The Complexity of Jump Dynamics in Cryptocurrencies and Forex Markets: A Multifractal Cross-Correlation Framework

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Abstract

Jumps in financial markets play a crucial role in disrupting financial systems, influencing trading behavior, and increasing market complexity. This study aims to quantify how jumps in decentralized markets have cross-correlation properties with centralized financial markets, particularly in multifractal context. We employ high frequency data from six major cryptocurrencies and six major forex markets at 5-minute intervals for the period of Aug 04, 2019 - Jul 27, 2024. We first extract daily jumps by using the MinRV-based jump method and employ multifractal detrended cross-correlation analysis (MF-DXA, also known as MF-DCCA) on jumps to understand their interconnected dynamics. The findings indicate all 36 pairs of jumps between cryptocurrencies and forex markets to have significant multifractality in cross-correlation. However, the strength of multifractal cross-correlation varies significantly across all combinations. Notably, all cryptocurrencies exhibit stronger cross-correlations with Japanese Yen, and weaker with Australian Dollar and British Pound. In addition, all the pairs of jumps have persistence behavior in the cross-correlation indicating the likelihood of positive/negative jumps in one market often propagate positive/negative jumps in another market. These findings offer valuable insights for market participants, investors and policymakers in making informed investment decisions, developing risk adjusted trading strategies, and enhancing efficiency in financial markets.

Keywords: jumps; co-jumps; multifractality; MF-DCCA; cryptocurrencies; forex exchange rates

Introduction

With the growing popularity of decentralized markets, understanding their complexity and relationship with centralized markets is emerging to be the heart of empirical research in Finance. In particular, this study examines jumps in high-frequency returns of cryptocurrencies and forex markets to explore cross-market jump dynamics through the lens of multifractality. This is to explore new insights into market interdependence and risk transmission. In general, jumps refer to sudden and irregular dramatic changes in the financial markets' prices, which are challenging to predict, explicitly define, or

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handle mathematically (Hanousek & Novotný, 2012). There are plenty of reasons which make the identification of jumps crucial. For instance, jump detection enables researchers to examine the types of information linked with various events such as geopolitical tensions (Gkillas et al., 2018), macroeconomic news announcements (Ayadi et al., 2024), market sentiments and herding behavior (Gao et al., 2022), natural disasters such as COVID-19 (Hu & Jiang, 2023; D. hai Zhou & Liu, 2023), recent cryptocurrency related factors such as the crash of FTX (Conlon et al., 2024), and among others. These events often cause significant fear among investors leading to overreactions to negative information, which in turn causes financial turbulence and extreme volatility in the form of jumps. Therefore, investigating jumps is valuable for modeling and forecasting asset prices, developing information driven trading and risk management strategies, as well as shaping policy decisions (Barunik & Vacha, 2018).

Co-jumps, on other hand, explains the tendency of simultaneous occurrence of discontinuities across multiple assets (W. Peng & Yao, 2022). As co-jumps are closely associated with financial market crashes and systemic risks, hence, making their accurate detection is crucial for mitigating financial risks. Despite attempts to manage risk by holding diverse assets, co-jumps can severely limit the benefits of diversification, leaving investors more exposed to risk than anticipated. Hawkes (1971) describes the similar phenomenon in context of earthquakes, referred to as self-excitation and cross-excitation. According to this, extreme events such as jumps not only increase the likelihood of subsequent jumps within the same market (self-excitation) but also trigger jumps in other markets (cross-excitation) (see Bacry et al. (2015) and Hawkes (2018) for a detailed review on its application in Finance). For example, Granelli & Veraart (2016) create an equity index by applying self-excitation and mutual excitation to examine the contagion effect among different stocks. Dungey et al. (2018) found significant evidence of mutually excited jumps for stocks, bonds and commodities especially during the periods of heightened market stress. In context of cryptocurrencies, C. Zhang, Zhang, et al. (2023) employed Boswijk et al. (2018) test and identified significant asymmetric excitation in Bitcoin jumps, where negative news caused more pronounced downward jumps than positive news caused upward jumps. Similarly, Gkillas et al. (2022) and Chen et al. (2024) explore co-jump dynamics between cryptocurrencies and S&P 500 and found evidence of co-jumping behavior, which also triggers future jumps.

The proliferation of intraday trading activities and the easy access of high-frequency data has also played a significant role in advancement of jump detection methods and shifted the focus from parametric jump methods to model free methods. For instance, the initial studies employed low frequency daily and weekly data and applied methods such as parametric method of Andersen et al. (2002), and the Markovian non-parametric approaches (Aït-Sahalia, 2002; Bandi & Nguyen, 2003; Johannes, 2004). Later on, Barndorff-Nielsen (2004) pioneered a model free method by using high frequency data, and estimated jumps by subtracting continuous volatility component (realized bi-power variation - BPV) from overall volatility (realized volatility - RV) as developed by Andersen et al. (2001). This breakthrough inspired numerous alternative approaches, including jump tests based on bi-power and tri-power variations (Andersen et al., 2007, 2010, 2012), variance swaps (Jiang & Oomen, 2008), semimartingale models and robust to microstructure noise based (Aït-Sahalia & Jacod, 2009, 2012; Jacod et al., 2010; Podolskij & Ziggel, 2010), factor based models based tests (Todorov & Bollerslev, 2010), machine learning and neural networking based tests (Au Yeung et al., 2020), and among others. Among these methods, MinRV-based jump detection method of Andersen et al. (2012) is more robust and computationally efficient which minimizes the impact of microstructure noise and spurious volatility spikes. Unlike BPV based methods, which might misclassify jumps due to extreme intraday fluctuations, or wavelet-based methods, which might require complex parameter tuning, MinRV provides a more stable framework, particularly for high-frequency data.

Despite significant advancements in jump modeling, understanding the intricate behavior of jumps not only over time but also across different markets adds an additional layer of complexity to the jump dynamics of financial markets. To capture this complexity by using conventional methods is challenging, particularly during extreme market conditions (Aït-Sahalia et al., 2015), hence it requires a more sophisticated framework. The multifractal context, with its ability to account for complexity, long memory, self-similarity, and multi-scaling, offers a powerful lens through which to examine the cross-correlation of jumps across assets. Interestingly, these properties offer significant potential to predict future prices, forecast volatility and anticipate market crashes. However, such findings run counter to the modern financial economic theory known as Efficient Market Hypothesis (EMH) of (Fama, 1970). It is because EMH roots from linear models, normal distribution and random walk behavior, and asserts that no one can achieve abnormal profits through arbitrage because asset prices fully and immediately reflect all available information. Consequently, price forecasting is deemed impossible due to the absence of predictable patterns in asset prices.

These deviations gave rise to alternative theories, such as Fractal Market Hypothesis (FMH) proposed by Peters (1993) which provides a robust framework to explain the complexities, irregular fractal structures, and long memory. FMH also introduced a range of quantitative methods for analyzing financial time series. Initial methods were based on mono-fractality such as rescaled range analysis (R/S) from Hurst (1951) and detrended fluctuation analysis (DFA) by C. K. Peng et al. (1994). Building on this foundation, Kantelhardt et al. (2002) introduced multifractal detrended fluctuation analysis (MFDFA), an extension of DFA, to capture the multifractality or multiscale fractality in nonlinear time series. MFDFA has since become one of the most widely used techniques for analyzing multifractal properties in complex systems, including stock markets (X. L. Fu et al., 2023; M. J. Lee & Choi, 2023; Mensi et al., 2024), commodities (Memon et al., 2022), forex markets (Czech & Pietrych, 2021; Han et al., 2019, 2020; Oh et al., 2012; Shahzad et al., 2018; Stošić et al., 2015), cryptocurrencies (da Silva Filho et al., 2018; de Salis & dos Santos Maciel, 2023; Lahmiri & Bekiros, 2020; Mensi et al., 2019; Ruan et al., 2021) and among others.

To further analyze the cross-correlation between two time series Podobnik & Stanley (2008) proposed detrended cross-correlation analysis (DXA) based on DFA. Likewise, it spuriously enhances multifractal cross-correlation values and lacks complete interpretation. To address this, W. X. Zhou (2008) combined DXA with MFDFA and proposed multifractal detrended cross-correlation analysis (MF-DXA), which gained significant popularity recently (Acikgoz, 2024; Ahmed et al., 2024; Aslam et al., 2023; Cao & Xu, 2016; Devi et al., 2021). For example, Z. Fu et al. (2023) applied both MFDFA and MF-DXA to examine multifractality in univariate as well as in their cross-correlation for Chinese energy markets, crude oil and gold.

Cryptocurrencies are regarded as one of the most complex markets due to their high volatility (Gupta & Chaudhary, 2022; Kakinaka & Umeno, 2021; P. Zhang et al., 2023), self-similar structures and long memory (Assaf et al., 2023; Lahmiri & Bekiros, 2021), frequent controversies and bubbles (Fry & Cheah, 2016; Molling et al., 2020), safe-haven attributes (Corbet et al., 2020; Kumah et al., 2021; Widjaja et al., 2024), and their remarkable ability to transition seamlessly between disordered and ordered phases (Wątorek et al., 2023). This complexity originally stems from its background of blockchain technology, decentralized properties and hence their potential threat to the existing payment system, financial stability, and monetary policies and conventional currencies (Ali et al., 2024). For instance, Bouri et al. (2022) found the jumps of Bitcoin significant dependence on the jumps of geopolitical risk index of Caldara & Iacoviell (2022). In addition, to geopolitics, cryptocurrencies are also exposed to kinds of Ponzi schemes such as FTX crash in 2022 which was the world's major cryptocurrency default and was due to factors such as speculatory bubbles, security breaches, market manipulation, and regulatory actions (Moro-Visconti & Cesaretti, 2023). Despite these challenges, the institutional adoption of cryptocurrencies seems to have skyrocketed with the introduction of Bitcoin futures, rise of tokenized assets, and the integration of artificial intelligence (AI) with blockchain technology. Global jurisdictions such as Singapore, Europe, and Hong Kong are leading their way with well-defined frameworks, while the U.S. continues to make progress with decisions on Bitcoin ETFs and digital asset custody.[§]

Forex market, known as the largest financial market, stands out for its immense trading volume, unmatched liquidity, diverse participants, and rapid dissemination of information, making them more volatile and complex than other traditional financial markets. However, unlike cryptocurrencies, forex markets operate as centralized and regulated systems and are heavily influenced by macroeconomic factors, and central bank policies. Therefore, it is commonly believed that cryptocurrencies and forex markets exhibit no correlation and operate independently. This has led to the perception of cryptocurrencies as a potential safe haven and a reliable hedge during extreme events such as the periods of economic and financial crises (Corbet et al., 2018; Manavi et al., 2020; Shahzad et al., 2022). However, some argue that cryptocurrencies are increasingly exhibiting properties similar to traditional markets such as forex, commodities, and equities, particularly in the post-COVID-19 era (Drozdz et al., 2020; Wątorek et al., 2021). This raises concerns about the decentralized and unique nature of cryptocurrencies. Given these contrasting perspectives, it is logical to explore whether there exists cross-correlation between cryptocurrencies and forex, particularly in their jumps which are characterized by extreme events. Hence, examining these cross-correlations through the lens of multifractality could provide deeper insights into their dynamics. Although, there exists only one study where they examine the multifractality of single jump series of cryptocurrencies and forex market by employing MFDFA (Ali et al., 2024). However, it is limited to univariate series,

leaving the multivariate cross-correlation aspect unexplored. Based on abovementioned complexities present in cryptocurrencies and forex markets, this study makes significant contributions in five main ways. Firstly, it is the pioneer study which explores the cross-market jump dynamics through the lens of multifractality, particularly between decentralized and centralized financial markets. Secondly, to address the limitations of daily data in capturing jumps, the study employs 5-minute high-frequency data for 6 main cryptocurrencies (Bitcoin, Ethereum, Litecoin, Dashcoin, EOS, and Ripple) against 6 prominent currency exchange rates (Euro, British Pound, Canadian Dollar, Australian Dollar, Swiss Franc, and Japanese Yen). Thirdly, to extract daily jumps from high-frequency data, the study employs MinRV-based jump detection approach of Andersen et al. (2012)

[§] https://www.ulam.io/blog/institutional-adoption-of-cryptocurrency#

which provides significant robustness to the microstructure noise. Fourthly, the study employs the advanced econophysics-based method of MF-DXA by W. X. Zhou (2008), which not only captures the multifractal properties of jumps but also ranks the strength of multifractality through the range of Hurst exponent Δh_{xy}. Finally, the findings of the study challenge the assumption of isolation between cryptocurrencies and forex markets and shed light on potential cross-market risk transmission mechanisms. Hence, it offers practical implications for market participants, including investors, policymakers, and regulators, by highlighting the necessity of incorporating jump dynamics and multifractal characteristics into risk management and policy frameworks.

Literature Review

The existing literature significantly discusses the insights into the dynamics of price movements, particularly during extreme market events. Within this framework, two interconnected streams of literature stand out to be relevant to this study. The first discusses the phenomenon of co-jumps, while the second explores the intricate cross-correlation behavior of financial markets within multifractal framework. As for co-jumps, the initial studies focused on developing co-jump identification methods. For instance, among the first studies, Bollerslev et al. (2008) proposed cross-product statistical measure through which one can detect various modest sized co-jumps as well as examine cross-covariation among various financial markets. Similarly, Bibinger & Winkelmann (2015) introduced co-jump method for high-frequency data which is robust to non-synchronous data and microstructure noise. Barunik & Vacha (2018) constructed co-jump method in background of wavelet covariance which quantifies the impact of co-jumps on covariance structures for forex markets. Recently, Yeh & Yun (2023) developed co-jump technique based on regression without using parametric model specification and found that co-jumps and covolatility have significant impact on extreme returns and extreme dependence. Song & Li (2023) further included persistence behavior in examining co-jump detection and addressed the effects of taking different frequencies.

In addition to co-jump detection methods, a significant body of literature further linked co-jumps to scheduled and unscheduled macroeconomic news announcements, particularly in forex markets (El Ouadghiri & Uctum, 2016; Piccotti, 2018). For instance, Chatrath et al. (2014) examined how macroeconomic news impact the jumps and co-jumps of Swiss Franc, Japanese Yen, British Pound, and Euro and found that approximately 15% of forex market jumps are driven by U.S. macroeconomic news. Ayadi et al. (2020) investigate the impact of public communication along with scheduled and unscheduled macroeconomic news announcements on Euro, Japanese

Yen and British Pound particularly in US mortgage crisis and the EU sovereign debt recession. S. S. Lee & Wang (2020) employ scheduled macroeconomic news, macroeconomic variables as well as trading market hours to examine the predictability of jumps in a large panel data of forex markets. Recently, for Turkish Lira, South African Rand, and Mexican Peso, Serdengeçti et al. (2021) found that macroeconomic news and central bank announcements have significant impact on the co-jumps of not only returns but liquidity as well.

As for cryptocurrencies, the literature on co-jumps is relatively limited, mainly because of their novelty and relatively short history in comparison to traditional markets. One of the earliest studies, Bouri et al. (2020) analyzed jumping and co-jumping for 12 major cryptocurrencies and find that jumps in one cryptocurrency often increase the likelihood of jumps in others, with exceptions of Bytecoin and Ripple. Xu et al. (2022) observed that cryptocurrency jumps have major impact on the jumps of US based blockchain and crypto-exposed company stocks. However, the co-jumping behavior remained unaffected by the COVID-19 pandemic. Meanwhile, L. Zhang et al. (2023), while examining co-jumping behavior among various cryptocurrencies, found Bitcoin influence on other cryptocurrencies to intensify during pandemic. In addition, there are also studies which examine the co-jumping behavior of cryptocurrencies in terms of value at risk (VaR) and expected shortfall (Nekhili & Sultan, 2020), pricing mechanism in cryptocurrency options (Hou et al., 2020) and futures (C. Zhang et al., 2022; C. Zhang, Ma, et al., 2023), geopolitics (Bouri et al., 2022), sentiment-related events (Aysan et al., 2024), and macroeconomic news (Ben Omrane et al., 2023).

The second stream of literature focuses on examining cross-correlations between financial markets, with particular emphasis on the application of MF-DXA, which has received significant recognition recently. Particularly, in terms of cryptocurrencies, studies have examined the return and volume cross-correlation (Alaoui et al., 2019; W. Zhang et al., 2018), crude oil and cryptocurrencies (Ghazani & Khosravi, 2020), economic policy uncertainty (EPU) and cryptocurrencies (Ma et al., 2022), public attention and cryptocurrencies (Telli & Chen, 2021), and among others. While as for forex markets, in particular, the studies have explored the cross-correlation between offshore and onshore Renminbi against US dollar (Sun et al., 2019), Renminbi with global commodities (Lu et al., 2017), Indian Rupee and crude oil and gold (Pal et al., 2014), market anxiety gauge VIX index and Japanese Yen (Lu, Sun, et al., 2017), interest rate differentials and forex (Li et al., 2021), and among others. These studies collectively suggest that financial markets exhibit non-linear complex characteristics which align with FMH where financial markets are fractally structured and are far from being purely efficient and exhibit multi-scaling properties in their cross-correlations.

In addition to the studies examining the relationship between cryptocurrencies and forex markets are relatively less and have mixed findings. For example, Kristjanpoller & Bouri (2019) found significant cross-correlation and persistent behavior between five major exchange rates (Euro, British Pound, Swiss Franc, Japanese Yen, and Australian Dollar), and five major cryptocurrencies (Ripple, Dash, Litecoin, Bitcoin, and Monero). Cao & Ling (2022) highlight that the Renminbi/US dollar, US dollar index, and gold significantly influence cryptocurrencies, with the Renminbi/US dollar showing the strongest impact. In the similar vein, Raza et al. (2022) observed overall positive relationship of cryptocurrencies and forex market at different quantiles, which contradict the safe-haven properties of cryptocurrencies. In contrast, other studies suggest that cryptocurrencies exhibit safe-haven and hedging properties relative to forex markets. For instance, Drozdz et al. (2019), found no cross-correlations behavior in Bitcoin/Ethereum and Euro/US dollar pairs, indicating cryptocurrencies decoupling from forex markets. Shahzad et al. (2022), while examining price explosivity and hedging potential between cryptocurrencies and forex markets, discovered that Japanese Yen offers stronger hedging benefits in comparison to Euro and Chinese Yuan. Urquhart & Zhang (2019) further highlighted Bitcoin's safe-haven role during extreme market turmoil for the British Pound, Swiss Franc, and Canadian Dollar. Additionally, Chemkha et al. (2021) investigated the tail dependence using copulas and observed that cryptocurrencies and forex markets move independently, suggesting potential diversification benefits for investors.

Data and Descriptive Statistics

We employ high frequency data of cryptocurrencies and forex exchange rates at 5-min intervals to better understand the inner cross-correlation characteristics in their jumps. It is well established in previous studies (Ali et al., 2024; Liu et al., 2015) that sampling at 5-min provides an optimal balance between high and low frequencies. The dataset includes six high-market-capitalization cryptocurrencies: Bitcoin, Ethereum, Litecoin, Dashcoin, EOS, and Ripple, along with six major forex markets: the Euro, British Pound, Canadian Dollar, Australian Dollar, Swiss Franc, and Japanese Yen. All the prices are taken against US dollars, which are sourced from Dukascopy.[**] The study time period aligns with the maximum availability of data (see Table 1 for details). In addition, to be consistent with forex markets, the weekend data was omitted for cryptocurrency markets. As a result, after data cleaning and data matching, 374,399 intraday returns

[**] www.dukascopy.com

remained for each market. These returns were then used to calculate the daily realized volatility and MinRV, and hence, daily jump series with 1,249 observations for each market.

Table 1: List of Cryptocurrencies & Forex Markets

S. No.	Cryptocurrencies	Symbols	Time period
1	Bitcoin	BTC	Aug 04, 2019 - Jul 27, 2024
2	Ethereum	ETH	Aug 04, 2019 - Jul 27, 2024
3	Litecoin	LTC	Aug 04, 2019 - Jul 27, 2024
4	Dashcoin	DSH	Aug 04, 2019 - Jul 27, 2024
5	EOS	EOS	Aug 04, 2019 - Jul 27, 2024
6	Ripple	XRP	Aug 04, 2019 - Jul 27, 2024
S. No.	**Forex**	**Symbols**	**Time period**
1	Euro	EUR	Aug 04, 2019 - Jul 27, 2024
2	British Pound	GBP	Aug 04, 2019 - Jul 27, 2024
3	Canadian Dollar	CAD	Aug 04, 2019 - Jul 27, 2024
4	Australian Dollar	AUD	Aug 04, 2019 - Jul 27, 2024
5	Swiss Franc	CHF	Aug 04, 2019 - Jul 27, 2024
6	Japanese Yen	JPY	Aug 04, 2019 - Jul 27, 2024

We present the descriptive statistics for intraday returns (in Table 2) as well as daily jumps (in Table 3) of cryptocurrencies and forex markets. In case of intraday returns, mostly markets exhibit negative average 5-min returns, with BTC, ETH, XRP, GBP and CHF, being exceptions. Within these, ETH records the highest intraday mean return of around 0.0007% while EOS shows the lowest at around -0.0005%. Moreover, XRP achieves the highest maximum return at 55.2777%, followed by DSH ($39.6578\,\%$) and ETH (30.5021%), whereas DSH and EOS show the highest losses at -30.9538% and -25.6832%, respectively. Cryptocurrencies exhibit higher return volatility, with DSH ($\sigma = 0.0225$) being the most volatile. Conversely, forex markets show relatively stable fluctuations from $\sigma = 0.0004$ to $\sigma = 0.0003$. Positive skewness is seen in ETH, DSH, XRP, EURO, CHF, and JPY, with the rest exhibiting negative skewness. High kurtosis in all markets suggests the presence of fat tails and stylized facts, confirming significant multifractal patterns. Further temporal evolution of the 5-min intraday returns is shown in Figure 1 and 2.

As for the jumps of cryptocurrencies and forex markets, Table 3 further highlights the descriptive statistics, with DSH having the highest mean of 3.4898 being followed by LTC at 1.5050 and EOS at 1.0024. Conversely, CAD records the lowest average value at 0.0727, followed by EURO at 0.0759 and JPY at 0.0797. As a whole, it is noted that almost all cryptocurrencies experience greater jump volatility compared to forex markets, with DSH demonstrating the highest volatility. Figures 3 and 4 present a visual representation of the jump movements in cryptocurrency and forex markets.

Table 2: Descriptive Statistics of the Returns of Cryptocurrency and Forex Markets

	BTC	ETH	LTC	EOS	DSH	XRP
Minimum	-0.1334667	-0.1541507	-0.2231436	-0.2568316	-0.3095376	-0.2274537
Maximum	0.1216104	0.3050206	0.2513144	0.2175317	0.3965783	0.5527772
Mean	0.0000049	0.0000072	-0.0000008	-0.0000054	-0.0000038	0.0000017
Standard Deviation	0.0024418	0.0034255	0.0055662	0.0040877	0.0225012	0.0040009
Kurtosis	237.2998011	303.3896760	63.8838479	353.0926421	85.1122973	1324.3442514
Skewness	-0.5262980	1.4835547	-0.3683136	-3.4749163	0.0388839	6.7611199
Count	374399	374399	374399	374399	374399	374399
	EURO	**GBP**	**CAD**	**AUD**	**CHF**	**JPY**
Minimum	-0.0097635	-0.0289145	-0.0147172	-0.0166296	-0.0115279	-0.0128702
Maximum	0.0126936	0.0211009	0.0072101	0.0177998	0.0142757	0.0173053
Mean	-0.0000001	0.0000002	-0.0000001	-0.0000001	0.0000003	-0.0000010
Standard Deviation	0.0002871	0.0003613	0.0002700	0.0004265	0.0002991	0.0003214
Kurtosis	48.3224484	184.6119192	53.7358998	61.6951135	55.0326666	130.7910341
Skewness	0.0830702	-0.9369247	-0.6919807	-0.1416814	0.0468082	1.7006592
Count	374399	374399	374399	374399	374399	374399

Table 3: Descriptive Statistics of the Jumps of Cryptocurrency and Forex Markets

	BTC	ETH	LTC	EOS	DSH	XRP
Minimum	0.1112	0.1496	0.3282	0.0000	0.0000	0.2275
Maximum	5.2125	5.8490	6.5115	7.9148	34.0678	7.5467
Mean	0.5948	0.8463	1.5050	1.0024	3.4898	0.8453
Standard Deviation	0.3898	0.5333	0.5743	0.6306	4.9772	0.6381
Kurtosis	28.5357	20.4542	13.6795	19.8974	7.7599	21.1209
Skewness	3.9077	3.1962	2.5607	3.3538	2.6504	3.7319
Count	1249	1249	1249	1249	1249	1249
	EURO	**GBP**	**CAD**	**AUD**	**CHF**	**JPY**
Minimum	0.0110	0.0201	0.0257	0.0241	0.0266	0.0185
Maximum	0.2843	0.7314	0.3233	0.7621	0.3439	0.4272
Mean	0.0759	0.0938	0.0727	0.1122	0.0806	0.0797
Standard Deviation	0.0330	0.0459	0.0285	0.0502	0.0296	0.0460
Kurtosis	5.6122	37.5624	12.0001	30.4671	12.8125	13.4744
Skewness	1.8311	4.2300	2.4306	3.7130	2.5262	2.8891
Count	1249	1249	1249	1249	1249	1249

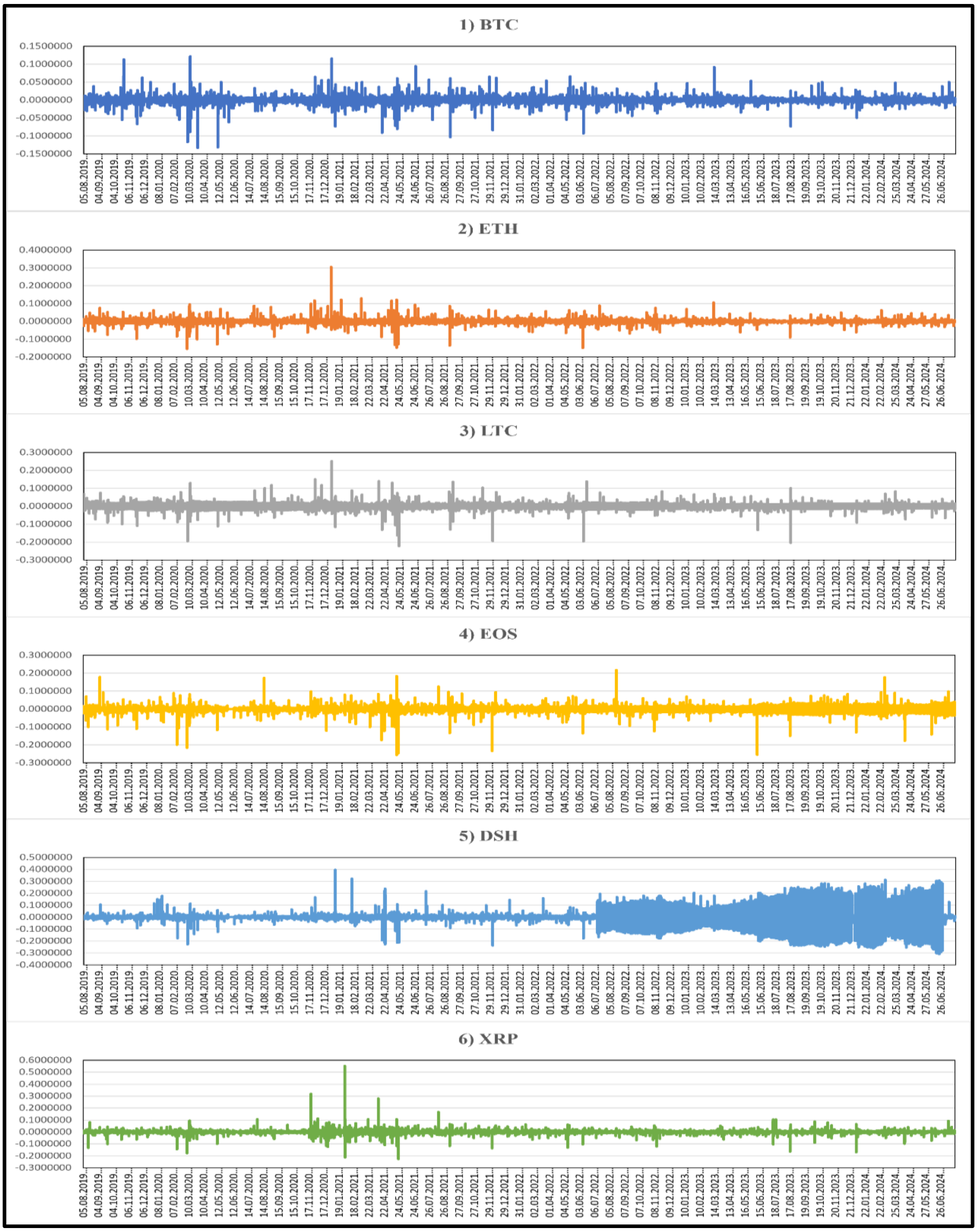

Figure 1: 5-Minute High-Frequency Returns of Cryptocurrency Markets

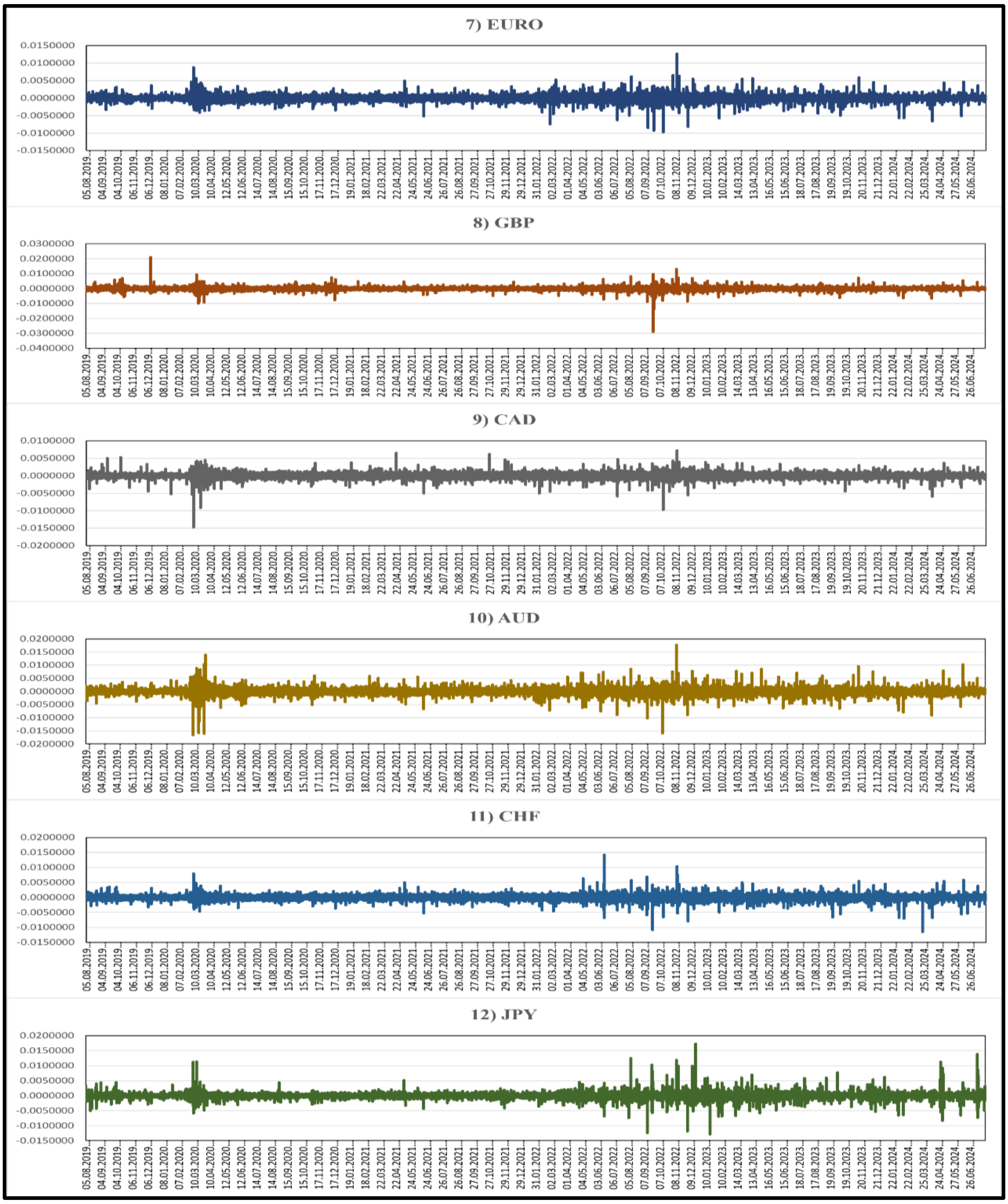

Figure 2: 5-Minute High-Frequency Returns of Forex Markets

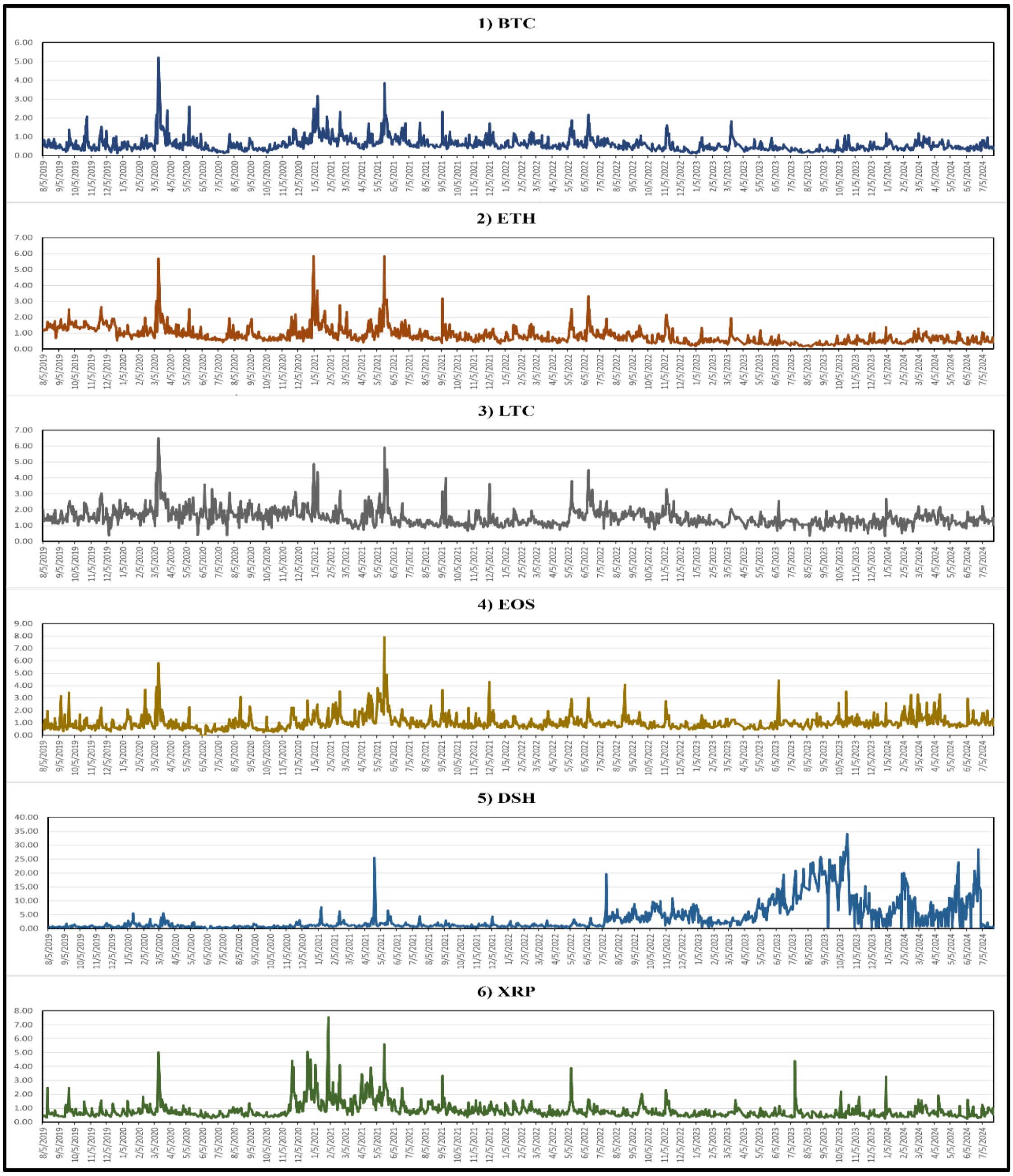

Figure 3: Daily Jump Estimates of Cryptocurrency Markets Derived from 5-Minute High-Frequency Data

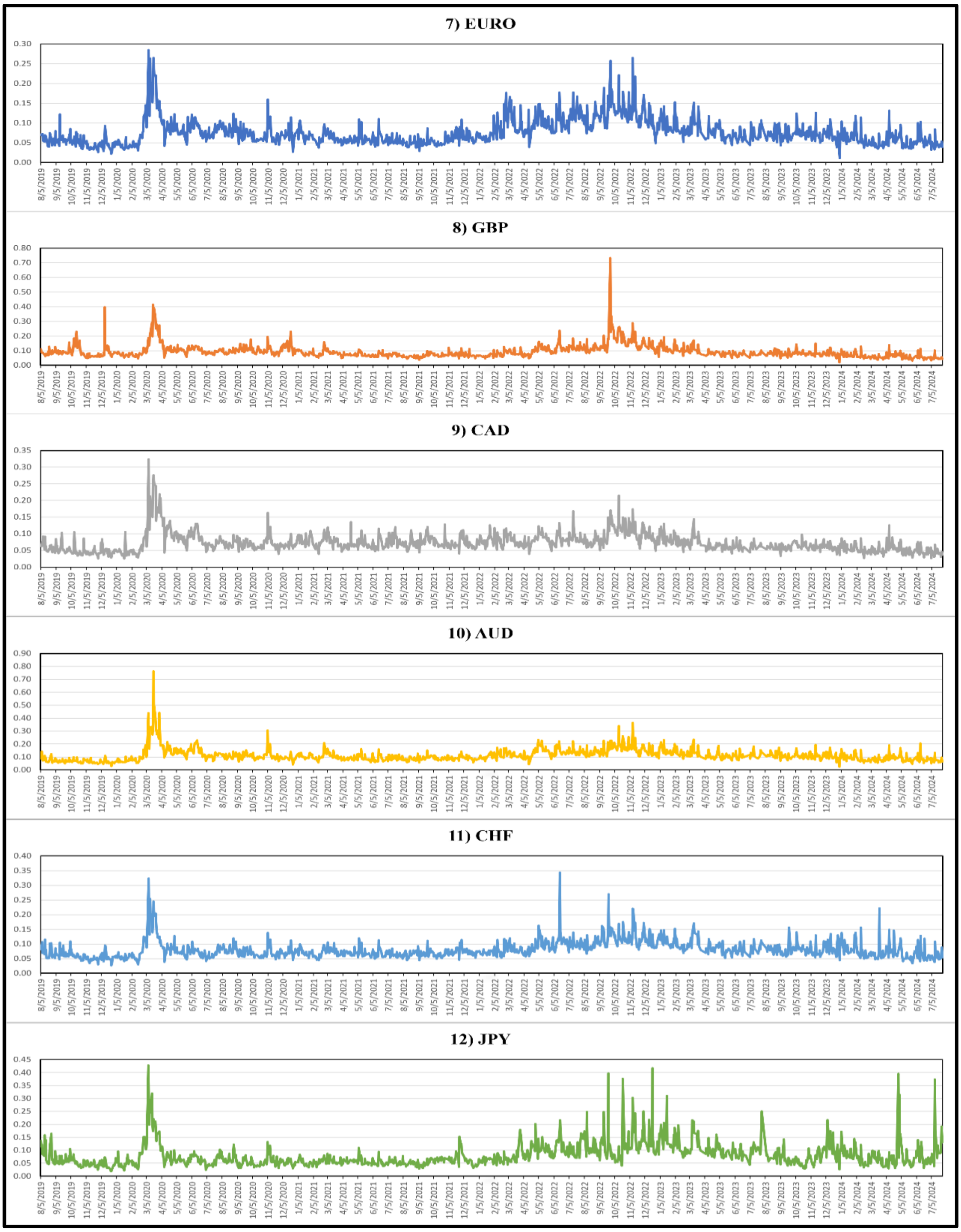

Figure 4: Daily Jump Estimates of Forex Markets Derived from 5-Minute High-Frequency Data

Methodology

The methodology section of this study comprises of two key approaches employed in this study i.e., the MinRV-based jump detection method and the multifractal detrended cross-correlation analysis (MF-DXA). Firstly, the jump components are isolated by subtracting the continuous volatility from the realized volatility. Subsequently, MF-DXA is applied on those jumps to further investigate the multifractal cross-correlation dynamics among the pairs of cryptocurrencies and forex markets.

MinRV Based Jump Detection Method

The first step is to compute the realized volatilities (RV) by Andersen et al. (2001)'s method. To do that, we calculate the intraday returns $r_{i,k}^{t}$ for each time series $i(i = 1, \dots, n)$ of cryptocurrency and forex market for each trading day $t(t = 1, \dots, T)$:

$$r_{i,k}^{t} = ln\left(\frac{p_{i,k}^{t}}{p_{i,k-1}^{t}}\right) , \qquad k = 1, \dots, \tau \tag{1}$$

where $p_{i,k}^{t}$ is the $k - th$ price of each series i on day t, and $p_{i,k-1}^{t}$ represents its 5-min lagged counterpart. τ indicates the number of high frequency intraday return observations in a day t, and T shows the annual count of trading days. Using these, the daily realized variance RD_{i}^{t} can be derived as:

$$RD_{i}^{t} = \sum_{k=1}^{\tau} {r_{i,k}^{t}}^{2} \quad t = 1, \dots, T. \tag{2}$$

Hence, to determine the realized volatility RV_{i}^{t} for any given day t can be computed as:

$$RV_{i}^{t} = \sqrt{T.RD_{i}^{t}}, \;\; t = 1, \dots, T. \tag{3}$$

The second step is to extract the realized jumps RJ_{i}^{t} from the realized volatility RV_{i}^{t}. The realized volatility captures the total quadratic variation encompassing both the observed time series returns and the cumulative squared jumps. In contrast, the integrated variance (IV) measures only the continuous portion of this variation. Thus, the difference $RV_{i}^{t} - IV$ represents the realized jumps RJ_{i}^{t}. Although, there exist many conventional IV estimators like bi-power, tri-power as well as the multi-power variations of Barndorff-Nielsen (2004), this study instead uses more robust measure of $MinRV_{i}^{t}$ as proposed by Andersen et al. (2012). This measure trims the absolute returns based on neighboring truncation method to reduce the influence of market microstructure noise. Specifically, the one-sided truncation compares each return with the next absolute return as:

$$MinRV_i^t = \frac{\pi}{\pi - 2}\left(\frac{\tau}{\tau - 1}\right)\sum_{k=1}^{\tau-1} min\left(\left|r_{i,k}^t\right|, \left|r_{i,k+1}^t\right|\right)^2 \tag{4}$$

Finally, realized jumps are then calculated as:

$$RJ_i^t = RV_i^t - MinRV_i^t \tag{5}$$

Multifractal Detrended Cross-correlation Analysis – MF-DXA

After decomposition of realized volatility and extraction of realized jumps for cryptocurrencies and forex markets, next step is to examine its cross-correlation properties. MF-DXA has proved to better quantify the multifractal characteristics of two non-linear and non-stationary time series data. We briefly explain this method in following steps:

Firstly, we take two jump time series of $\{x(i)\}$, and $\{y(i)\}$, $i = 1,2, \ldots, N$, with N as the length of these series, and compute their profiles as:

$$X(i) = \sum_{k=1}^{i}(x(k) - \bar{x}) \tag{6}$$

$$Y(i) = \sum_{k=1}^{i}(y(k) - \bar{y}) \tag{7}$$

with $\bar{x}$ and $\bar{y}$ representing the mean values of the respective series $x(i)$ and $y(i)$.

Secondly, the above computed profiles $X(i)$ and $Y(i)$ are then divided into $N_s \equiv int(N/s)$ non-overlapping equal-length components of size s. In most cases, length N is not exactly divisible by s, hence, a small portion at the end of each profile might remain unsegmented. To incorporate these, the same division process is repeated from the reverse end of the profiles, which results in in $2N_s$. For each of these segments, local trends are then determined using the mth order polynomial fitting method.

Thirdly, the detrended covariance for each segment λ is estimated as:

$$F^2(s,\lambda) = \frac{1}{s}\sum_{\mathrm{j}=1}^{s}\left|X_{(\lambda-1)s+j}(\mathrm{j}) - \tilde{X}_{\lambda}(\mathrm{j})\right| \left|Y_{(\lambda-1)s+j}(\mathrm{j}) - \tilde{Y}_{\lambda}(\mathrm{j})\right| \tag{8}$$

for $\lambda = 1,2, \dots N_s$ and as

$$F^2(s,\lambda) = \frac{1}{s}\sum_{\mathrm{j}=1}^{s}\left|X_{N-(\lambda-N_s)s+j}(j) - \tilde{X}_{\lambda}(j)\right| \left|Y_{N-(\lambda-N_s)s+j}(j) - \tilde{Y}_{\lambda}(j)\right| \tag{9}$$

for $\lambda = N_s + 1, N_s + 2, \dots 2N_s$. The measures $\tilde{X}_{\lambda}(j)$ and $\tilde{Y}_{\lambda}(j)$ show the polynomial fit with m order in λ segment. We employ first-order polynomial fitting which is widely used in literature due to its simplicity and effectiveness in removing linear trends without overfitting. While higher polynomial orders like second order, cubic or quadratic might introduce artificial smoothing and distort the scaling properties. A first-order polynomial ensures that only basic linear trends are removed, maintaining the integrity of the multifractal structure and cross-correlation analysis.

Fourthly, the qth-order fluctuation function is calculated by averaging over all the segments

$$F_{q(s)} = \left\{\frac{1}{2N_s}\sum_{\lambda=1}^{2N_s}[F^2(s,\lambda)]^{q/2}\right\}^{1/q} \tag{10}$$

for any $q \neq 0$, and

$$F_{0(s)} = exp\left\{\frac{1}{4N_s}\sum_{\lambda=1}^{2N_s} ln[F^2(s,\lambda)]\right\} \tag{11}$$

for $q = 0$.

Finally, the $log - log$ plots of $Fq(s)$ against s are plotted to examine the scaling of fluctuations for each value of q. In case of long-range cross-correlation, $Fq(s)$ follows a power law behavior and increases for larger s values.

$$F_q(s) \sim s^{h_{xy}(q)} \tag{12}$$

Here the generalized cross-correlation exponent $h_{xy}(q)$ also known as the scaling exponent, is estimated using ordinary least squares (OLS) by observing the slopes of $log - log$ plots of $Fq(s)$ against s. In addition, the bivariate Hurst exponent $h_{xy}(q = 2)$ behaves similarly to its univariate counterpart. For instance, the cross-correlation behavior is cross persistent when $h_{xy}(q = 2)$ values are greater than 0.5, showing that an increase (decrease) for $\Delta X_i \Delta Y_i$ is more likely to be followed by another increase (decrease) for $\Delta X_{i+1} \Delta Y_{i+1}$. In contrast, there exist anti-persistent cross-correlation, where $h_{xy}(q = 2)$ is less than 0.5, indicating that an increase (decrease) in $\Delta X_i \Delta Y_i$ is likely to be followed by another decrease (increase) in $\Delta X_{i+1} \Delta Y_{i+1}$. If the series $\{x(i)\}$ and $\{y(i)\}$ are identical, the method reverts to classical DFA.

Furthermore, the bivariate Renyi exponent $\tau_{xy}(q) = \mathrm{q}h_{xy}(q) - 1$ also highlights the multifractal characteristics. A non-linear $\tau_{xy}(q)$ shows significant multifractality while a linear variation suggests mono-fractality. The singularity strength $\alpha_{xy}(q)$ and the singularity spectrum $f_{xy}(\alpha)$ are computed through Legendre transform as:

$$\alpha_{xy} = h_{xy}(q) + \ q{h'}_{xy}(q) \qquad (13)$$

$$f_{xy}(\alpha) = q\alpha_{xy} - \tau_{xy}(q) \qquad (14)$$

$$= q\left(\alpha_{xy} - h_{xy}(q)\right) + 1$$

Other measures such as range of Hurst exponent $\Delta h_{xy} = \{\max(h_{xy}) - \min\,(h_{xy})\}$ and the width of multifractal spectrum $\Delta\alpha_{xy} = \{\max(\alpha_{xy}) - \min\,(\alpha_{xy})\}$ denote the multifractal strength or the degree of multifractality.

Results

This section deals with the cross-correlation results of MF-DXA for the jumps of six major cryptocurrencies and six major forex markets. MF-DXA is effective in terms of removing the impact of local trends across different scales, hence enabling a more precise analysis of fractal characteristics in non-stationary time series. The analysis involves a total of 12 jump series i.e., six from cryptocurrencies and six from forex markets, thereby forming 36 pairs by pairing each cryptocurrency with six forex markets. Figures 5 to 10 present the findings of MF-DXA, with each pair represented by three major plots.

The first plot for all the pairs of jumps between cryptocurrencies and forex markets presents the $log - log$ fluctuation function $Fq(s)$, where the scaling order increases stepwise from $q = -10\ to\, q = 10$. It is clear that the scaling order for $q = -10\ (black), q = 0\ (blue) and\ q = 10\ (grey),$ increases progressively from bottom to top which shows strong power-law correlations among all the pairs of cryptocurrency and forex market jumps. The second plot for the pairs highlights the generalized Hurst exponent $h_{xy}(q)$, while the while the third focuses on the multifractal spectrum α.

The findings in Table 4 and 5 present the varying values of cross-correlation exponent $h_{xy}(q)$ over $q = -10$ to $q = 10$, indicating evident multifractal characteristics in the cross-correlation of all the pairs of cryptocurrencies and forex market jumps. This variation is also reflected in the second plot of Figures 5 to 10, where $h_{xy}(q)$ exhibits a dynamic pattern, further validating multifractality. For instance, as for BTC/GBP in Table 4, the value of $h_{xy}(q)$ starts at 1.0331 at $q = -10$, which further deviates to 1.0143 at $q = 0$, and reaches to its lowest of 0.6317 at $q = 10$. In the similar vein, for XRP/JPY in Table 5, $h_{xy}(q)$ decreases from 1.1916 at $q = -10$, to 0.9551 at $q = 0$, and ultimately reaches to 0.6775 at $q = 10$. Interestingly, across all pairs, $h_{xy}(q)$ is larger for $q < 0$ than at $q > 0$, which reflects greater persistence in smaller fluctuations in comparison to the larger ones.

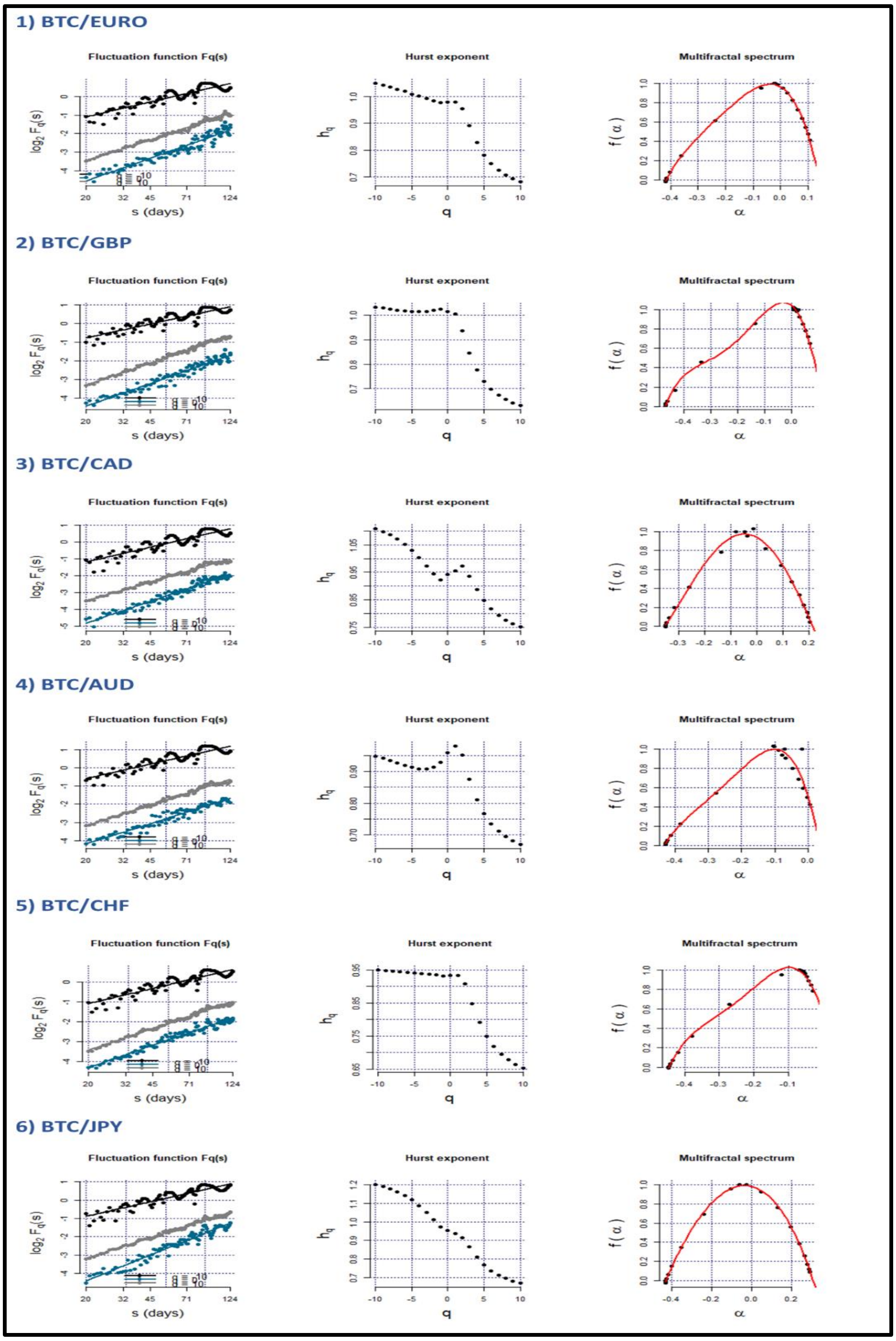

Figure 5: MF-DXA Comparison: Log-log Plots, Hurst Exponents, and Multifractal Spectra of Jump Pairs between Bitcoin and Forex Markets

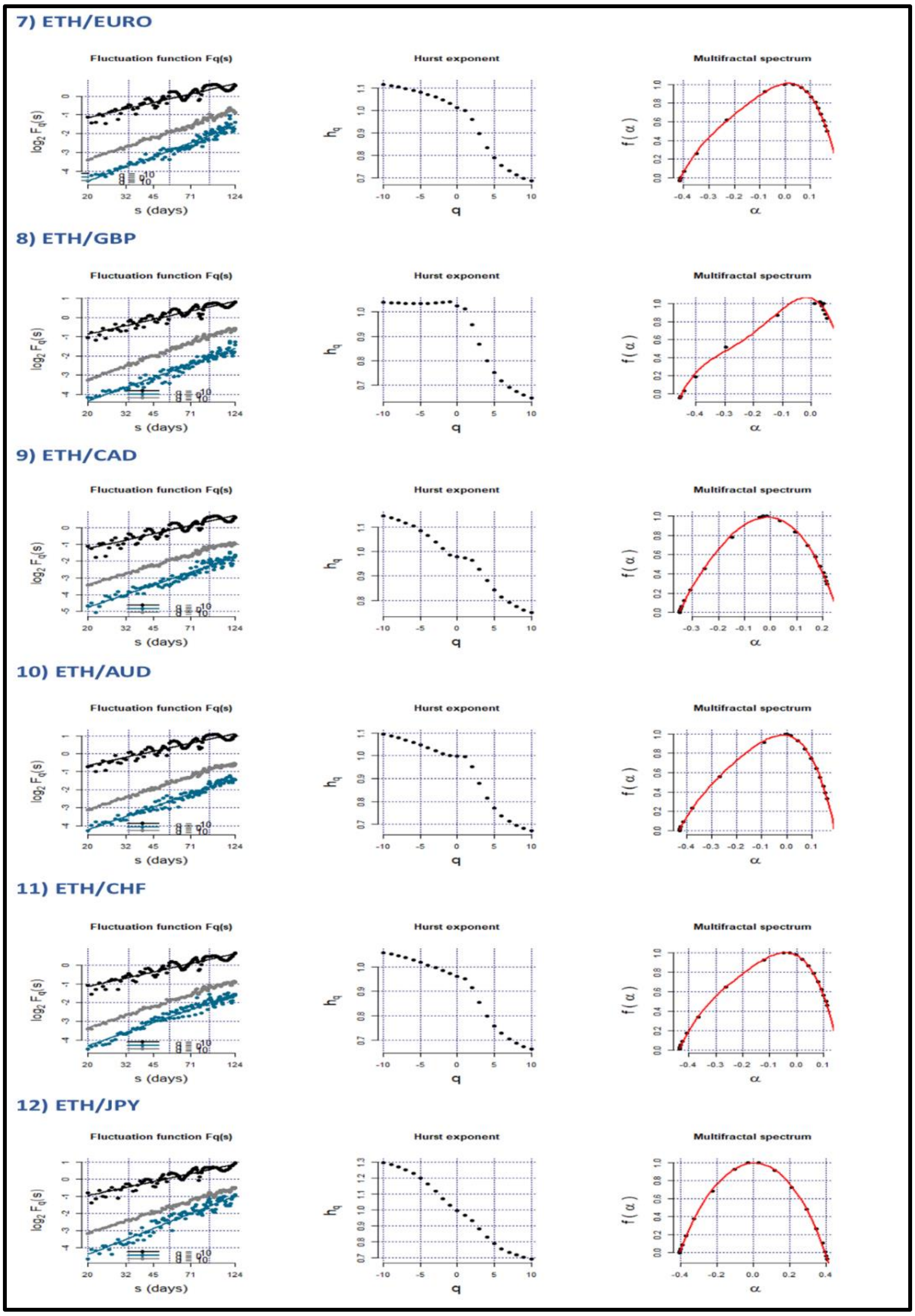

Figure 6: MF-DXA Comparison: Log-log Plots, Hurst Exponents, and Multifractal Spectra of Jump Pairs between Ethereum and Forex Markets

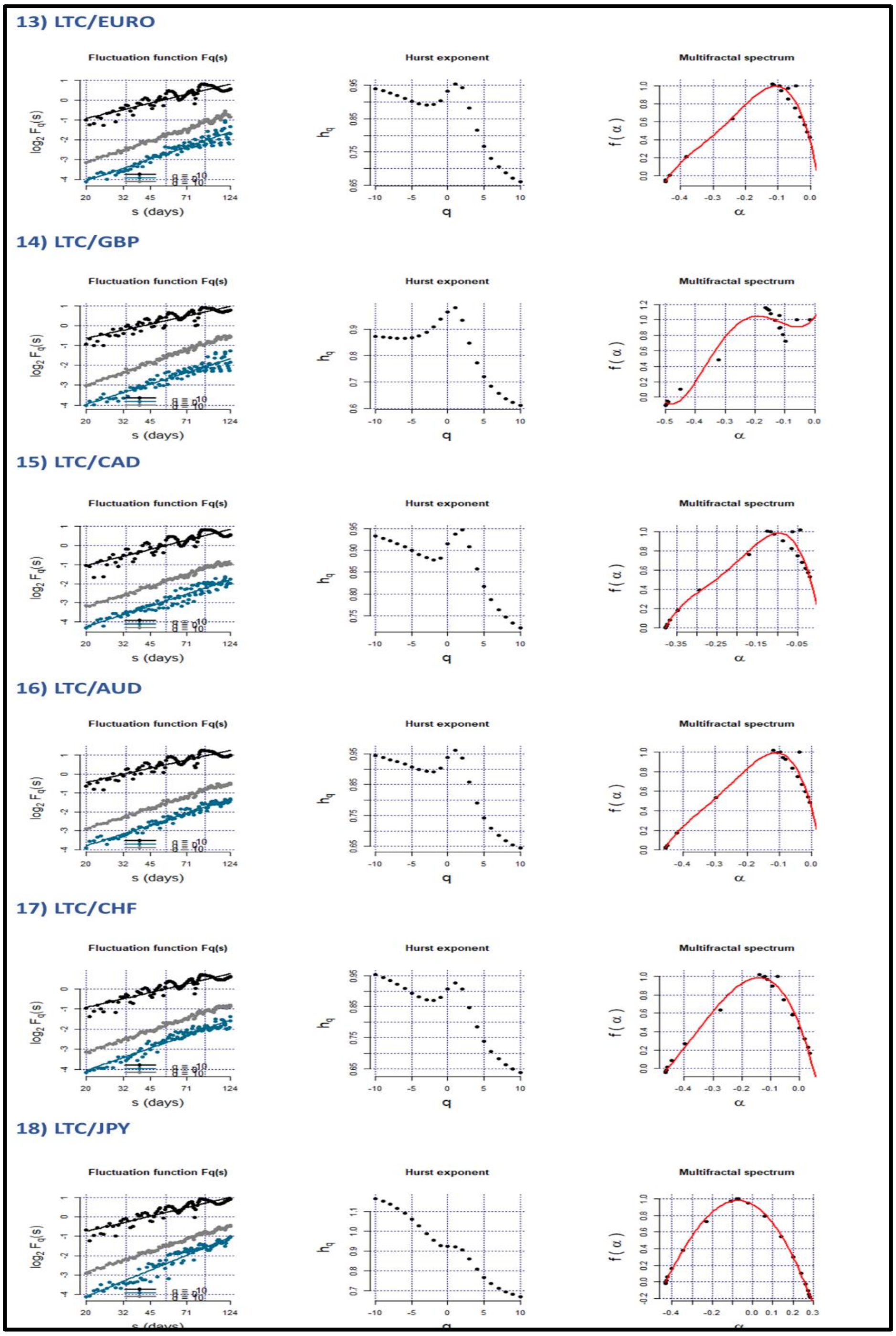

Figure 7: MF-DXA Comparison: Log-log Plots, Hurst Exponents, and Multifractal Spectra of Jump Pairs between Litecoin and Forex Markets

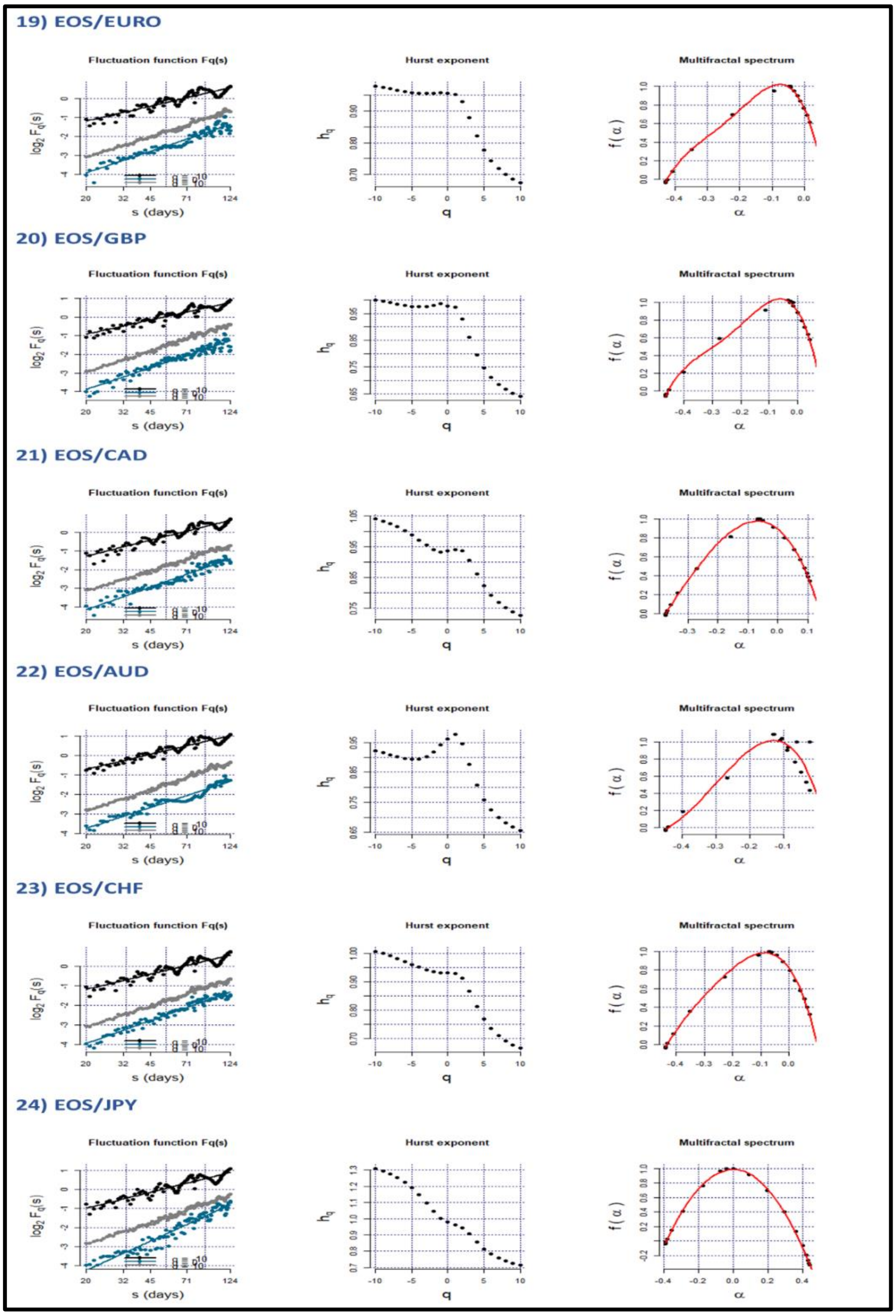

Figure 8: MF-DXA Comparison: Log-log Plots, Hurst Exponents, and Multifractal Spectra of Jump Pairs between EOS and Forex Markets

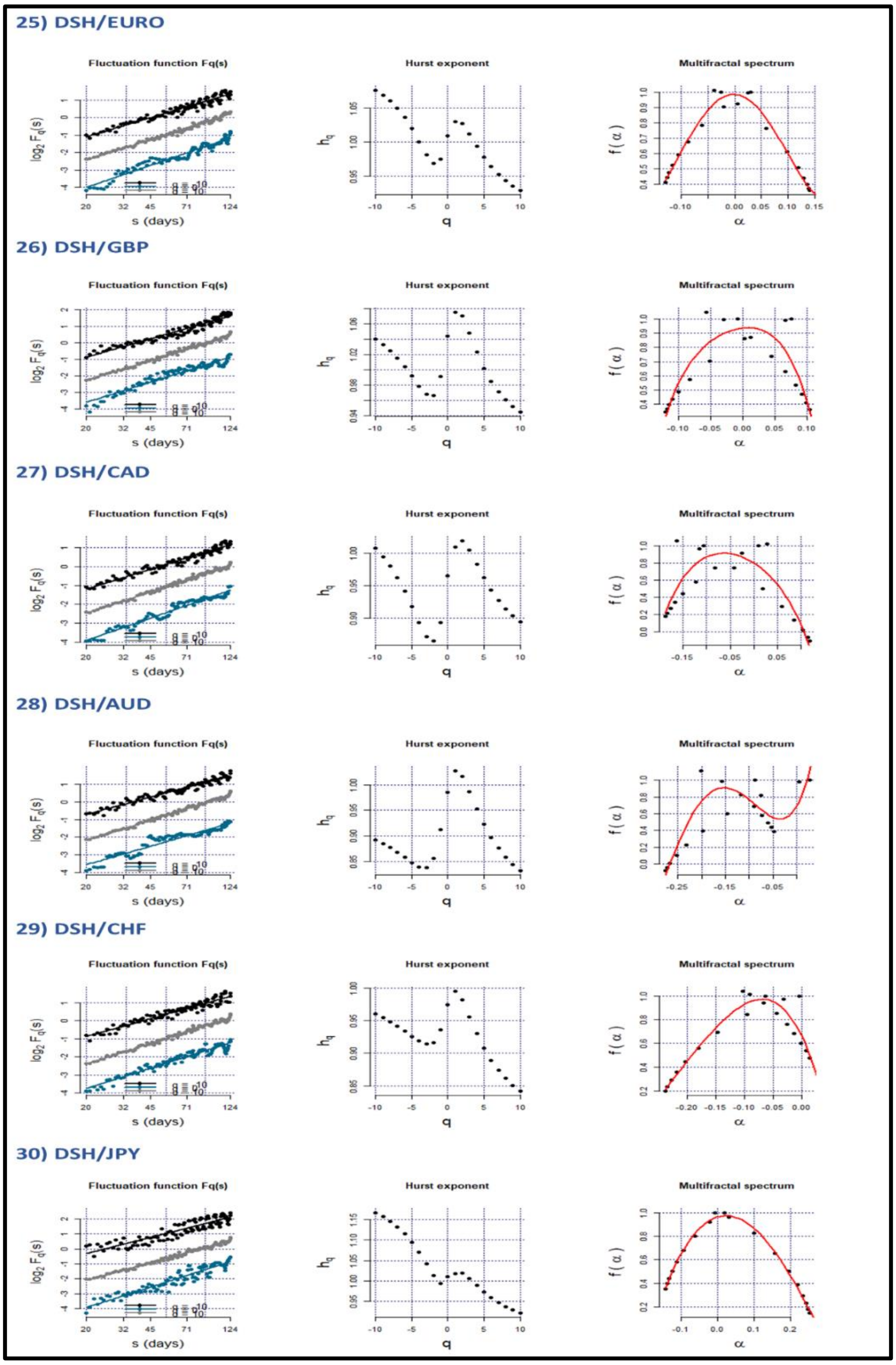

Figure 9: MF-DXA Comparison: Log-log Plots, Hurst Exponents, and Multifractal Spectra of Jump Pairs between Dashcoin and Forex Markets

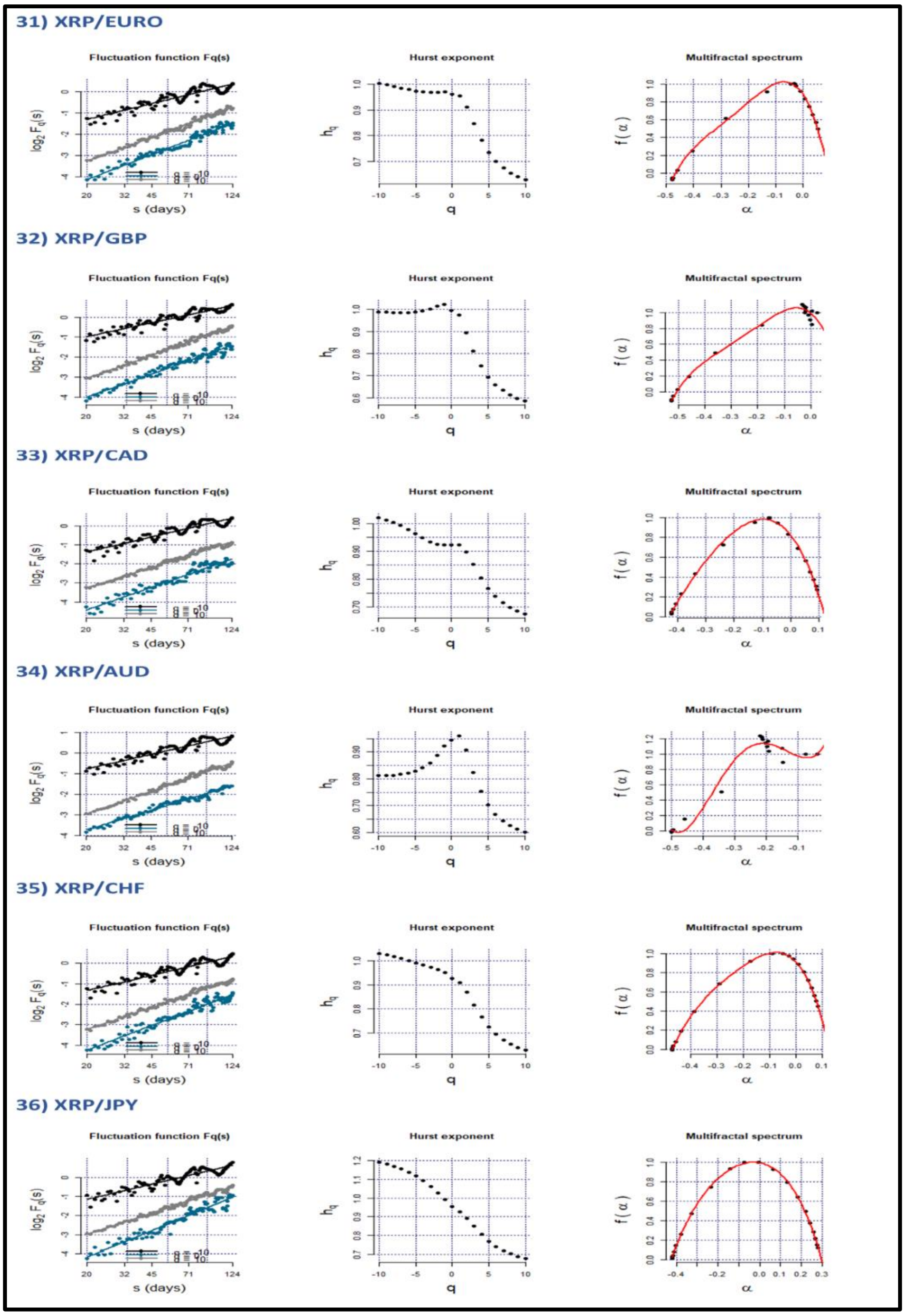

Figure 10: MF-DXA Comparison: Log-log Plots, Hurst Exponents, and Multifractal Spectra of Jump Pairs between Ripple and Forex Markets

The multifractal strength of the cross-correlation is measured by the range of Hurst exponent Δh, which are presented in the final row of Table 4 and 5. All the values of Δh are significantly above zero, confirming strong but varying degrees of multifractal strength. It is interesting to note that within all 36 pairs, JPY exhibits stronger multifractal patterns in its cross-correlation for all cryptocurrencies with Δh values of 0.87, 0.99, $0.83, 1.02, 1.09,$ and 0.87 for BTC, ETH, LTC, EOS, DSH, and XRP, respectively. In contrast, AUD has the lowest strength in its cross-correlation with EOS($\Delta h = 0.58$), DSH ($\Delta h = 0.72$), and XRP ($\Delta h = 0.41$). Similarly, GBP exhibits low strength with ETH ($\Delta h = 0.69$) and LTC ($\Delta h = 0.49$), while CHF has a low Δh of 0.60 with its cross-correlation with BTC. The plots of the width of the multifractal spectrum shown in Figures 5 to 10 further support these findings, where broader spectra indicate significant differences between smaller and larger fluctuations, and hence highlight non-uniform distributions of jumps. In addition, these substantial non-zero spectrum widths also validate a clear departure from random walk behavior. These multifractal traits in cross-correlation align with the adaptive market hypothesis by Kristoufek & Vosvrda (2019).

Lastly, the bivariate Hurst exponent $h_{xy}(q = 2)$ shown in Table 4 and 5 share the similar interpretations as the univariate Hurst exponent. This measure is used to determine whether the multifractal cross-correlations exhibit persistent or anti-persistent behavior. Remarkably, all of the 36 pairs of the jumps of cryptocurrencies and forex markets show significant persistent cross-correlations with $h_{xy}(q = 2)$ values greater than 0.5. On other hand, Podobnik & Stanley (2008) suggest that long-range cross-correlation implies that each series remembers its own historical data as well as that of the other series. Additionally, a rise or fall in one variable increases the likelihood of a corresponding change in the other.

Table 4: Generalized Hurst exponents ranging from q = −10 to q = 10 for the pairs of Bitcoin, Ethereum, and Litecoin Jumps with Forex Markets Jumps

Order Q	BTC/EURO	BTC/GBP	BTC/CAD	BTC/AUD	BTC/CHF	BTC/JPY	ETH/EURO	ETH/GBP	ETH/CAD	ETH/AUD	ETH/CHF	ETH/JPY	LTC/EURO	LTC/GBP	LTC/CAD	LTC/AUD	LTC/CHF	LTC/JPY
-10	1.0487	1.0331	1.1092	0.9477	0.9498	1.2009	1.1162	1.0394	1.1460	1.0947	1.0578	1.2984	0.9406	0.8744	0.9341	0.9435	0.9535	1.1657
-9	1.0422	1.0292	1.0986	0.9413	0.9474	1.1908	1.1106	1.0376	1.1382	1.0873	1.0518	1.2865	0.9342	0.8713	0.9289	0.9378	0.9442	1.1526
-8	1.0349	1.0253	1.0860	0.9344	0.9452	1.1782	1.1044	1.0360	1.1288	1.0789	1.0449	1.2716	0.9271	0.8687	0.9230	0.9314	0.9335	1.1366
-7	1.0268	1.0214	1.0707	0.9272	0.9432	1.1625	1.0975	1.0348	1.1175	1.0693	1.0371	1.2530	0.9193	0.8668	0.9162	0.9242	0.9214	1.1169
-6	1.0182	1.0179	1.0522	0.9198	0.9415	1.1428	1.0899	1.0342	1.1035	1.0586	1.0282	1.2294	0.9111	0.8666	0.9086	0.9163	0.9080	1.0925
-5	1.0091	1.0154	1.0298	0.9132	0.9403	1.1180	1.0814	1.0344	1.0862	1.0467	1.0183	1.1995	0.9029	0.8692	0.9002	0.9080	0.8941	1.0627
-4	1.0002	1.0145	1.0033	0.9087	0.9391	1.0873	1.0718	1.0355	1.0649	1.0340	1.0075	1.1625	0.8957	0.8762	0.8915	0.8999	0.8814	1.0276
-3	0.9916	1.0162	0.9734	0.9080	0.9376	1.0507	1.0608	1.0375	1.0393	1.0212	0.9961	1.1190	0.8913	0.8895	0.8837	0.8937	0.8725	0.9894
-2	0.9836	1.0206	0.9435	0.9137	0.9350	1.0107	1.0475	1.0401	1.0113	1.0096	0.9847	1.0728	0.8929	0.9107	0.8790	0.8926	0.8708	0.9539

-1	0.9772	1.0264	0.9221	0.9284	0.9320	0.9733	1.0320	1.0422	0.9857	1.0018	0.9741	1.0299	0.9041	0.9403	0.8827	0.9029	0.8804	0.9286
0	0.9788	1.0143	0.9420	0.9596	0.9329	0.9523	1.0131	1.0240	0.9779	0.9977	0.9613	0.9953	0.9335	0.9661	0.9153	0.9378	0.9069	0.9240
1	0.9795	1.0059	0.9556	0.9805	0.9335	0.9365	0.9988	1.0117	0.9724	0.9948	0.9517	0.9688	0.9547	0.9833	0.9386	0.9622	0.9260	0.9206
2	**0.9549**	**0.9361**	**0.9719**	**0.9515**	**0.9074**	**0.9152**	**0.9607**	**0.9472**	**0.9646**	**0.9519**	**0.9148**	**0.9334**	**0.9427**	**0.9343**	**0.9480**	**0.9363**	**0.9077**	**0.9056**
3	0.8907	0.8464	0.9362	0.8757	0.8482	0.8638	0.8970	0.8664	0.9273	0.8782	0.8557	0.8806	0.8816	0.8488	0.9088	0.8587	0.8467	0.8600
4	0.8281	0.7769	0.8873	0.8110	0.7915	0.8095	0.8352	0.7991	0.8818	0.8144	0.8008	0.8287	0.8159	0.7742	0.8581	0.7897	0.7857	0.8083
5	0.7823	0.7297	0.8470	0.7661	0.7492	0.7670	0.7886	0.7508	0.8436	0.7691	0.7595	0.7880	0.7662	0.7211	0.8171	0.7420	0.7400	0.7664
6	0.7497	0.6973	0.8167	0.7346	0.7184	0.7357	0.7551	0.7165	0.8144	0.7372	0.7292	0.7576	0.7309	0.6842	0.7866	0.7094	0.7071	0.7351
7	0.7260	0.6739	0.7938	0.7117	0.6954	0.7123	0.7307	0.6916	0.7921	0.7139	0.7067	0.7348	0.7054	0.6579	0.7638	0.6861	0.6829	0.7117
8	0.7080	0.6563	0.7762	0.6943	0.6778	0.6944	0.7123	0.6729	0.7749	0.6963	0.6894	0.7172	0.6863	0.6385	0.7463	0.6686	0.6645	0.6938
9	0.6939	0.6427	0.7623	0.6806	0.6640	0.6804	0.6980	0.6584	0.7613	0.6824	0.6757	0.7033	0.6715	0.6237	0.7325	0.6551	0.6500	0.6797
10	0.6826	0.6317	0.7511	0.6696	0.6528	0.6690	0.6865	0.6468	0.7502	0.6713	0.6647	0.6921	0.6598	0.6120	0.7214	0.6443	0.6384	0.6684

Delta H	**0.7313**	**0.6648**	**0.8603**	**0.6173**	**0.6026**	**0.8699**	**0.8027**	**0.6862**	**0.8962**	**0.7660**	**0.7225**	**0.9905**	**0.6004**	**0.4864**	**0.6555**	**0.5878**	**0.5919**	**0.8341**

Table 5: Generalized Hurst exponents ranging from q = −10 to q = 10 for the pairs of EOS, Dashcoin, and Ripple Jumps with Forex Markets Jumps

Order Q	EOS/EURO	EOS/GBP	EOS/CAD	EOS/AUD	EOS/CHF	EOS/JPY	DSH/EURO	DSH/GBP	DSH/CAD	DSH/AUD	DSH/CHF	DSH/JPY	XRP/EURO	XRP/GBP	XRP/CAD	XRP/AUD	XRP/CHF	XRP/JPY
-10	0.9780	1.0000	1.0401	0.9215	1.0056	1.3094	1.0761	1.0400	1.0069	0.8914	0.9608	1.1673	1.0026	0.9886	1.0205	0.8119	1.0297	1.1916
-9	0.9737	0.9953	1.0328	0.9152	0.9981	1.2946	1.0690	1.0329	0.9946	0.8846	0.9550	1.1578	0.9970	0.9869	1.0124	0.8123	1.0236	1.1818
-8	0.9694	0.9903	1.0243	0.9087	0.9898	1.2765	1.0603	1.0247	0.9798	0.8768	0.9486	1.1464	0.9910	0.9857	1.0028	0.8137	1.0167	1.1700
-7	0.9652	0.9853	1.0140	0.9024	0.9807	1.2539	1.0496	1.0152	0.9623	0.8677	0.9415	1.1326	0.9848	0.9852	0.9916	0.8163	1.0089	1.1560
-6	0.9614	0.9804	1.0017	0.8969	0.9707	1.2256	1.0363	1.0041	0.9418	0.8577	0.9340	1.1158	0.9787	0.9860	0.9786	0.8209	1.0004	1.1390
-5	0.9581	0.9765	0.9873	0.8938	0.9604	1.1903	1.0199	0.9917	0.9183	0.8472	0.9261	1.0953	0.9732	0.9887	0.9640	0.8285	0.9912	1.1182
-4	0.9558	0.9745	0.9710	0.8948	0.9502	1.1472	1.0006	0.9785	0.8933	0.8384	0.9188	1.0705	0.9691	0.9940	0.9485	0.8405	0.9816	1.0931
-3	0.9549	0.9758	0.9544	0.9024	0.9412	1.0978	0.9812	0.9676	0.8717	0.8371	0.9140	1.0419	0.9674	1.0025	0.9344	0.8591	0.9720	1.0630
-2	0.9555	0.9804	0.9400	0.9179	0.9344	1.0472	0.9686	0.9666	0.8653	0.8559	0.9164	1.0128	0.9684	1.0136	0.9251	0.8867	0.9622	1.0284

-1	0.9567	0.9856	0.9313	0.9408	0.9305	1.0039	0.9756	0.9909	0.8938	0.9124	0.9363	0.9936	0.9709	1.0232	0.9233	0.9232	0.9507	0.9918
0	0.9546	0.9782	0.9362	0.9618	0.9299	0.9805	1.0094	1.0440	0.9649	0.9850	0.9741	1.0104	0.9610	0.9955	0.9233	0.9450	0.9273	0.9551
1	0.9524	0.9723	0.9400	0.9772	0.9292	0.9615	1.0299	1.0756	1.0093	1.0276	0.9952	1.0182	0.9532	0.9755	0.9234	0.9603	0.9093	0.9258
2	**0.9290**	**0.9290**	**0.9364**	**0.9461**	**0.9109**	**0.9446**	**1.0277**	**1.0709**	**1.0188**	**1.0163**	**0.9816**	**1.0187**	**0.9101**	**0.8953**	**0.8981**	**0.9062**	**0.8688**	**0.8927**
3	0.8787	0.8607	0.9046	0.8760	0.8650	0.9055	1.0118	1.0481	1.0043	0.9860	0.9556	1.0055	0.8460	0.8101	0.8526	0.8232	0.8163	0.8506
4	0.8222	0.7951	0.8607	0.8081	0.8114	0.8564	0.9938	1.0233	0.9829	0.9529	0.9300	0.9887	0.7836	0.7428	0.8054	0.7526	0.7656	0.8066
5	0.7765	0.7457	0.8218	0.7586	0.7673	0.8140	0.9776	1.0020	0.9619	0.9227	0.9079	0.9726	0.7351	0.6941	0.7671	0.7031	0.7250	0.7696
6	0.7430	0.7106	0.7917	0.7242	0.7345	0.7817	0.9640	0.9849	0.9434	0.8970	0.8895	0.9586	0.6999	0.6589	0.7381	0.6691	0.6944	0.7410
7	0.7184	0.6853	0.7687	0.6996	0.7102	0.7575	0.9527	0.9714	0.9277	0.8756	0.8742	0.9467	0.6743	0.6328	0.7161	0.6449	0.6715	0.7191
8	0.6999	0.6665	0.7510	0.6811	0.6918	0.7391	0.9434	0.9606	0.9147	0.8579	0.8616	0.9367	0.6551	0.6130	0.6991	0.6269	0.6539	0.7020
9	0.6855	0.6520	0.7371	0.6669	0.6774	0.7247	0.9357	0.9518	0.9038	0.8434	0.8510	0.9283	0.6404	0.5975	0.6858	0.6130	0.6401	0.6885
10	0.6741	0.6405	0.7258	0.6555	0.6659	0.7132	0.9292	0.9445	0.8947	0.8314	0.8421	0.9211	0.6287	0.5851	0.6750	0.6019	0.6289	0.6775

Delta H	**0.6521**	**0.6405**	**0.7659**	**0.5770**	**0.6715**	**1.0226**	**1.0053**	**0.9845**	**0.9016**	**0.7228**	**0.8029**	**1.0884**	**0.6313**	**0.5737**	**0.6955**	**0.4138**	**0.6586**	**0.8691**

Conclusion and Recommendations

In these modern times of heightened uncertainty and interconnected global financial systems, the literature on jumps and co-jumps has gained significant attention. This interest stems from the potential of jumps in one market to rapidly create jumps in other markets, which as a result impact everything from risk management to portfolio strategies and asset allocation. Therefore, in this paper, we focus on examining the cross-correlation of the jumps of cryptocurrencies and forex markets in multifractal context. This provides a superior approach to analyzing the complexities that may emerge, especially during extreme events. The analysis begins with high-frequency returns of six major cryptocurrencies and six major forex exchange rates, spanning from August 4, 2019, to July 27, 2024. The time period of data is based on the maximum data availability. We then employ MinRV-based realized jump method and separate daily jumps from realized volatility. These returns are subsequently used to apply MF-DXA to investigate the cross-correlation dynamics among the jumps. This approach allows us to examine 36 pairs in total, with each cryptocurrency forming six pairs with forex markets.

The findings of this study imply that all of the measures including fluctuation function, generalized Hurst exponent and multifractal spectrum, confirm the existence of significant multifractal cross-correlation and power-law behavior for all 36 pairs of jumps. The intensity of these multifractal patterns, however, varies across all these pairs. Particularly, all cryptocurrencies jumps show the weakest multifractal cross-correlation with the Australian Dollar and British Pound, while their strongest multifractal cross-correlation is observed for Japanese Yen. This suggests a higher level of integration and interdependence between cryptocurrency markets and the Japanese financial market. This might be driven by favorable economic conditions, market structure, investor preferences, and regulatory factors. For instance, Japan is considered home to cryptocurrencies and was one of the first countries to legally recognize Bitcoin as means of payment (Florea & Pustelnik, 2021). It was also one of the first countries to establish infrastructure for cryptocurrency trading and implemented proactive regulatory measures such as enforcing AML/CFT responsibilities, mandating KYC checks, and setting strict record-keeping standards.[6] Such measures have enhanced transparency, security, and investor confidence, which might have resulted in potentially strengthening the cross-correlation between cryptocurrencies and the Japanese Yen.

Conversely, the weaker cross-correlation with the Australian Dollar and British Pound indicates a lesser degree of interaction with

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6 https://www.sanctionscanner.com/blog/cryptocurrency-regulations-in-japan-492

cryptocurrency markets. The limited market exposure, strict regulatory actions, and regional economic dynamics could be the reasons which might reduce the channels through which shocks in the cryptocurrency market propagate to these currencies. For example, in United Kingdom, the financial regulators such as Financial Conduct Authority (FCA) and Prudential Regulation Authority (PRA), and the Australian Securities and Investments Commission (ASIC), have taken a cautious approach toward cryptocurrencies which may limit institutional participation and market liquidity, reducing the integration of cryptocurrencies with these currencies.[7] Additionally, post-Brexit regulatory uncertainty may have further complicated the landscape and may have weaker the ties between the UK forex and cryptocurrency markets.

These results are partially consistent with Gajardo et al. (2018) and Kristjanpoller & Bouri (2019), who found several prominent cryptocurrencies to have significant multifractal cross-correlations with forex markets. Furthermore, the results also show that all the jumps' pairs have persistent behavior in cross-correlations, indicating the higher likelihood of positive and negative jumps in one market to trigger positive and negative jumps in other market.

The findings of study indicate several recommendations, policy implications, and suggestions. For instance, the presence of cross-correlations in the jumps of cryptocurrencies and forex markets highlights market inefficiency which is against the tenets of EMH and random walk hypothesis. This, however, aligns with FMH, which explains multifractality as a consequence of diverse investor behaviors and varying time horizons. The presence of long-memory effects and self-similar structures in jumps suggests that financial markets are not purely random but exhibit predictable patterns. This indicates that the OLS based linear models are insufficient and the financial decisions made on these models should be revisited. Therefore, researchers and financial analysts should explore non-linear and multifractal methods to better understand the jump dynamics in financial markets. As for regulators and policymakers, the stronger cross-correlation between the jumps of Japanese Yen and cryptocurrencies indicate the need of enhancing systemic risk assessments and implement contingency measures to mitigate financial instability during crypto-related market shocks. As for the lower cross-correlations of cryptocurrencies with Australian Dollar and British Pound, policymakers in these countries should evaluate whether their relatively lower integration with cryptocurrency markets is advantageous or a missed opportunity for

7 https://www.nortonrosefulbright.com/en/knowledge/publications/e383ade6/cryptocurrency-exchanges-and-custody-providers-international-regulatory-developments

growth and innovation to enhance transparency. Hence, regulators in Australia and UK should reassess their stance to strike a balance between investor protection and fostering greater market participation in the crypto space. In addition, the investors and market participants should develop risk management and diversification strategies by incorporating multifractality for risk assessment and hedging models. Particularly, the pairs with stronger (Japanese Yen and cryptocurrencies) and weaker cross-correlations (British Pound/Australian Dollar and cryptocurrencies) should be paid close attention to for better diversification benefits, enhanced prediction, arbitrage opportunities, and strategic allocation. Furthermore, hedging strategies should account for multifractal characteristics, particularly in markets where jumps exhibit persistent memory effects.

Although, this study makes significant contributions to the cross-correlation characteristics between cryptocurrencies and forex markets, it has certain limitations. Firstly, this study is limited to six major cryptocurrencies and six forex markets. Future research could expand the scope by incorporating other markets like stocks and commodities to provide a more comprehensive perspective. Secondly, we employed 5-minute high-frequency data, hence analyzing jumps at different frequencies could offer a more robust understanding of market dynamics. Thirdly, the analysis presents only fixed results, future studies could explore the dynamic evolution of these relationships using rolling window approaches at varying window lengths. Future studies should also examine whether there exist asymmetries in the cross-correlation of jumps and volatilities by employing asymmetric multifractal cross-correlation models.

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