Bitcoin and gold (Figure 4) reveals the following:

1. Increased short-term coherence post-2018.
2. A notable medium-term cluster from 2019-Q3 to 2021-Q2, with Bitcoin leading gold.
3. Growing long-term coherence post-2018.

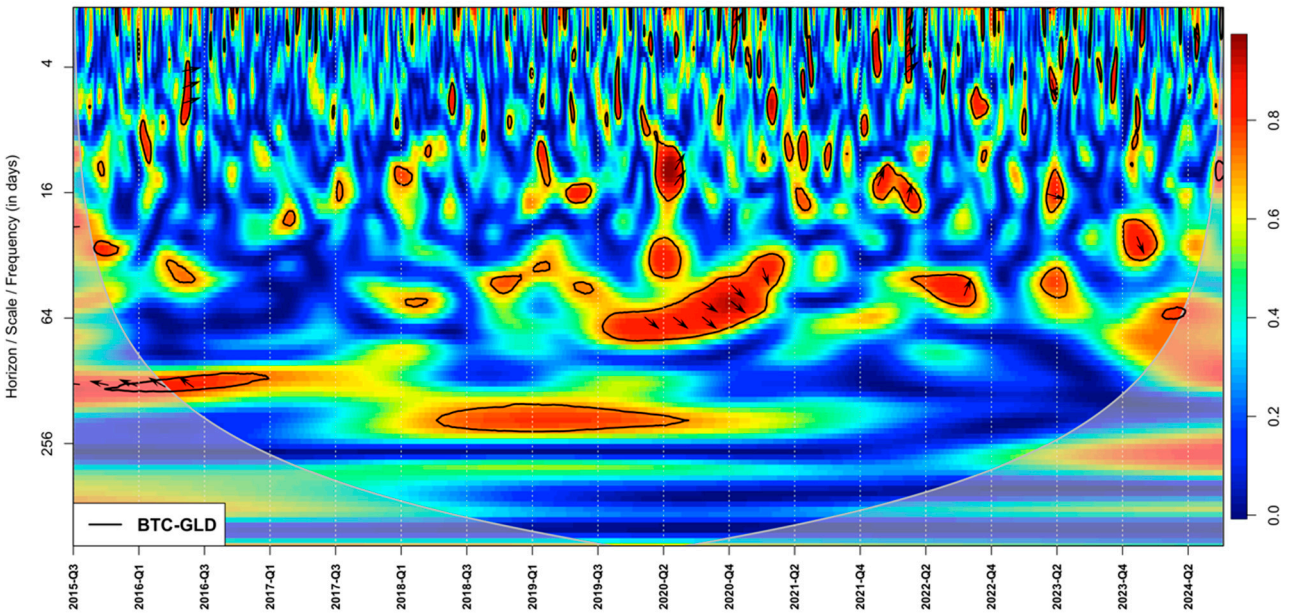


Figure 4. A WTC heatmap of BTC–Gold.

BTC coherence with gold seems to show a gradual pattern of increase past 2019. This may be explained by both assets being considered safe havens, which is in line with the findings of Chemkha et al. (2021). Further, while it is expected for safe-haven assets to be distant from the rest of the assets, the shorter-term movements of gold and Bitcoin show that they are coherent in response to short-term economic events. As such, the first and second null hypotheses of this paper are rejected for gold.

Figure 5 below shows the coherence between Bitcoin and oil. As explained above, the price movement of oil can be influenced by factors that go beyond supply and demand dynamics. As such, one needs to be careful when analyzing the price movement of oil in relation to any other asset. The timescale analysis is as follows:

- Short Term: Low general coherence with sudden spikes suggests a limited short-term relationship with similar sharp responses to specific economic events.
- Medium Term: Moderate coherence is observed, particularly during the volatile oil prices of the COVID-19 crisis.
- Long Term: Increased coherence post-2017 in the 265–512-day frequency spectrum, similar to other assets analyzed.

Overall, the coherence between oil and Bitcoin seems to be lower, which can be explained by the different factors influencing the price of oil, including production demand, geopolitical turmoil, and oil supplier policies, as shown by Kilian (2014). However, given the significance levels shown in the heatmap and the pattern of increasing coherence, the first and second null hypotheses of this paper are rejected for oil.

4.2.2. Equity Markets

Figures 6 and 7 display the WTC between Bitcoin and global equities (Dow Jones Global Index) and U.S. equities (S&P 500), respectively. Key observations include the following:

1. Increasing short-term coherence post-2020 for both indices.
2. Significant medium-term coherence during the COVID-19 crisis.
3. Prolonged coherence clusters post-2017 in the long-term spectrum.

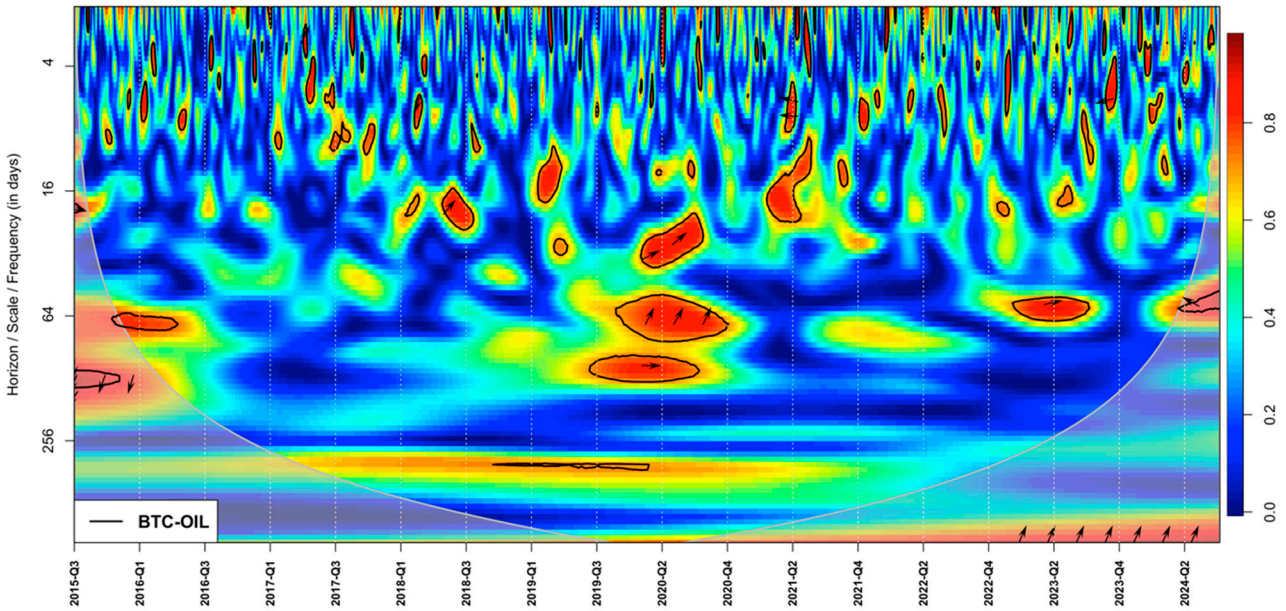


Figure 5. A WTC heatmap of BTC–oil.

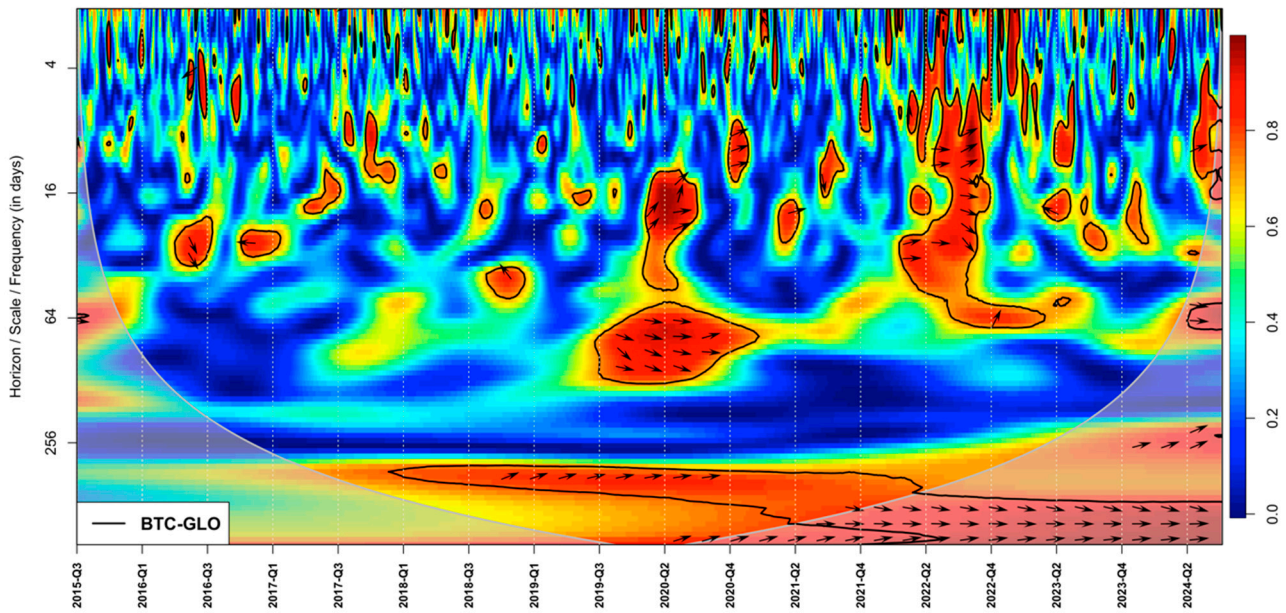


Figure 6. A WTC heatmap of BTC–GLO (global equities).

Overall, and in line with the findings of Jia et al. (2024), the general increase in coherence clusters between Bitcoin and global equities shows an increasing acceptance of Bitcoin as a mainstream asset comparable to global equities, sometimes to the degree of Bitcoin being the leader of such coherence. As such, both the first and the second null hypotheses of this paper are rejected for global equities.

The findings above are in line with the findings of Buncic and Gisler (2016) and Hung (2022), indicating a high degree of interconnectedness between US equities and Bitcoin, with US equities being transmitters of spillover. Given the similarity with the GLO graph above, and given the presence of significance contours, both the first and the second null hypothesis of this paper are rejected for US equities as represented by the S&P 500 index.

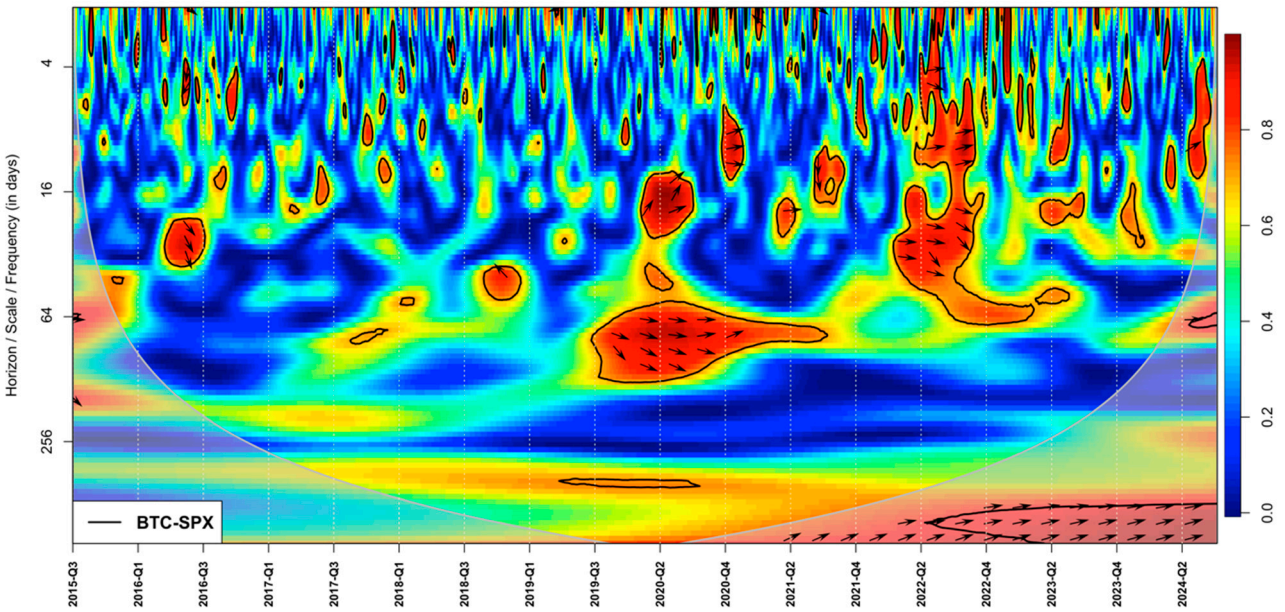


Figure 7. A WTC heatmap of Bitcoin–SPX.

Figure 8 below shows the WTC between Bitcoin (BTC) and the Dow Jones Islamic Market World Index (ISL). We observe the following:

- Short Term: Similar patterns of coherence to global equities and SPX.
- Medium Term: Stronger coherence around late 2017 to early 2018 and mid-2019, and during the COVID-19 crisis.
- Long Term: From late 2020 to mid-2022, there is consistently high coherence, suggesting a strong, long-term relationship between BTC and ISL.

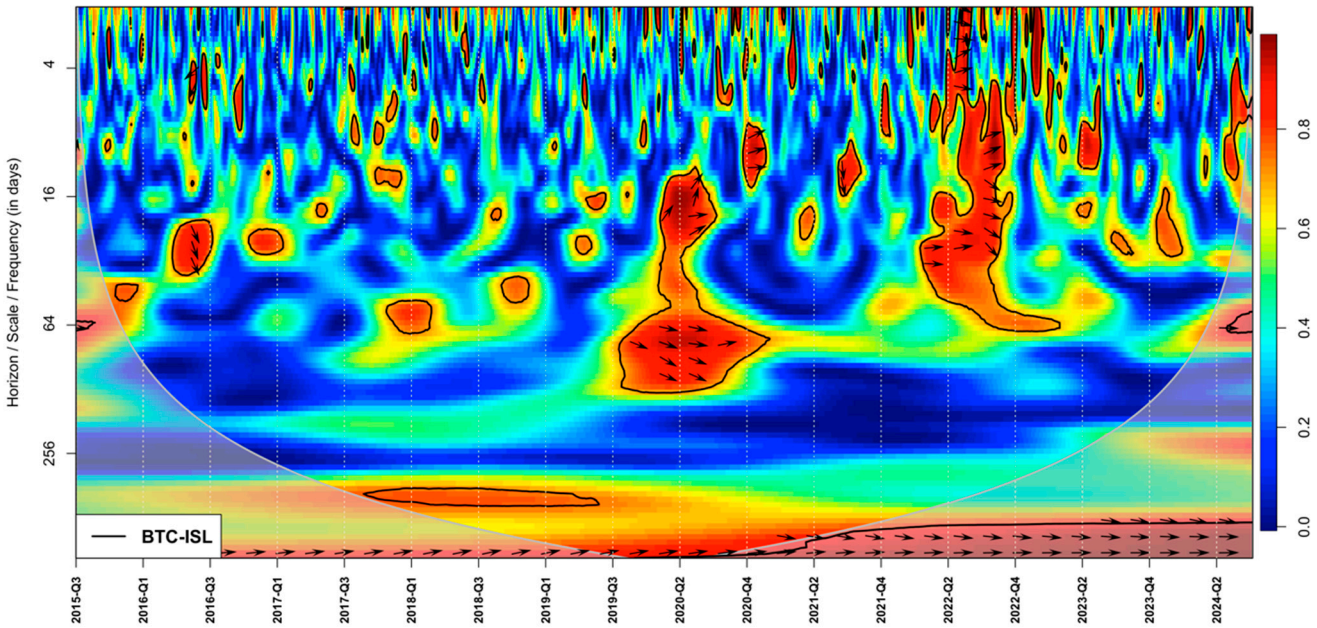


Figure 8. A WTC heatmap of BTC–ISL (Islamic equities).

Overall, the WTC analysis shows that BTC and ISL have periods of strong coherence, particularly during significant financial events or trends. The findings are in line with Disli et al. (2021), confirming the systematic spillover effect between BTC and Islamic equities. As such, the first and second hypotheses are rejected for ISL.

4.2.3. Cryptocurrency Market

Figure 9 below shows the coherence between Bitcoin and Ethereum's Ether. As explained above, both are expected to show a high level of coherence in line with the findings of Aysan et al. (2023). Analyzing the coherence here eliminates the need to explain similar coherence patterns between the two assets and other assets. Overall, the graph shows a general trend across the frequency spectrum of moderate coherence that increases significantly post Q3-2017. In the short term, the general trend referenced above is shown, with a significant level of coherence between the two. The same general trend is also evident in the medium term and the long term. The long-term coherence trend has become more prominent after 2020.

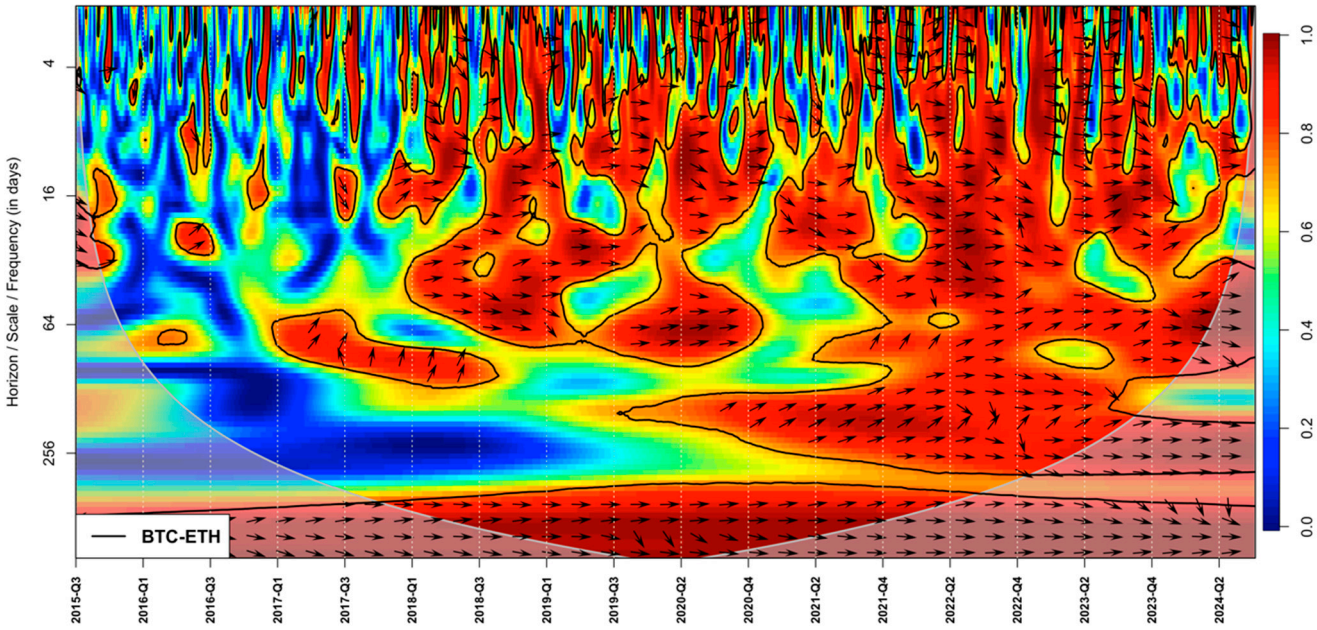


Figure 9. A WTC heatmap of BTC–ETH.

As such, given the strong coherence between Bitcoin and Ethereum, information that influences one asset seems to be sufficient in predicting a great deal of the movement of the other, and the more prominent asset here is Bitcoin, given its market cap and age. The arrows show a strong in-phase relationship, indicating that the assets are mostly positively correlated, with Bitcoin leading through the northeast arrows. Such a relationship is further emphasized through the strong and consistent coherence clusters in the short term, contrary to the coherence patterns with other assets analyzed in this study. While there are trends of Ethereum leading Bitcoin through a few southeast arrows, they can be explained by a market trend of trying to beat the correlation relationship through predatory purchasing of Ethereum and not by much improvement in the Ethereum fundamentals per se. The first and second null hypotheses are rejected for Ethereum.

4.2.4. Interest Rates

Figure 10 shows the WTC between Bitcoin and SOFR. Notable features include the following:

1. Intermittent short-term coherence.
2. Significant medium-term coherence in 2018–2019 and late 2020.
3. Consistent long-term coherence from late 2019 to early 2022.

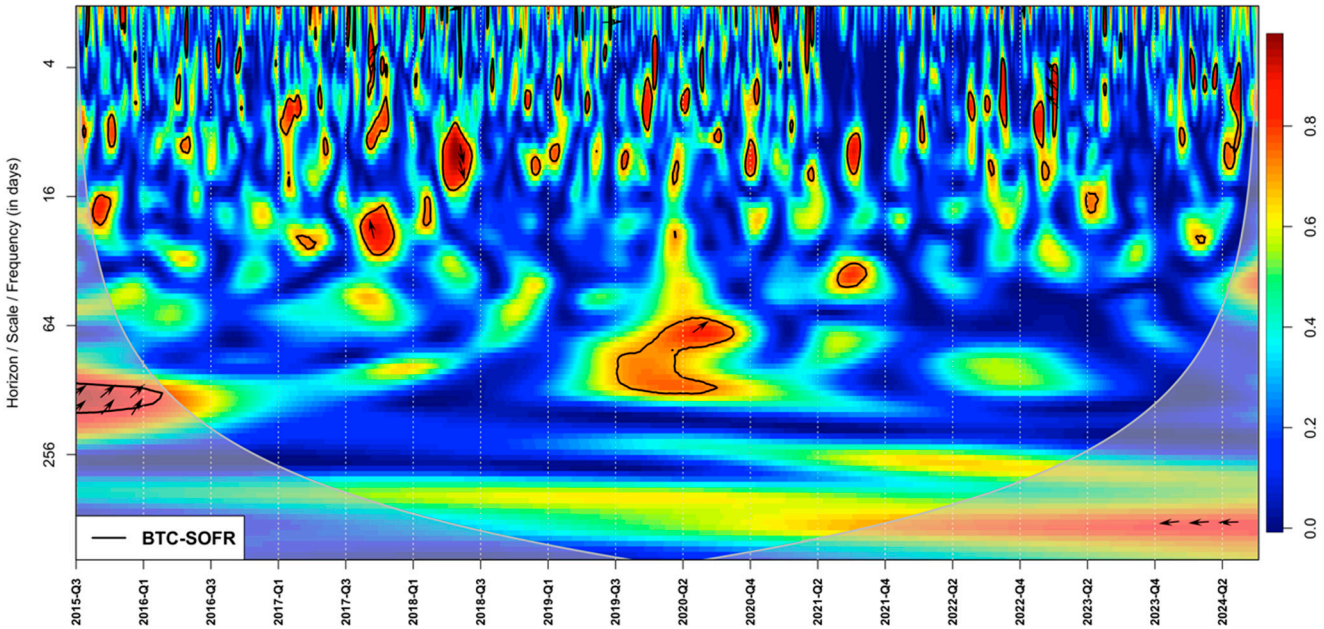


Figure 10. A WTC heatmap of BTC–SOFR.

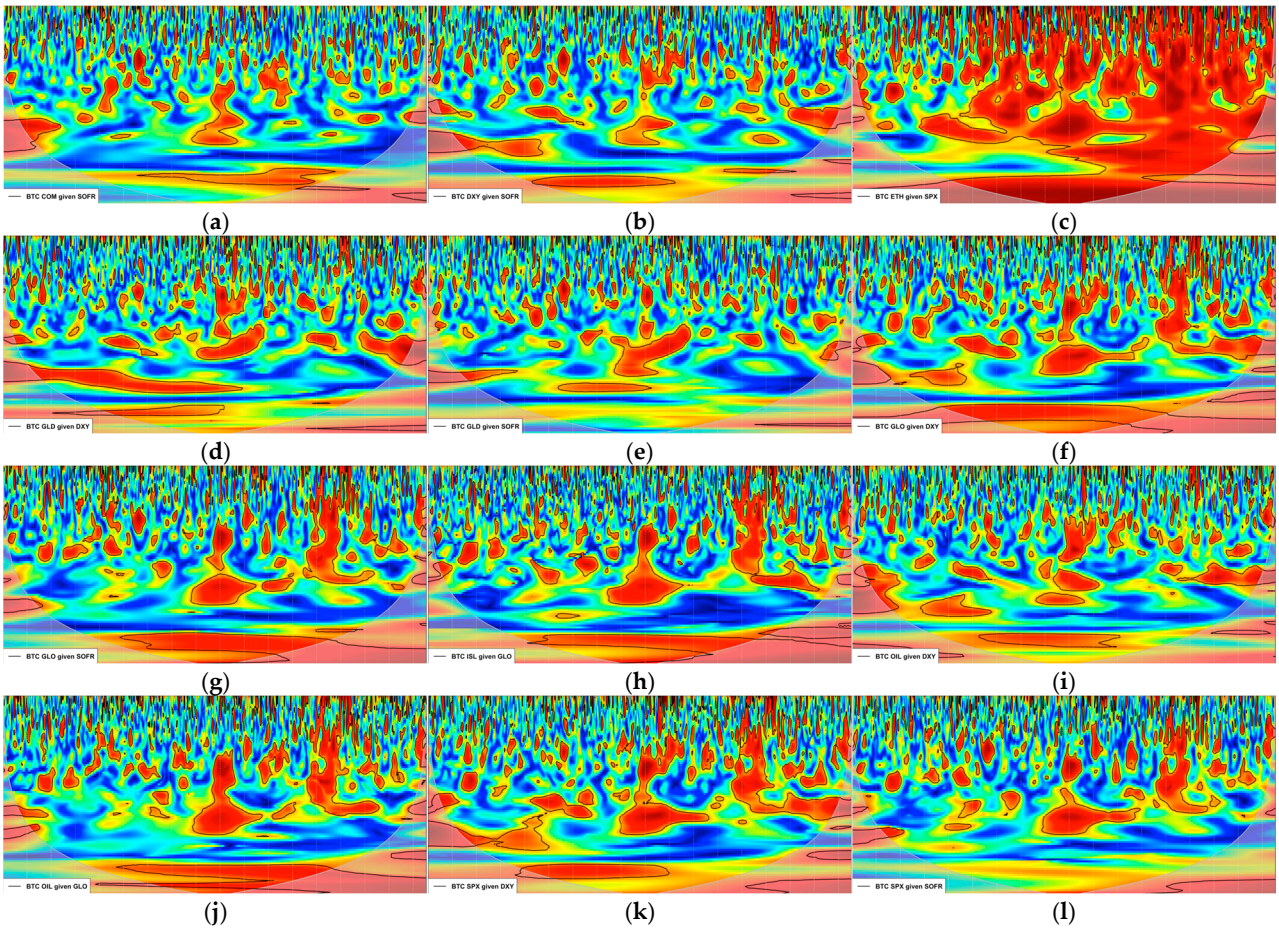
We also note that the co-movement was not necessarily influenced by the movement magnitude of the SOFR. As such, investors of BTC seem to respond similarly to events moving of both BTC and SOFR irrespective of magnitude. The first hypothesis for SOFR is therefore rejected.

4.3. Multiple Wavelet Coherence Analysis

The fourth question is the following: Does Bitcoin move coherently with a combination of systematic risk factors? Recognizing the benefit of comparing Bitcoin to individual risk factors, it makes as much sense to test the coherency of Bitcoin with a combination of systematic risk factors since financial assets are not isolated from the influence of such combinations of factors. This approach avoids under-specifying the models by omitting important variables and accounts for interconnectedness and spillover effects among financial markets. Combining this approach with others can provide a more comprehensive representation of Bitcoin's risk profile.

MWC heatmaps are plotted below. Similarly to WTC, the coherence values for MWC range from 0 to 1. Low coherence is represented by blue, indicating a weak or no relationship between A and the combined effect of B and C time series at that particular time and scale. High coherence is represented by red, indicating a strong relationship between A and the combined effect of B and C time series at that particular time and scale. Black contour lines outline regions where the coherence is statistically significant at a certain confidence level, such as 5% based on a Monte Carlo simulation.

The MWC analysis shown in Figure 11 below reveals high coherence between Bitcoin and multiple combinations of systematic risk factors, supporting the rejection of our third null hypothesis. This finding is in line with the literature on systematic risk, such as the findings of Jia et al. (2024) on the interconnectedness between Bitcoin and other markets and on the effect of financialization on assets (Silvennoinen & Thorp, 2013).



(**a**) (**b**) (**c**)

(**d**) (**e**) (**f**)

(**g**) (**h**) (**i**)

(**j**) (**k**) (**l**)

Figure 11. A grid of 12 plots representing the MWC analysis for combinations of three time series: A (representing BTC), B, and C. Each plot shows the coherence between BTC and the combined effect of the two other series specified in the respective subfigure captions above. (**a**) Coherence between BTC and the combined effect of COM and SOFR. (**b**) Coherence between BTC and the combined effect of DXY and SOFR. (**c**) Coherence between BTC and the combined effect of ETH and SPX. (**d**) Coherence between BTC and the combined effect of GLD and DXY. (**e**) Coherence between BTC and the combined effect of GLD and SOFR. (**f**) Coherence between BTC and the combined effect of GLO and DXY. (**g**) Coherence between BTC and the combined effect of GLO and SOFR. (**h**) Coherence between BTC and the combined effect of ISL and GLO. (**i**) Coherence between BTC and the combined effect of OIL and DXY. (**j**) Coherence between BTC and the combined effect of OIL and GLO. (**k**) Coherence between BTC and the combined effect of SPX and DXY. (**l**) Coherence between BTC and the combined effect of SPX and SOFR. Colors represent coherence strength (0–1) between time series, with red indicating strong coherence and blue indicating weak coherence. Black contours outline regions of statistical significance at 5% level. The curved lines (Cone of Influence) mark boundary regions; areas outside COI should be interpreted with caution.

4.4. Partial Wavelet Coherence Analysis

With PWC, this section answers the fifth question: Do systematic risks persist if other sources of risk are isolated? A PWC heatmap between three time series, A, B, and C, where C is the time series controlled for, offers a detailed view of the coherence between A and B while controlling for the influence of C. When B and C are correlated in a PWC analysis involving three time series (A, B, and C, where C is controlled for), a PWC analysis removes some of the shared variance between B and C, leading to lower residual coherence between A and B.

The null hypothesis to be tested answers the question in this section: if another major source of systemic risk is controlled for, Bitcoin will show no coherence with major sources of systematic risk. The null hypothesis is rejected by significance counters. Based on the

literature above, systematic risk factors can be highly correlated, exhibit interconnectedness, and be subject to spillover effects. Therefore, PWC significance testing as conducted in this section is more stringent compared, for example, to significance testing in WTC as conducted above.

The PWC heatmaps are shown below. Compared to WTC heatmaps as described above, a PWC heatmap will still include a color scale ranging from blue (low coherence) to red (high coherence). However, if B and C are highly correlated, controlling for C may reduce the apparent coherence between A and B in regions where the correlation between B and C is strong. As a result, red areas indicating high coherence might be less pronounced or more scattered if B and C's correlation significantly impacts the relationship between A and B. Conversely, blue regions indicating low coherence might become more prevalent, especially in areas where B and C are strongly correlated, because the overlapping information or shared variance between B and C is removed, leaving less residual coherence between A and B. The black contour lines representing statistically significant coherence regions might shift or change in density. If B and C's correlation is strong, significant coherence regions might be smaller or less frequent, as much of the shared variance is accounted for by C. The phase arrows within the heatmap will still indicate the phase relationship between A and B, but interpretation of these arrows will be more nuanced because the influence of C (which is expected to be correlated with B) is controlled for.

The PWC analysis in Figure 12 below reveals significant coherence between Bitcoin and individual risk factors, even when controlling for other systematic sources. This result leads to the rejection of our fourth null hypothesis and suggests that Bitcoin's relationship with various systematic risk factors is robust to the influence of other financial variables.

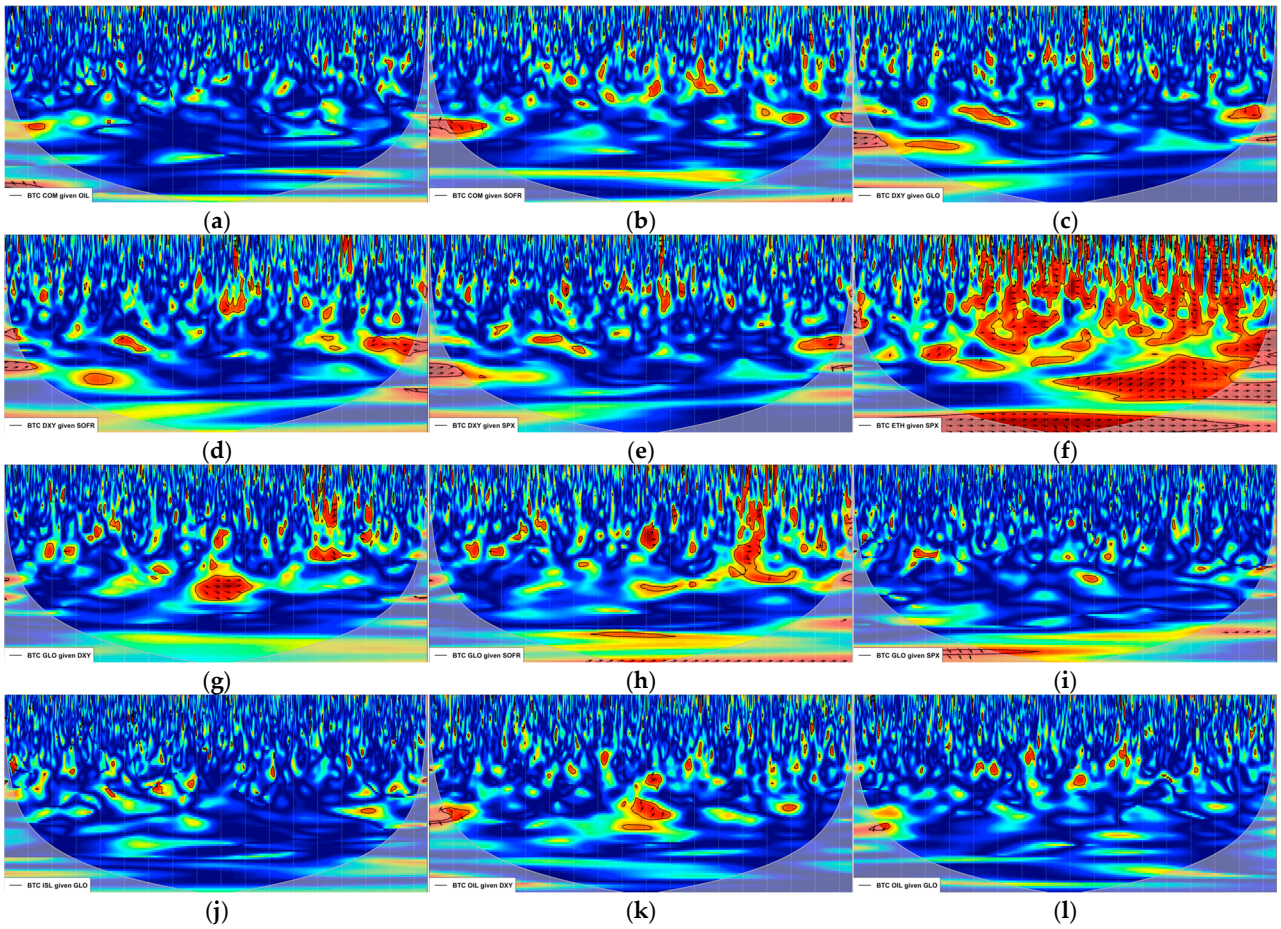
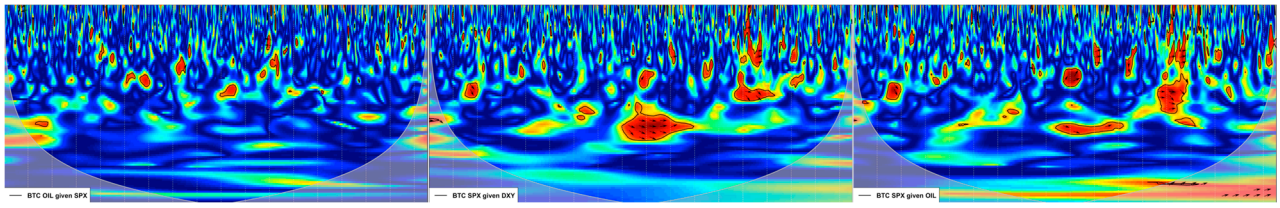


Figure 12. *Cont.*



(**m**) (**n**) (**o**)

Figure 12. A grid of 15 plots representing the PWC analysis for combinations of three time series: A (representing BTC), B, and C. Each plot shows the coherence between BTC and B, controlled for the effect of C. Subfigures (**a**–**o**) provide detailed coherence information. (**a**) Coherence between BTC and COM, controlled for OIL. (**b**) Coherence between BTC and COM, controlled for SOFR. (**c**) Coherence between BTC and DXY, controlled for GLO. (**d**) Coherence between BTC and DXY, controlled for SOFR. (**e**) Coherence between BTC and DXY, controlled for SPX. (**f**) Coherence between BTC and ETH, controlled for SPX. (**g**) Coherence between BTC and GLO, controlled for DXY. (**h**) Coherence between BTC and GLO, controlled for SOFR. (**i**) Coherence between BTC and GLO, controlled for SPX. (**j**) Coherence between BTC and ISL, controlled for GLO. (**k**) Coherence between BTC and OIL, controlled for DXY. (**l**) Coherence between BTC and OIL, controlled for GLO. (**m**) Coherence between BTC and OIL, controlled for SPX. (**n**) Coherence between BTC and SPX, controlled for DXY. (**o**) Coherence between BTC and SPX, controlled for OIL. Colors represent coherence strength (0–1) between time series, with red indicating strong coherence and blue indicating weak coherence. Black contours outline regions of statistical significance at 5% level. The curved lines (Cone of Influence) mark boundary regions; areas outside COI should be interpreted with caution.

In summary, our wavelet analysis reveals that Bitcoin's risk profile is increasingly aligned with systematic risk factors, while maintaining some unique characteristics. These findings have important implications for Bitcoin's role in portfolio diversification and its potential function as a monetary asset.

5. Conclusions

This study examines Bitcoin's viability as a monetary asset by analyzing its volatility and coherence with systematic risk factors using wavelet analysis. Our dataset spans from 13 August 2015 to 29 June 2024, encompassing a period of significant evolution in cryptocurrency markets.

We challenge the conventional application of the threefold test of money (medium of exchange, unit of account, and store of value) to Bitcoin, arguing for a more nuanced approach that focuses on the store of value function as a desirable feature rather than a defining characteristic. Our empirical strategy compares Bitcoin's information risk profile to major systematic risk factors, positing that if Bitcoin's risk is largely explained by these factors, its idiosyncratic risk becomes less problematic for its monetary function.

Starting by exploring the nature of Bitcoin's volatility across different time scales, we utilized a pure projection of BTC price, a GARCH modeling, and a WT heatmap, revealing various aspects of BTC's risk profile. Bitcoin's volatility exhibits both short-term reactivity to market events and longer-term persistence, consistent with the stylized facts of financial asset returns. Answering this question required no hypothesis testing. Second, having had the first null hypothesis rejected, we found Bitcoin's information risk to be explainable by systematic factors on the short-, medium-, and long run, revealing the co-movement pattern between Bitcoin and the systematic factor investigated. Third, having had the first null hypothesis rejected, we found Bitcoin's risk exposure to be increasingly systematic over time, suggesting a growing integration of Bitcoin into the broader financial system. Fourth, having had the third null hypothesis rejected we found Bitcoin's price movement to be coherent to a combination of systematic risk factors, further supporting its integration into various financial markets. Fifth, having had the fourth null hypothesis rejected, we

found Bitcoin's systematic risk exposures persisting despite controlling for other systematic risk sources, indicating robustness in these relationships.

These results lead us to conclude that a substantial portion of Bitcoin's risk can be attributed to systematic factors, mirroring the financialization trends observed in other asset classes. While Bitcoin retains unique risk characteristics, its increasing alignment with systematic risk factors suggests that its idiosyncratic risk may be diversifiable within a broader portfolio context.

Our findings have several implications for financial theory and practice:

1. They challenge the notion that Bitcoin's volatility necessarily precludes its function as a monetary asset, given the significant systematic component of its risk profile.
2. They suggest that regulatory approaches to Bitcoin should evolve to recognize its increasing integration with traditional financial markets.
3. They indicate that Bitcoin may itself be emerging as a source of systematic risk, given its high coherence with established risk factors.

These conclusions support a reconsideration of Bitcoin's role in monetary theory and financial markets. However, we acknowledge several limitations of our study. Our analysis is restricted to the asset classes included and does not directly examine Bitcoin's relationship with national currencies, particularly those experiencing high inflation. Additionally, we do not explore Bitcoin's idiosyncratic risk in depth or its implications for monetary policy.

Future research could address these limitations by the following:

1. Investigating Bitcoin's relationship with a broader range of national currencies, especially in high-inflation economies.
2. Conducting a detailed GARCH analysis of Bitcoin's idiosyncratic risk.
3. Examining trading and liquidity data to extract further information about Bitcoin's risk profile, particularly regarding accumulation and distribution trends.
4. Comparing Bitcoin's implicit monetary policy characteristics with those of traditional currencies.

In conclusion, our findings suggest that Bitcoin's risk profile is increasingly aligned with systematic factors, supporting its potential role as a monetary asset. However, further research is needed to fully understand its place in the evolving landscape of global finance and monetary systems.

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