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RESEARCH ARTICLE

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The isotropy of cryptocurrency volatility

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Abstract

We examine the fractal volatility and long-range dependence of Bitcoin, Ethereum, Tether and USD Coin by employing the continuous wavelet transform, maximal overlap discrete wavelet transform and rescaled range. Our dataset consists of daily prices spanning from January 2017 through to October 2022, encapsulating pre- and post-epidemic eras. Generally, our findings suggest that Tether presents the least overall volatility throughout the time-frequency spectrum. USD Coin demonstrates ephemeral turbulence, contrary to Tether's maturity in influencing market equilibrium through token issuance and trade responses. In the post-epidemic sample, both stablecoins indicate mean reversion, with USD Coin showing marginally better efficiency. Conversely, investment tokens display persistent clusters due to retail traders and long-term fundamental institutions. Although both tokens illustrate multifractal volatility, Ethereum unveils more essence of self-similarity than Bitcoin. Hence, there is no evidence that Ethereum truly duplicates Bitcoin since policy-related events differ between them, as both return series move incongruously. Conditional dynamics signify that all cryptocurrencies, except Tether, were affected by the pandemic transition of COVID-19 and subsequent macroeconomic news. The unconditional volatility of stablecoins evinces zero-mean errors, antithetical to investment tokens exhibiting annual cycles. The fractal geometry suggests that investment tokens simulate one-dimensional lines, whereas stablecoins mimic two-dimensional planes.

KEYWORDS

bitcoin, cryptocurrency, efficiency, Ethereum, Stablecoin, token, volatility, wavelet

1 | INTRODUCTION

It has been 14 years since a pseudonym published a white paper on an electronic, peer-to-peer payments system that they termed Bitcoin (Nakamoto, 2008). Specifically, Bitcoin operates through a decentralized and trustless system, with transactions approved by incentivized miners on the blockchain. This method is in stark contrast to traditional banks verifying the derivation and recipients of money (Berg, 2020). Although most central banks are not in favour of recognizing Bitcoin as a medium for exchange, these monetary authorities are contemplating introducing cryptocurrencies of their own (Härdle et al., 2020). While some believe that switching remains unpalatable for the masses (Hairudin et al., 2020), others suggest that cryptocurrencies are gaining widespread acceptance due to loss of trust in the traditional financial system (Saiedi et al., 2020). The revolutionary creation of Nakamoto led to a multitude of these virtual phenomena, serving many unique purposes, and thereby provoking controversial opinions on Bitcoin's use as a true medium of exchange.

The rise of Bitcoin eventually became the catalyst for newer cryptocurrencies to be birthed outright. Bitcoin is also notoriously known for its pervasive nature in disrupting other cryptocurrencies (Kumar & Anandarao, 2019), summoning hackers and the theft of millions (Bucko et al., 2015; Wei, 2018), resulting in it having a contentious legal status in many countries (Enyi & Le, 2018). These traits may impede its valuation. Aside from these negative factors, some posit that macro-financial factors such as stock and oil indices may determine cryptocurrency prices (Wijk, 2013). On the other hand, Kristoufek (2013) and Ciaian et al. (2015) propose that microeconomic aspects such as market forces of supply and demand, alongside investor expectations, may impact cryptocurrency prices instead. In essence, these facets influence the price discovery process of Bitcoin and other major cryptocurrencies greatly, resulting in extreme volatilities in their returns.

Besides price discovery, other topics on cryptocurrencies revolve around the historical movement of returns for portfolio diversification, hedging purposes, and testing market efficiency levels. Under the efficient market hypothesis (EMH), when a market is weak-form efficient, the asset's price reflects merely historical data, which suggests futility in attempting to gain abnormal profit through technical analysis. In semi-strong-form efficiency, public information is reflected and therefore both technical and fundamental analyses are inefficacious. Finally, when a market is strong-form efficient, the asset's price fully reflects all publicly and privately available information, hence beating the market becomes impossible (Fama, 1970). As with traditional securities, cryptocurrency prices can be inferred from its market efficiency. Bartos (2015) and Urquhart (2016), for example, argue that cryptocurrencies are gradually becoming efficient. However, consecutive studies such as Feng et al. (2017), Caporale et al. (2018), Celeste et al. (2020), and Grobys and Huynh (2022) argue that cryptocurrencies are far from mature enough to act as alternative currencies. Besides the pure examination of the market efficiency of cryptocurrencies (e.g., Abakah et al., 2020; Kakinaka & Umeno, 2022; Noda, 2021; Omane-Adjepong et al., 2019; Yaya et al., 2020), other insightful streams of cryptocurrency research have sprouted. Some of these strands include news impact and investor attention (e.g., Al Guindy, 2021; Cheikh et al., 2020; Corbet, Cumming, et al., 2020; Corbet, Larkin, et al., 2020; Lucey et al., 2022), trading volume dependency (e.g., Bouri et al., 2019; Corbet et al., 2022; Leirvik, 2022), forecasting returns based on tickers or signals (e.g., Fang et al., 2020; Ftiti et al., 2021; Ma et al., 2020; Miura et al., 2019; Walther et al., 2019), volatility spillovers between cryptocurrencies only (e.g., Katsiampa et al., 2019; Koutmos, 2018; Qiao et al., 2020; Yi et al., 2018) and those between other financial markets (e.g., Attarzadeh & Balcilar, 2022; Liu & Serletis, 2019). Volatility in cryptocurrencies is indeed a popular avenue for research, but studies pertaining to their fractal volatility are rather minimal.

Our research is inspired by the notion that alternative assets can either be a medium of exchange or a financial tool for investment. To be a medium of exchange, one of the key requirements is that the asset must be a stable intermediary—an asset that can facilitate the purchase and sale of goods without the price of the asset fluctuating excessively. Conversely, an investment tool would not meet such a strict condition, but would rather function as a financial instrument where market participants can profit from important moments in buying and selling of that asset. In essence, cryptocurrencies can fall into either one of the two categories but rarely both, due to their disparate mechanics and market-exclusive stakeholders who seek different purposes (e.g., crypto-investors versus crypto-consumers). The dichotomy in their features means that one category exhibits far more shocks than the other. However, substantive evidence supporting the assumptions that (1) all investment tokens trend in the exact same (i) level and (ii) direction as Bitcoin, and (2) all stablecoins present the same minimal volatility, is lacking. Hence, besides measuring individual volatility, this study investigates two hypotheses: We test the second-biggest investment token (Ethereum) to see if it truly mimics every Bitcoin pattern, and we determine whether the second largest stablecoin (USD Coin) truly shares the same level of minimum turbulence as its prime counterpart (Tether). Although pure cryptocurrency studies exist regarding volatility spillovers (e.g., Koutmos, 2018), these papers determine interdependency, which identifies the mover(s) of a lead–lag relationship. In contrast, our paper does not examine co-movement but rather compares scale-dependent volatilities of each cryptocurrency. Spillover studies do not examine the fractal structures of Bitcoin etc. to ascertain the true individual volatility level and direction. Our paper employs two robust wavelet methodologies that complement each other in the assessment of univariate volatility, followed by the rescaled range to summarize long-term efficiency.

First, this research uniquely applies the continuous wavelet transform (CWT) and maximal overlap discrete wavelet transform (MODWT) together to decompose cryptocurrency returns, and thereby thoroughly examine their individual fractals. In detail, we employ the continuous wavelet power spectrum (CWPS) to identify and measure multifractal volatility, then verify the continuous data results using multiresolution analysis (MRA) for a robustness check of amplitude and direction. This dual technique allows for finer inferences regarding volatility level and expected recurring patterns. To our best knowledge, the only papers similar to ours that study fractal volatility in cryptocurrencies are Delfin-Vidal and Romero-Meléndez (2016), who discover Bitcoin through CWT-CWPS, and Celeste et al. (2020), who investigate Bitcoin, Ripple and Ethereum through various CWT models. To complement these previous works, we examine the currently largest assets based on market capitalization and trading volume (Bitcoin, Ethereum, Tether and USD Coin), then employ the MODWT-MRA for stronger verification of the results. Other papers, such as Al-Yahyaee et al. (2020), Kakinaka and Umeno (2022), and Naeem et al. (2021), examine cryptocurrencies using multifractal detrended fluctuation analysis (MF-DFA). However, the focal point of these studies is fractal efficiency and not fractal volatility. In other words, they measure multirange dependence by observing dynamic Hurst values, while we mainly focus on measuring volatility by scrutinizing pure multiscale returns. Second, we analyse two categories of cryptocurrencies (i.e., stablecoin and investment tokens) and then juxtapose their scale-dependent returns to see if they are distinguishable by nature. If the two categories are indeed different, we then examine whether there are any differences between the number one in their respective class (i.e., Bitcoin and Tether) and the runner-up (i.e., Ethereum and USD Coin). The purpose is to detect levels of shared self-similarity and self-affinity within the same cryptocurrency classification. Third, we extend the previous works with approximately three years of post-epidemic data. Hence, this study links macroeconomic events (e.g., COVID-19 epidemic and pandemic windows) and recent news pertaining to cryptocurrency policy, such as Ethereum's upgrades, Non-Fungible Token events and so on. Fourth, besides analysing volatility, we briefly evaluate the post-epidemic data using efficiency and dimension tests, thereby adding to recent market efficiency studies inspecting long memory properties. This research contribution aims to benefit the crypto-financial intelligentsia consisting of institutional investors, retail traders, regulators, and academicians.

Our findings suggest that Tether exhibits the least overall volatility throughout the time-frequency spectrum, in comparison to its counterparts. The newer stablecoin of USD Coin presents short-term volatility for an indefinite period, in contrast to the largest and most mature stablecoin that is Tether. This distinction is likely due to the latter's long-term history of influencing market equilibrium through token issuance and trade responses, and thus its better price stability. In the post-epidemic sample, both stablecoins indicate strong anti-persistence, with USD Coin showing marginally better efficiency. Nevertheless, the statistical significance of the Hurst exponent suggests that both stablecoins are still deeply inefficient. Conversely, investment tokens display persistent volatility clusters due to the presence of long-term fundamental institutions and retail traders who hold varying investment horizons. Although both tokens illustrate multifractal volatility with scattered variation, Bitcoin presents more evidence of self-affinity while Ethereum possesses greater self-similarity. Hence, there is no definitive proof that traders in Ethereum's market truly duplicate every Bitcoin move–policy-related events that solely pertain to Ethereum (currency-wise and company-wise) differ from those pertaining to Bitcoin and will therefore impact the tokens differently. The fractal patterns demonstrate that the two return series move incongruously, as Bitcoin is more turbulent than Ethereum. Conditional dynamics signify that none of the cryptocurrencies reacted when COVID-19 was discovered in China. However, all cryptocurrencies except Tether, were affected by the pandemic transition of the virus and subsequent macroeconomic news. The unconditional volatility of stablecoins evinces zero-mean errors, antithetical to the investment tokens which exhibit yearly cycles. The fractal dimension suggests that investment tokens imitate one-dimensional lines and curves, whereas stablecoins mimic two-dimensional planes and boxes.

The remainder of this article is organized as follows: We provide a review of relevant literature in Section 2, then elaborate the data and methodology in Section 3. In Section 4, we present our discussion of empirical results, followed by a brief discourse in Section 5. Finally, conclusive remarks are established in Section 6.

2 | REVIEW OF RELATED LITERATURE

2.1 | Investor sentiment and attention

Investor sentiment towards cryptocurrencies is one of the many determinants of their volatility. Crypto-investors tend to depend heavily on market-related news to make decisions, with herding behaviour generally more prevalent in bull markets than in bearish ones (Kyriazis, 2020). In fact, traders even refer to news posted on Twitter highlighting the most popular cryptocurrencies to date, thus uncovering market volatility (Al Guindy, 2021). Aloosh and Ouzan (2020) examine this investment behaviour based on a sample of 57 cryptocurrencies and surmise that investors tend to behave irrationally. Furthermore, they find that the cryptocurrencies with smaller market capitalizations display higher volatility, as retail traders react significantly to news, thus influencing their active management. Hence, crypto-investors seem to move with market sentiment rather than using fundamental knowledge of economics (Fang et al., 2020). Measuring negative sentiment, Corbet, Cumming, et al.

(2020) assess the responses of Bitcoin, Bitcoin Cash, Litecoin, Ethereum, Ripple, Monero, Stellar and Cardano to cybercrime. They find that cybercrime activities such as hacking and other fraudulent events increase price volatility due to compulsive decision-making. Likewise, Lucey et al. (2022) explain how news articles can affect and forecast investor decisions in crypto-markets. Specifically, they include two curated indicators, called the cryptocurrency uncertainty index (UCRY) Price and Policy, respectively, designed based on weekly news pertaining to cryptocurrency price movements and policy modifications. They claim that past major events were significant in increasing both uncertainty indicators. For example, 2017 news such as China banning initial coin offerings (ICOs), and the launch of Bitcoin futures, attracted more general uncertainty in crypto-markets. The Chinese ban in September 2017 led to Bitcoin's price declining, whereas the Bitcoin futures guided the token to its second major climb in December 2017. Moreover, the authors propose that amateur retail traders react to price-related news, whereas institutional investors lean more towards policy-related announcements.

2.2 | Cryptocurrency exchanges and liquidity

An intriguing strand of research highlights the liquidity metrics of cryptocurrencies and cryptocurrency exchanges. Brauneis et al. (2020) investigate the liquidity of Bitcoin, Litecoin, Ethereum and Ripple across four different crypto-exchanges, namely Kraken, Bitfinex, Coinbase Pro and Bitstamp. They conclude that liquidity is not affected by general financial market variables such as the equity and FX markets. Liquidity is rather affected by crypto-specific variables, including trading volume and activity. Bitcoin and Coinbase Pro are identified as the most liquid token and crypto-exchange, respectively. Similarly, Kim et al. (2020) examine Bitcoin futures and their impact on Bitcoin returns. After studying five crypto-exchanges worldwide (Coinbase Pro, Bitstamp, BitFlyer, Binance and Coincheck), they conclude that the pre-Bitcoin-futures era showed regular levels of volatility before the Chicago Board of Exchange (CBOE) introduced the Bitcoin derivative as a tradeable instrument. With regard to the Korean market, Eom (2020) analyzes bubble levels of Bitcoin and finds that the 'Kimchi premium' (i.e., the difference between Bitcoin's price in Korea versus that in other countries) exists due to the positive association between volatility and trading volume in Korea. This observation indicates higher speculative trade in the Asian market (Korbit) than in the European counterpart (Bitstamp). Generally, investors in Korea tend to price Bitcoin above its fundamental value, thus creating a surplus or 'premium' for Bitcoin. Eom (2020) concludes with the speculative bubble theory, hypothesizing that the asset price will increase when trading volume and volatility increase–contrary to the traditional asset pricing theory which states that asset prices will decrease when trading volume and volatility increase. Moving on to the post-epidemic era, Corbet et al. (2022) examine the interaction between cryptocurrency liquidity and price during the introductory period of COVID-19, discovering the presence of safe-haven behaviour. The sample consists of the 12 largest tokens, including Bitcoin, Ethereum and Tether, with data split into (1) pre-contagion, (2) contagion in China, and (3) international contagion periods. They discover that the lagged shocks in trading volume impact volatility of returns during the pre-coronavirus period, and these effects begin to intensify during the virus' introduction. In essence, volatility moves in tandem with liquidity changes. However, no evidence suggests that sharp price spikes were present during the domestic epidemic period, but only during the period of international contagion. Hence, trading volume increased staggeringly when the WHO officially declared COVID-19 a pandemic. Thus, the period of the international outbreak showed the most evidence of safe-haven behaviour during market duress. Similarly, Leirvik (2022) explains the interaction between cryptocurrency price and liquidity and, unlike the former study, incorporates macroeconomic variables. Leirvik (2022) discovers that liquidity is positively correlated with the rate of return. In essence, when liquidity volatility increases, investors then view liquidity as a major risk and will expect higher returns as a trade-off. However, liquidity risk does not pose a threat for Bitcoin, possibly due to its popularity. An exception exists only for Bitcoin where investors have a higher risk appetite and invest in it, rather than in other tokens.

2.3 | Fractal markets

The literature derived from investor sentiment and crypto-exchanges ultimately leads to the burning question–how quickly do cryptocurrencies react to price-related information? Like with traditional securities, the efficiency of cryptocurrencies is a subject of intense debate. In lieu of the classical EMH, some believe that cryptocurrencies are defined by the fractal market hypothesis (FMH). According to the FMH, liquidity offers a smooth price discovery process between investors with different investment horizons, which results in a stable market. However, when market stress arises, passive investors switch from long-term fundamentals to active trading, thereby flooding the short-run market with other agents. This inundation causes liquidity imbalance between scale-dependent horizons, eventually leading to a market crash (Kristoufek, 2012; Peters, 1994). With recent developments, the FMH has been applied to cryptocurrencies as a way to understand their market volatility or efficiency. The earliest known work on fractal volatility with respect to cryptocurrencies was undertaken by Delfin-Vidal and Romero-Meléndez (2016). They explore its dynamics and find that Bitcoin's volatility dominates transitory periods, in comparison to the medium and long terms. The distinct shapes of Bitcoin's turbulence are maintained as the scale increases in the CWT. Similarly, Celeste et al. (2020) apply the FMH by using the rescaled range and CWT models on Bitcoin, Ripple and Ethereum. They find that Bitcoin exhibits persistence across the entire sample period, but gradually dissipates as time passes. Moving to fractal efficiency, Al-Yahyaee et al. (2020) examine Bitcoin, Ripple, Ethereum, Monero, Litecoin and Dash using the rolling MF-DFA and quantile regression methodologies. They conclude that all investment tokens display multifractality and long memory processes in their returns, with time-varying inefficiency. In addition, they claim that high liquidity in the cryptocurrency market improves efficiency, thus suggesting potential market maturity. Similarly, Naeem et al. (2021) inspect Bitcoin, Ethereum, Ripple and Litecoin using the asymmetric MF-DFA. They argue that inefficiency of cryptocurrencies before COVID-19 was at a normal level. However, inefficiency increased significantly when the virus was introduced to the world, as Bitcoin and Ethereum were the most affected. Nevertheless, the two powerhouse assets were the quickest to recover from the efficiency plunge. Lastly, also using the asymmetric MF-DFA, Kakinaka and Umeno (2022) analyse the short- and long-range dependencies of Bitcoin and Ethereum. Splitting a two-year sample, they claim that after December 2019 (i.e., the domestic COVID-19 outbreak in China), inefficiency was present in the short term for Bitcoin and Ethereum during 2020. However, in the long run, the authors suggest that fractal efficiency was progressing for the two investment tokens, as the year-end approached.

2.4 | Crypto-folio and risk management

Like hard currencies and traditional securities, cryptocurrencies have been discussed regarding their ability to diversify portfolios or hedge risk. While a portfolio consisting of cryptocurrencies only (i.e., a 'crypto-folio') is possible, other risk-based literature looks at how tokens can be used to diversify, with other asset classes. Białkowski (2020) applies stop-loss rules to 10 cryptocurrencies for the purpose of institutional risk management. He reports that stop-loss rules on constrained portfolios can reduce the volatility of a crypto-folio, suggesting that industrial-level investors could incorporate cryptocurrencies in their books. In the same spirit, Burggraf and Rudolf (2020) construct a crypto-folio of 1000 cryptocurrencies. They find that low-volatility strategies are not effective in crypto-markets, to the extent that strategies can even generate negative returns, which indicates progressive market efficiency. In another study, Silahli et al. (2020) calculate Value-at-Risk (VaR) levels of a crypto-folio consisting of Bitcoin, Dash, Litecoin and Ripple. They propose that investors can maximize portfolio returns merely using cryptocurrencies, despite the common consensus that cryptocurrencies are positively correlated in general. Moving on to diversifying with other asset types, Yin et al. (2021) analyse the relationship between oil and cryptocurrencies. The data consist of tokens, namely Bitcoin, Ethereum, and Ripple, against six oil market variables–oil price return, oil realized volatility, oil realized skewness, oil supply shocks, and two oil demand shocks. They argue that all market variables have both negative and positive impacts on the long-term volatility of cryptocurrencies. In fact, adverse oil market movements often present crypto-markets as safe havens, as a hedge against traditional investment. Similarly, using returns and volatility spillover, Attarzadeh and Balcilar (2022) explain the connectedness between Bitcoin, energy stocks, traditional stocks, and crude oil. They discover that clean energy and traditional stocks transmit return shocks to oil and Bitcoin yet receive volatility shocks from them in reverse. The total connectedness index (TCI) claims that, on average, 25% of individual returns receive shocks from others, whereas 24% of volatility receives spillovers from counterparts. In addition, Bitcoin generally has low connectedness with other markets during non-crisis periods. All four asset groups strengthened their connectedness during the pandemic period. Nonetheless, Bitcoin is not a major net transmitter nor receiver during crisis periods, making it a worthy portfolio diversifier, specifically with clean-energy stocks.

2.5 | Volatility indices and COVID-19 uncertainty

Uncertainty indices can give investors the overall outlook of a nation based on macroeconomic and geopolitical factors. Notably, cryptocurrencies have been tested against these indices for hedging purposes. Akyildirim et al. (2020) assess the relationships between VIX and VSTOXX (indicators of stock uncertainty in the US and European markets, respectively) and 22 cryptocurrencies. They unveil that both volatility indices are positively correlated with the cryptocurrencies, implying that virtual assets become riskier as financial market stress deepens. On a similar note, López-Cabarcos et al. (2020) explore the effects of the S&P500, VIX, and social network sentiment on Bitcoin's volatility. Their results indicate that Bitcoin becomes attractive to speculative investors when stock markets are stable but a safe haven when stock markets are in turmoil. In other words, Bitcoin and stocks become inversely correlated when traditional markets switch from harmonious periods to phases of unrest. In another study, Yen and Cheng (2021) scrutinize the relationships between global economic policy uncertainty (EPU) indices, Bitcoin, Litecoin, and Ripple. Their findings indicate that Chinese investors view Bitcoin and Litecoin as safe havens when traditional markets face a downturn. However, this impact appears to dissipate after 2017, when the Chinese government imposed a ban on cryptocurrency trading within its borders. Similar to governmental trade restriction and uncertainty, there has been a rise in the literature due to the coronavirus' effects on investment, and thus strict capital controls within financial instruments. Demir et al. (2020) examine the relationship between COVID-19 cases and cryptocurrencies. The data consist of tokens, namely Bitcoin, Ethereum, and Ripple, and world confirmed cases (WCC) and world confirmed deaths (WCD). They find the relationship between Bitcoin prices and COVID-19 to be negative in the beginning, but to turn positive towards the end of March 2020. As daily cases rose, governments imposed more stringent macroeconomic restrictions, therefore tightening capital control, which led investors to seek alternative assets as a hedge against traditional markets. The relationships were similar for Ethereum and Ripple, but the correlations with coronavirus were weaker. Likewise, using the same WCC and WCD proxies, Apergis (2022) explains how COVID-19 can predict the conditional volatility of cryptocurrencies. The data include Bitcoin, Dash, Ethereum, Litecoin, Ripple, New Economy Movement (NEM), DigiByte, and Dogecoin–tokens that encapsulated 80% of the total trading volume in crypto-markets at that time. He claims that both WCC and WCD show significantly negative impacts on cryptocurrency returns in general. The asymmetric effects on conditional volatility show that the negative shocks are more influential than the positive ones, especially when using WCD. In essence, as death tolls increased, conditional volatility rose in the overall cryptocurrency market due to perturbed sentiment.

2.6 | Volatility of cryptocurrencies

Finally, the bulk of related literature pertains to the pure returns of cryptocurrencies. In this section, we review works that solely observe cryptocurrency returns as the variables under study, as well as papers investigating the market influence of stablecoins on those returns. Jia et al. (2020) inspect higher moments, particularly the skewness and kurtosis, of 84 cryptocurrencies. They report that volatility and kurtosis are positively related to expected returns. Essentially, extremely positive outliers significantly impact the return predictability of higher moments, but negative outliers do not, implying a prevalence of lottery-type investors in crypto-markets. In the same context, Nagy and Benedek (2020) compute Sharpe ratios to assess the risk–return trade-off of 72 cryptocurrencies based on their co-moments. They conclude that investors seem to prefer co-skewness and are averse to co-kurtosis, indicating their preference for lower rates of return. Rational investors favour cryptocurrencies with positively skewed distributions and thin tails, thus avoiding leptokurtosis and negative outliers. Compellingly, their results suggest that there are far more rational investors in the crypto-markets than expected, contrary to the findings in Jia et al. (2020). Moreover, Kozlowski et al. (2020) survey the reversal effects of 199 cryptocurrencies. They document that past 'cryptocurrency losers' outperform past 'cryptocurrency winners' in the sample period. Return reversals are mainly evident in smaller market-cap cryptocurrencies regardless of time. However, for large-market-cap tokens, this effect is only pronounced in shorter holding periods. Along the same lines, Bouri et al. (2020) test for volatility surprise among large cryptocurrencies, namely Bitcoin, Ripple, Ethereum, Litecoin, Stellar, Monero, Dash, and NEM. Although evidence exists of transitory and permanent causality linkages between the cryptocurrencies, the shocks are not necessarily stemming from Bitcoin–causality linkages instead appear to be dependent on the chosen horizon. Smaller cryptocurrencies tend to be influenced by transitory shocks when compared to a large powerhouse (e.g., Bitcoin), suggesting that volatility could be idiosyncratic rather than caused by one massive archetype. Moving on to forecasting, Ftiti et al. (2021) investigate whether jumps can predict cryptocurrency volatility during crisis periods. Unlike Demir et al. (2020) and Apergis (2022), they do not use pandemic indicators (e.g., daily cases or deaths), but rather bull and bear signals, as factors to estimate returns. By decomposing the realized volatility of Bitcoin, Ethereum, Ethereum Classic and Ripple, they claim that only negative jumps significantly predict an incoming downturn during the international COVID-19 outbreak. During this period, investors overreact to preliminary news regarding the virus, causing market unrest to ensue. Similarly, Gradojevic and Tsiakas (2021) examine the volatility cascades of Bitcoin, Ethereum and Ripple. They seek to determine whether volatility transitions are symmetric across timescales.

Although there is evidence of long-term volatility predicting its short-term counterpart in terms of an equally positive behaviour, the reverse scenario does not appear. High-long volatility will lead to high-short volatility, whereas high-short volatility does not necessarily lead to high-long volatility. In essence, short-term turbulence will always lead to low long-term variation in cryptocurrency returns, such that the impact decreases as we shift to a more globalized view.

Lastly, we move on to the potential impact of stablecoins. The earliest known working paper is by Griffin and Shams (2018), who claim that Tether issuances were timed to spike Bitcoin's price. Countering this argument, Wei (2018) suggests no evidence exists to prove Tether grants were used to influence Bitcoin. Since then, more literature has sprawled across the scene. Ante et al. (2021) explain the relationship between the returns of investment tokens and stablecoin issuances. The investment tokens looked at are Bitcoin, Ethereum, Ripple and Litecoin. The stablecoins viewed are USD Coin, Huobi USD, Tether, Paxos, BUSD, DAI, and Gemini. The authors posit that demand for stablecoins is driven by short-term demand for investment tokens. The market sees stablecoin grants as a positive signal of demand for other cryptocurrencies–hence, investors purchase stablecoins as an entry point. In addition, issuance size does not significantly affect abnormal returns. Tether shows the largest volume of tokens per issuance, not necessarily due to increased demand, but rather due to the production of more than is needed. Tether's treasury keeps extra coins for when they will eventually have to meet market demand with sufficient supply. In contrast, USD Coin exhibits the most frequent number of issuances, as opposed to distributing large-sized grants. Bitcoin's returns during the pre-issuance of stablecoins differ, suggesting that either motives for grants vary or each market simply interprets issuances differently. The authors conclude that stablecoins can be used for arbitraging or as a safe haven for future cryptocurrency investment. Likewise, Kristoufek (2021) investigates whether stablecoin issuances have a direct effect on the three major cryptocurrencies–Bitcoin, Ethereum, and Ripple. He analyzes 10 stablecoins regarding their supply levels, including Tether and USD Coin. He finds no proof that stablecoin issuances manipulate major cryptocurrency prices, hence agreeing with Wei (2018). On the contrary, stablecoin issuances occur *after* the counterparts have increased in price–this scenario is in line with the investor demand theory, as pointed by Ante et al. (2021). The increased demand for investment tokens leads to more stablecoin demand, such that participants will enter crypto-markets by exchanging fiat money for stablecoins. Moreover, Grobys and Huynh (2022) explain how Tether's returns, specifically jumps, could potentially impact Bitcoin's returns. They claim that Tether has a higher average number of jumps than Bitcoin, and that the interaction of Tether's positive returns negatively Granger-causes Bitcoin returns. This event could be attributable to investors selling the prime cryptocurrency, which then spikes Tether demand as a consequence. A possible explanation is that large Bitcoin sales could lead to stop-loss orders, as the lagged price drop of Bitcoin is seen to take place after Tether has exhibited positive jumps. Lastly, Saggu (2022) inspects a potential relationship between Bitcoin and Tether's supply. He observes Tether's issuances (i.e., minting) and destruction (i.e., burning) of its own coins, to see if Bitcoin responds to these incidents. These events are factored in by the announcements of a famous Twitter handle (Whale Alert) and overall sentiment around the time Tether produces or burns its supply. He discovers that Bitcoin responds positively to Tether's issuances within 5- and 30-minute windows–however, these influences dissipate beyond the one-hour mark. During some minting events, Bitcoin responses show a greater increase when the overall sentiment is positive. Nonetheless, an asymmetric impact exists, with Bitcoin displaying no significant response to Tether burning supply.

3 | DATA AND METHODOLOGY

3.1 | Motivation for using wavelet analysis

In time-series analysis, it is common to examine the relationship between one time series and its own historical data to anticipate its future path. If the series can be predicted accurately by combining its past movements with the variations between those sequential movements, known as 'errors' (i.e., using autoregressive moving average, or ARMA), then the precise fit of the model will give us a better forecast of its expected outcome. Moreover, there are models which purely observe the volatility of one time series so as to make inferences about its future trends. These models include autoregressive conditional heteroscedasticity (ARCH) and its generalized variation (GARCH). Finally, models such as the autoregressive distributed lag (ARDL) and vector error correction (VEC), allow us to examine the relationship between one time series and another. These methods can determine the future movement of one variable given that they are *potentially* influenced (i.e., Granger-caused), but *not definitively* caused, by the movement of another variable.

Although these models generally provide researchers with well-suited information regarding a variable's potential movement and influence, several drawbacks can be observed. First, these models offer only two scale dimensions. That is, we are limited to viewing the short run and long run, with no information available in between the two periods (In & Kim, 2013). For example, in the ARDL and VEC models, if we wish to observe the impact of the exogenous factor on the endogenous variable, we are only able to analyse the short- and long-term impacts and nothing in between. Similarly, with ARCH models, researchers are only provided with the short- and long-term variances of a time series, also known as the conditional and unconditional volatilities respectively. Using wavelet analysis, we can capture as many time and frequency resolutions as we like in between these two periods. This spectrum is extremely useful for stakeholders who hold different investment horizons.

Second, classical time-series econometric models require the user to test for certain conditions (e.g., unit root tests) to determine whether the data is suitable for model generation. For example, ARCH effects need to be identified, such as evidence of inconstant variance and autocorrelation, which must be inherent in the dataset before the model is implemented. In addition, ARMA models require us to identify the optimal difference(s) of the time series to convert the process from non-stationary to stationary [e.g., AR (1), AR (3), …, MA (1), MA (3)] before computation. Model generation would then require us to choose the best differencing length to stabilize the series, insofar as not compromising on data granularity. Extending differences to a higher degree would eventually create a loss of information regarding the time series' potential behaviour. One issue with this classical technique is that we need to find the best choice of differences, and this decision solely relies upon our intellect and reasoning as researchers. Conversely, wavelet analysis does not require us to convert the data from non-stationary to stationary processes as its function bypasses these inherent features in time series (In & Kim, 2013). Particularly, we do not need to implement tests for non-stationary conditions, which removes the burden of having to select the optimal differencing length before running the data. This method saves us time, but also means we do not lose any information embedded in the dataset–as wavelet decompositions begin from the shortest and go up to the longest available scale, given the number of observations available in the sample.

Finally, classical time-series models tend to require post-estimation results after they have been executed. For example, the multivariate GARCH with dynamic conditional correlation (i.e., MGARCH-DCC) model demands that we test the validity of the estimated results, given the return series inputted. These tests can be implemented using the Kolmogorov–Smirnov (KS) test, the probability integral transform (PIT) for uniformity of the distribution, and so on. In essence, if the model is a 'good fit,' then the estimation ends. However, if the model is "not a good fit", then we will need to re-estimate it with either new assumptions or a new dataset (Pesaran & Pesaran, 2009). In contrast, wavelet modelling does not require post-estimation, and this advantage saves the time otherwise needed to undertake vast data reiteration. Although we adopt the MODWT, it is not used to ultimately decide whether the CWT estimations are valid, but rather to support and complement the CWT based on their unique differences. In this context, the main difference is the assumption that the data type is of either finite or infinite duration (In & Kim, 2013).

3.2 | Dataset and wavelet description

The cryptocurrencies in our dataset include Bitcoin (XBTC), Ethereum (XETM), Tether (XTET) and USD Coin (XUSC). We obtain daily prices of each cryptocurrency (in US dollars) from CoinGecko.com, a reputable source of information on digital currencies. This data source is open 24 hours and tracks the price of each cryptocurrency based on a global volume-weighted average, with the selected crypto-exchanges trading worldwide.[1] Currently, these top four assets dominate the cryptocurrency industry based on market capitalization and trading volume. Hence, they are chosen for their high liquidity. To apply the FMH, high liquidity is needed to ensure a stable market has enough traders to fulfill different investment horizons (Peters, 1994). The length of the raw series spans from 1 January 2017 to 31 October 2022, totaling 2130 price observations including weekends and public holidays. The exception is USD Coin, beginning 5th October 2018 due to its recent inception, and thus providing a total of 1488 observations. The length of this sample thoroughly captures the pre- and post-epidemic periods of cryptocurrency volatility. We compute daily returns by applying the first difference through the natural log-transform of consecutive prices: $r_t = \ln(P_t/P_{t-1})$. To describe wavelet periods, we define the J scales of 1 to 8 (i.e., a period of 2 to 256 days) as follows: 2–4 days (intra-weekly), 4–8 days (weekly), 8–16 days (fortnightly), 16–32 days (monthly), 32–64 days (bimonthly), 64–128 days (quarterly), and 128–256 days (semi-annually to annually) respectively. For simplicity, periods from 2 to 8 days will be denoted as short term (intra-weekly and weekly), those between 8 and 32 days as medium term (fortnightly and monthly), those from 32 to 128 days as longer term (bimonthly and quarterly), and those beyond 128 days as unconditional volatility (semi-annually and annually).

3.3 | The continuous wavelet transform

A 'wave' exhibits transported energy through an oscillating motion across space and time, thereby travelling through matter. The magnitude of energy displaced from its equilibrium is the wave's amplitude, manifesting its level of power in the medium. This physical, mathematical foundation is extended with the 'wavelet,' a smaller form of wave that has its focal energy concentrated in time and position, allowing analysis of time series which frequently display pendular phenomena (Burrus et al., 2015). Specifically, a wavelet is a function with zero mean, localized in both time and frequency dimensions (Grinsted et al., 2004). The CWT is suited for observing values within a dimensionless time-frequency domain. It is defined as the integral over all time of the signal multiplied by shifted and scaled versions of the wavelet function ψ, resulting in wavelet coefficients as a function of scale, time, and position (In & Kim, 2013). In detail, if the signal is a function of a continuous variable, and a transform that is a function of two continuous variables is desired, the CWT can be defined, as per Burrus et al. (2015), by

$$F(a,b) = \int f(t)\psi\left(\frac{t-a}{b}\right)dt, \tag{1}$$

followed by an inverse transform of

$$f(t) = \int\int F(a,b)\,\psi\left(\frac{t-a}{b}\right)da\,db, \tag{2}$$

where $\psi(t)$ is the basic wavelet and a, $b \in \mathbb{R}$ are real continuous variables. In essence, increasing (decreasing) variable a causes the wavelet to advance (delay) across the time series, thus changing its position, while increasing (decreasing) variable b causes the wavelet to expand (compress) in scale length. This continuous wavelet process is used to capture the infinite levels of granularity in cryptocurrency returns, such that the spectrum encompasses the shortest (i.e., highest frequency) and longest (i.e., lowest frequency) possible scales within the time-frequency domain.

3.3.1 | Continuous wavelet power spectrum

The CWPS is adopted to observe the individual volatility of cryptocurrency returns under an infinite resolution. Following Grinsted et al. (2004), the chosen Morlet wavelet is defined by

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\frac{1}{2}\eta^2}, \tag{3}$$

where ω_0 is the dimensionless frequency and η is the dimensionless time. The wavelet is expanded or compressed in time by the varying of its scale length (s), such that $\eta = s{\cdot}t$, and its normalization so that it has unit energy. The Morlet wavelet with a length of $\omega_0 = 6$ is chosen as the basis function due to providing a well-balanced application between time and frequency localizations. The CWT of a time series (X_n, $n = 1, ..., N$) with uniform time steps δt, is defined as the convolution of the series with the scaled and normalized Morlet wavelet:

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{n'=1}^{N} x_{n'}\,\psi_0\left[(n'-n)\frac{\delta t}{s}\right]. \tag{4}$$

Hence, the absolute value squared of this process, or $|W_n^X(s)|^2$, is defined as the wavelet power. The CWT has edge components produced where some wavelet coefficients are not entirely localized in time. Therefore, the cone of influence is applied–effects located in this bordered region are wavelet power caused by a discontinuity at the edge that may distort the image process. Values located in this region are not interpreted for analysis due to being potentially biased estimates.

3.4 | The maximal overlap discrete wavelet transform

Unlike the CWT, the discrete wavelet transform (DWT) captures only the important scales and translations, given that the time-series data have finite duration and interval. However, the dyadic nature of the DWT method restricts the number of observations to be equivalent to an integer multiple of 2^J (i.e., any sample size divisible by 2^J). Fortunately, the MODWT, which is an extension of the DWT, is suitable for any sample period. Hence, this option is chosen due to its higher flexibility.

3.4.1 | Multiresolution analysis decomposition

The MRA will decompose the returns of each token so that we can view volatility changes at fixed frequencies, which complements the strength of the CWT-CWPS. Unlike the CWPS, the MRA is able to distinguish amplitude and direction within each scale, rendering it useful for identifying signals. Following In and Kim (2013), the MODWT of scale J for a time series X_t is a largely redundant, non-orthogonal transform, generating the column vectors $\tilde{D}_1$, $\tilde{D}_2$, ..., $\tilde{D}_J$ and $\tilde{S}_J$, each of dimension N. The vector of $\tilde{D}_j$ contains the MODWT coefficients associated with changes in X_t between scales $j-1$ and j, while the $\tilde{S}_J$ output contains the MODWT scaling coefficients associated with the smoothing of X_t at scale J, and similarly the variations of X_t at scale $J+1$ and above. Like the DWT, the MODWT method deconstructs the time series using the same decomposing pyramid algorithm, but adopts rescaled filters instead, as given in the expression below:

$$\tilde{h}_j = \frac{\tilde{h}_j}{2^j},\ \tilde{g}_j = \frac{\tilde{g}_j}{2^j}, \tag{5}$$

where the $\tilde{h}_j$ and $\tilde{g}_j$ coefficients denote the MODWT's rescaled wavelet and scaling filters, respectively. Using its output as filtered in each scale, a time series is simplified into its smoothed and detailed wavelet components, as

$$x_t = \sum_{j=1}^{J} \tilde{D}_j + \tilde{S}_J. \tag{6}$$

In this context, we implement the periodic boundary condition to solve for coefficients at the endpoints of the MRA. The Daubechies wavelet filter with least asymmetry and length of 8 (LA8) is chosen for decomposing each cryptocurrency, due to the sample size and for orthogonality purposes.

3.5 | Market efficiency and dimension analyses

We observe long-range dependence of the four cryptocurrencies during the post-epidemic period. We aim to determine market efficiency after roughly 3 years of enduring the coronavirus, thereby updating past efficiency works that observed tokens during pre-epidemic (e.g., Urquhart, 2016) and early epidemic/pandemic (e.g., Kakinaka & Umeno, 2022) periods.

3.5.1 | Rescaled range and Hurst exponent

To measure efficiency levels, we employ the rescaled range (R/S) analysis, followed by the classical Hurst exponent (Hurst, 1956). The R/S analysis requires observations to be level-differenced, as well as samples to contain a dyadic length of 2^J. Since USD Coin is a newer cryptocurrency when compared to its three counterparts, we restrict our maximum subsample length to $n=512$. Therefore, for fairness, all four time series are sampled from 12 January 2020 to 31 October 2022, providing 1024 observations for each token during the post-epidemic period. Since log-return computation was discussed earlier, we begin our explanation here with the indexing of returns as quotients for subsample identification, followed by calculating the means of each subsample. Following Celeste et al. (2020), each full series of N observations is divided into A continuous subsamples of length n, where A x $n=N$. Each subdivision M_a is assembled for $a=1, 2, ..., A$ and the elements within that respective M_a are indexed by $N_{k,a}$, such that $k=1, 2, 3, ..., n$. The subsample mean of each M_a with length n can then be calculated as

$$\mu_a = \frac{1}{n}\sum_{k=1}^{n} N_{k,a}. \tag{7}$$

Next, we construct $Z_{k,a}$, which categorizes the mean-adjusted series. In essence, we find the demeaned returns by subtracting the subsample mean from each element of every subdivision, then sum the cumulative deviations based on their respective subsample:

$$Z_{k,a} = \sum_{k=1}^{n} (X_{i,a} - \mu_a). \tag{8}$$

Hence, we can calculate the subsample ranges by finding the difference between the maximum and minimum values of the demeaned returns within each subdivision M_a:

$$R_{M_a} = \max(Z_{k,a}) - \min(Z_{k,a}). \tag{9}$$

The standard deviation S_{M_a} of the indexed returns is produced by

$$S_{M_a} = \sqrt{\sum_{k=1}^{n} (N_{k,a} - \mu_a)^2}. \tag{10}$$

Therefore, each subsample range R_{M_a} is divided by the corresponding standard deviation S_{M_a}. The rescaled range of every subdivision M_a is thus equal to R_{M_a}/S_{M_a}. Due to subdivisions being adjacent, the rescaled ranges are then averaged by their respective length n, as follows:

$$(R/S)_n = \frac{1}{n}\sum_{a=1}^{a} \frac{R_{M_a}}{S_{M_a}}. \tag{11}$$

The estimation of the Hurst exponent requires fitting the power law to the data, such that

$$\mathbb{E}(R/S)_n = Cn^H. \tag{12}$$

Hence, the Hurst exponent is identified through linear regression, by estimating a line of best fit between the log-transformations of the averaged R/S values and the corresponding n lengths:

$$\log(R/S)_n = H\log(n) + \log(C), \tag{13}$$

where the gradient H denotes the classical Hurst exponent–since we have a large sample size (thus more scaled subsamples), and are testing for long-range dependence only, it is not mandatory to adjust the exponent for short memory (Mandelbrot, 1972). The Hurst boundary ranges from 0 to 1, with 0.5 as the expected Hurst value. $0 < H < 0.5$ imply mean reversion, whereas $0.5 < H < 1$ evinces the presence of long memory. If $H = 0.5$, the returns follow a standard Brownian motion. To determine significance at the 1% level, the exponents are tested against a two-tailed t-distribution using the difference between their actual values and the expected Hurst, divided by their standard errors.

3.5.2 | Fractal dimension and V-statistic

For variables that display self-similarity, the fractal dimension is directly related to the Hurst exponent (Hurst et al., 1965) and represents the non-integer dimension for which the series falls within a geometric spectrum. Since both self-similarity and multifractality exhibit isotropic growth (Chen & Wang, 2013), for simplicity, we assume that the long-range Hurst and fractal dimension of cryptocurrencies are intertwined. Computing the Hurst approximations, we then extract the fractal dimension to determine whether returns follow one side of geometry. The non-integer dimension is defined by

$$D = 2 - H, \tag{14}$$

such that $1 < D < 2$. Values nearer to 1 indicate that the returns closely resemble lines and curves, whereas values closer to 2 reveal mimicry of planes and boxes (Mandelbrot & Hudson, 2006). Finally, as proposed by Hurst (1956), we test the robustness of each Hurst exponent by calculating the V-statistic to confirm expected trends or reversions:

$$V_n = \frac{(R/S)_n}{\sqrt{n}}. \tag{15}$$

The V-statistic will be graphed to provide visuals. If the estimated line of the V-statistic slopes upward, the cryptocurrency is persistent. If the estimation reveals a downward slope, the cryptocurrency is mean-reverting and therefore anti-persistent. However, if the line is parallel to the horizontal $\log(n)$ axis, then returns are unpredictable and thus follow a random walk.

4 | RESULTS AND DISCUSSION

4.1 | Descriptive statistics

Table 1 highlights the descriptive statistics of Bitcoin (XBTC), Ethereum (XETM), Tether (XTET), and USD Coin (XUSC) for the chosen sample period. Panel A shows their daily prices in US dollar, while Panel B summarizes their daily returns. In Panel A, we see that Bitcoin is the most expensive cryptocurrency, with even its minimum value higher than Ethereum's maximum. Both Tether and USD Coin have minimal fluctuation bandwidth due to their nature as a medium of exchange–their mean values oscillate around the one-dollar mark, as they are supposed to. The standard deviation of Bitcoin's prices surpasses the rest by a good distance, with a dispersion of $17,003 making it far riskier than the others. However, since this particular token generally swings much higher in its raw series than does its competitors, this statistic can be ignored. With regard to their symmetries, all four series display positively skewed distributions, signifying that extremely positive outliers exist. Particularly, Tether is the most asymmetric (9.7145), followed by USD Coin (3.0132) and Ethereum (1.4084). Interestingly, Bitcoin is the least asymmetric (1.1892), which indicates that it has the least amount of extremely positive outliers. The excess kurtosis is positive in all cases. Thus, all assets display leptokurtic distributions (i.e., fat-tails), with Tether being the riskiest at 168.3168 and Bitcoin the least volatile at 0.1248. The Jarque-Bera test is employed to measure data normality through skewness and kurtosis. The p-values are significant at the 1% level for all test statistics, rejecting the null hypothesis that the price data follow a normal distribution. Therefore, all four cryptocurrency prices are asymmetric and not mesokurtic, and thus not normally distributed.

Moving to Panel B, Ethereum possesses both the strongest maximum (0.31213) and minimum (−0.56308) return observations, making its range larger than Bitcoin's. At 0.05471, Ethereum's standard deviation confirms that its returns are the most dispersed of the four tokens. As for the stablecoins, their smaller means and standard deviations showcase that their price changes do

TABLE 1 Descriptive statistics

Panel A (price)	XBTC	XETM	XTET	XUSC
Maximum	67617.016	4815.005	1.32310	1.04346
Minimum	784.278	8.065	0.91382	0.97169
Mean	17633.960	985.906	1.00121	1.00138
SD	17003.024	1168.851	0.01541	0.00483
Skewness	1.1892	1.4084	9.7145	3.0132
Kurtosis (excess)	0.1248	0.8580	168.3168	18.4118
Jarque-Bera	503.406	769.479	2547836.791	23269.218
p-value	4.862E-110*	8.124E-168*	0*	0*
Observations	2130	2130	2130	1488
Panel B (returns)	**XBTC**	**XETM**	**XTET**	**XUSC**
Maximum	0.28710	0.31213	0.12654	0.02537
Minimum	−0.43371	−0.56308	−0.28334	−0.02096
Mean	0.00144	0.00248	2.4831E-08	−4.343E-06
SD	0.04116	0.05471	0.01055	0.00352
Skewness	−0.61022	−0.53689	−7.64323	0.15253
Kurtosis (excess)	9.30226	8.45967	281.945	8.99137
Jarque-Bera	7811.908	6453.809	7075725.000	5014.771
p-value	0*	0*	0*	0*
Observations	2130	2130	2130	1487

Note: This table displays the descriptive data of cryptocurrency daily prices (Panel A) and returns (Panel B) of Bitcoin (XBTC), Ethereum (XETM), Tether (XTET), and USD Coin (XUSC) for the chosen sample period (1 January 2017 to 31 October 2022, except for XUSC which begins on 5 October 2018). The * denotes the significant *p*-values at 1% level, using the right-tailed chi-square distribution when assessing each Jarque-Bera test statistic for data normality.

not shift drastically, unlike with investment tokens. Except for USD Coin, all cryptocurrencies display negatively skewed distributions, which reveal the presence of extremely negative outliers. Remarkably, Tether exhibits the deepest trough at −7.64323. The excess kurtosis is positive for all assets, implying leptokurtic distributions with Tether the riskiest again (281.945), but Ethereum being the least volatile this time (8.45967). All p-values are significant at the 1% level according to the Jarque-Bera test statistics, rejecting the null hypothesis that returns follow a normal distribution. Therefore, all four-return series are asymmetric and not mesokurtic, and thus not normally distributed.

As Naeem et al. (2021) mention, the presence of (1) fat-tailed distributions and (2) fluctuations following a period of similar oscillations within a regime, but not across regimes, are signs of multifractality. Specifically, a combination of self-similarity (i.e., the same patterns under scale invariance) and self-affinity (i.e., distorted, yet similar patterns as scale lengths change) defines a multifractal series (Chen & Wang, 2013). Keeping this foundation in mind for identifying the presence of complex fractals, we move on to the wavelet analysis.

4.2 | Wavelet analysis

4.2.1 | Bitcoin (XBTC)

Figure 1 displays the log-return series movement of Bitcoin, obtained using the CWT-CWPS. We ignore values located in the cone of influence region due to edge effects that potentially create biased estimates. The pink line separates the diagram into pre- and post-epidemic time windows, thus marking the event of the WHO first being informed of the disease's presence. The purple line signifies the WHO's announcement that the virus had transitioned from epidemic to pandemic. Hence, the time window between these two vertical lines represents the domestic epidemic period in China.

At first glance, we notice a huge level of volatility, from April 2017 until June 2018, with this extreme variation encompassing short-, medium- and longer-term horizons. Bitcoin peaks to five figures in November 2017, breaking the $10,000 mark for the first time. On 1st December 2017, the CBOE and the Chicago Mercantile Exchange (CME) announced that they were introducing Bitcoin futures. This event led to a multitude of speculative traders

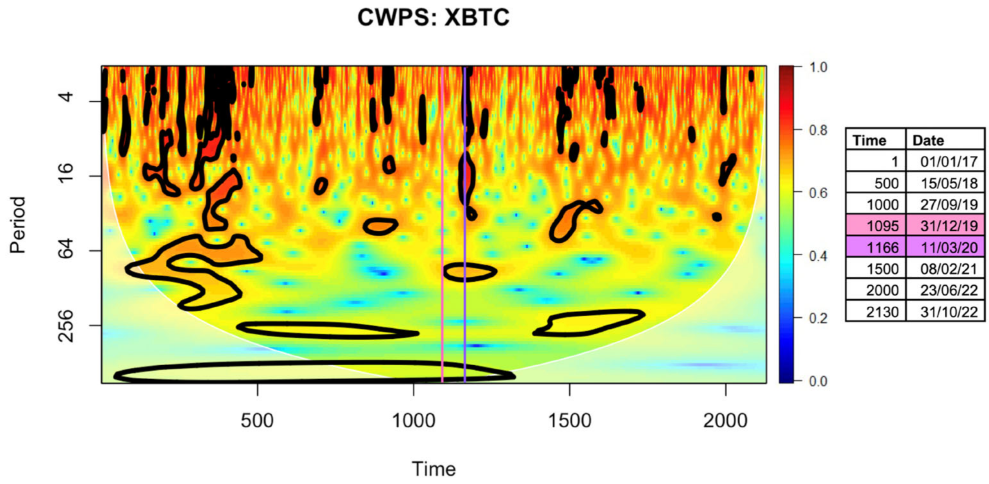


FIGURE 1 This figure shows the continuous wavelet power spectrum (CWPS) of Bitcoin's (XBTC) log-return series from 1 January 2017 to 31 October 2022, using the continuous wavelet transform (CWT) with Morlet wavelet application. The thick black contour indicates the 5% significance level against red noise (region of significance). The cone of influence (faded area) borders the region affected by edge effects. The code for power ranges from blue to red, as denoted in the colour bar (colours closer to 1.0 indicate higher power). Vertical lines mark the two significant WHO events on COVID-19—pink reveals the organization's awareness of the epidemic in China and purple represents the pandemic transition announcement. [Colour figure can be viewed at wileyonlinelibrary.com]

becoming bullish in the Bitcoin market, knowing that the new futures contract could act as a means of safeguarding them from volatility. Ironically, Corbet et al. (2018) suggest that Bitcoin futures had no positive impact on stabilizing Bitcoin's value since spot volatility increased after the introduction of the financial derivative. Hence, this event implies that Bitcoin demand exceeded expectations, leading Bitcoin futures to become superfluous in terms of their real purpose. Following the first major bull run in 2013, this was the second for the powerhouse cryptocurrency. The token peaked at the end of December 2017, then began declining in mid-January 2018, entering the infamous cryptocurrency crash that continued until November 2018. This volatility is thus explained in the CWPS, where we see significant variation occurring (in red) before there is a shift to orange and yellow colours in the longer term, suggesting that returns were strongly persistent. Bitcoin's returns were stable from June 2018 until the beginning of 2019.

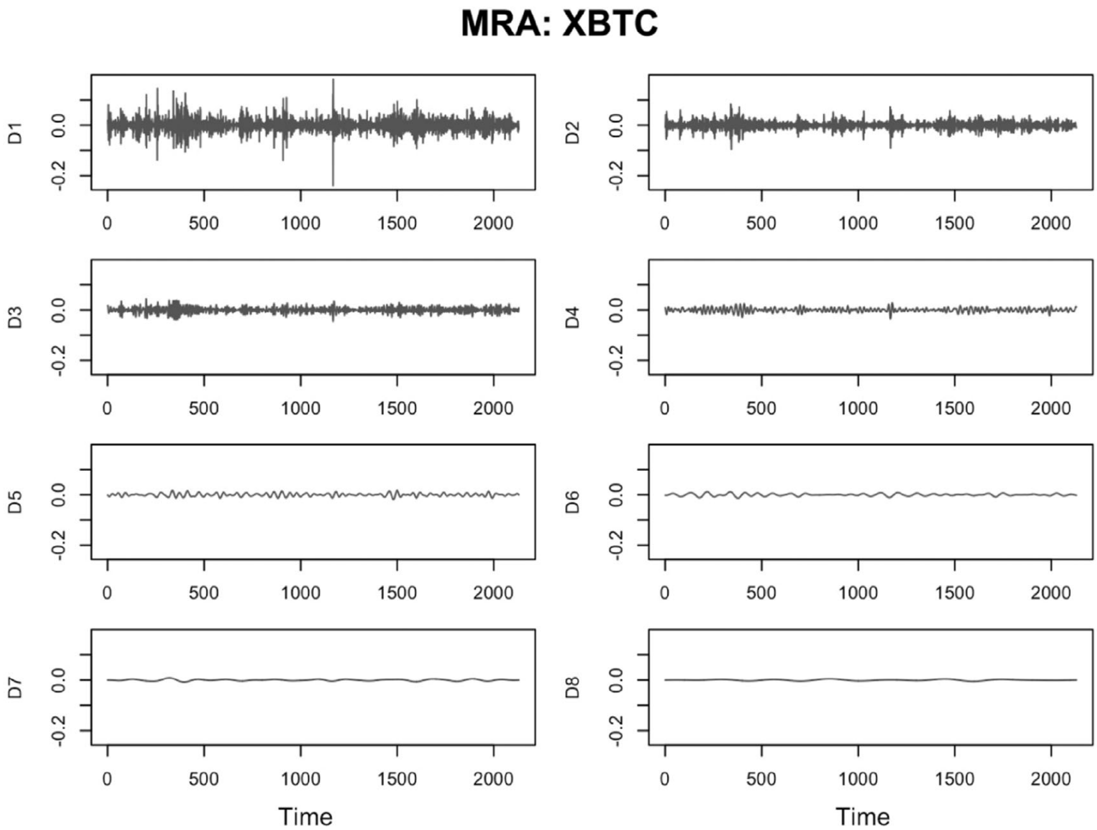
From this point onwards, Bitcoin's returns show fractal dynamics in all horizons – significant volatility patterns that seem to be cyclical across the timeframe, happening approximately every 250 days, beginning from November 2018. The recurring patterns stretch vertically and project further into the longer term as time passes, suggesting that volatility fractals are more self-affine than they are self-similar. In essence, the switches between Bitcoin's market regimes are ephemeral, yet the persistence becomes stronger in each consecutive regime. This phenomenon is likely caused by traders who (1) time their trades seasonally based on calendar events, and (2) the unbalanced switch of horizons between active and passive investors during unstable periods. This result is contrary to the previous notion that Bitcoin's market only entices retail traders who actively manage their portfolios (e.g., Al Guindy, 2021; Białkowski, 2020) – later, we will see Bitcoin attracting institutions that believe in fundamentals.

In mid-December 2019, a cluster of patients in Wuhan began experiencing 'unknown pneumonia-like symptoms,' leading the WHO office in China to be informed of these rare cases on 31 December 2019 (Centers for Disease Control and Prevention, 2022). Although January and February show no interesting information, a significant amount of power is unveiled in all horizons during March 2020, as Bitcoin enters a fast bear run. With the WHO officially declaring the coronavirus' transition to a global pandemic on 11 March 2020, the world began receiving daily news of COVID-19's international spread. Inevitably, countries commenced law enactments for nationwide lockdowns, including the Trump administration's announcement on 13th March of a national emergency and travel ban. This devastation subsequently led to traders shorting their Bitcoins, causing the token to plummet rapidly, and reaching around $5000 per coin in the same month. Traders were becoming pessimistic about the global environment, sensing an incoming market downturn due to the persistent ongoing news of high death tolls and job retrenchment. The turbulence in Bitcoin continued throughout March before gradually quieting down in April, as Bitcoin returned to a steady equilibrium in May 2020 right below the five-figure mark. Marked by the purple line, this three-month event explains the red power in the CWPS, signaling a moment of great turmoil for Bitcoin. Significant volatility is non-existent until October 2020, when the third major bull run occurs for Bitcoin. In this month, the financial markets witnessed an influx of cashflows from massive corporations seeking cryptocurrency investment. In mid-October 2020, PayPal stated in a press release that the company had partnered with Paxos, a FinTech firm (Browne, 2020). The partnership would provide a cryptocurrency service to PayPal's large consumer base by primarily offering Bitcoin, Bitcoin Cash, Ethereum, and Litecoin on its server. Moreover, PayPal claimed that users on the network could adopt cryptocurrencies to make real purchases. Within the same month, Block Inc. (a payments platform previously known as Square Inc.) announced their $50 million investment in Bitcoin, claiming that "Bitcoin has the potential to be a more ubiquitous currency in the future" (Effron, 2020). Investors noticing these two conglomerates making large Bitcoin purchases for the future of payments meant that demand for Bitcoin would soon increase. Hence, a bullish period ensues, as investors fear missing out on abnormal gains–a sign of true herding behaviour. As a result, Bitcoin finally breaks the $20,000 barrier in mid-December 2020, with growth continuing in the following year.

On 8th February 2021, Tesla announced their $1.5 billion investment in Bitcoin and that they were preparing protocols for accepting it as payment from consumers (Kovach, 2021). Ironically, the preparations backfired when Tesla suddenly halted crypto-payments due to energy consumption concerns, and when China declared an attempt to tackle illegal cryptocurrency mining/trading within its borders (Wilson, 2021). Perturbed by these events, investors can be seen exiting the Bitcoin market early and thus forcing the asset into a slump. The CWPS highlights these events with extreme volatility around the 1500th observation, revealing turbulence in all horizons. Specifically, 2021 shows Bitcoin breaking the $60,000 mark in April, after which it entered a trough in July when its value halved, before smashing its record again at beyond $67,000 in November. This long annual cycle is evident from the significant yellow region in the CWPS (period 256) from November 2020 until October 2021–evincing that returns are unconditionally volatile. On 26th November 2021, a new variant of COVID-19 (i.e., Omicron) was announced, with claims that the variant was more transmissible and less subject to vaccine protection (Centers for Disease Control and Prevention, 2022). Concomitantly, Bitcoin prices fall again but more quickly this time, until mid-January 2022. The recrudescence of the virus may have persuaded investors to be less optimistic about the overall rising interest rates, inflation, and unemployment, leading them to be bearish. Global markets worsened when the Russo-Ukrainian war advanced further, with Russia's massive invasion at the end of February 2022. Although these events globally affected all financial markets, and not just Bitcoin, crypto-specific events can be identified. For example, Three Arrows Capital (i.e., 3AC) became the largest ever cryptocurrency hedge fund to file for bankruptcy in June 2022. The liquidation followed the plummeting of TerraUSD and Luna, cryptocurrencies in which 3AC had invested heavily, in May. When these tokens became worthless, 3AC was unable to repay its loans nor meet margin calls. The fall of this multibillion-dollar company that specialized in digitized-asset portfolios sent a shockwave into all crypto-markets and was possibly the main reason for Bitcoin's decline in the first half of 2022. Nevertheless, Bitcoin fluctuated moderately between $30,000 and $40,000 after the trough, before falling and remaining in a stable band between $20,000 and $30,000. The CWPS exhibits significant power in the short and medium terms, and it is unlikely that these Omicron and 3 AC events will continue to impact Bitcoin's returns in the long run.

Overall, Bitcoin displays significant volatility throughout the time-frequency spectrum. While showcasing multifractality, these volatility patterns suggest that Bitcoin exhibits more self-affine fractals than self-similar ones. Price discovery reveals that Bitcoin traders were heavily influenced by the news pertaining to institutional investors, market makers, governments, and the pandemic transition. Significant unconditional volatility is inherent in Bitcoin, as is evident in the CWPS.

In Figure 2, we present the decomposition of Bitcoin's log-return series, using the MODWT-MRA. In this figure, notice that the series is scaled up to $J = 8$. Although it would be possible to increase the scale length to a maximum of 11 (since $\log_2(2130) \approx 11.06$), we chose 8 to capture the most balanced information about the long term without compromising data granularity. Hence, the same MRA scale length is applied for the rest of the upcoming cryptocurrencies. We categorize the D1, D2 and D3 scales as the short term, D4 and D5 as the medium term, D6 and D7 as the longer term, and finally D8 as the unconditional volatility. Besides quantifying amplitude and direction, this wavelet method can observe fluctuations of returns during different market regimes, thereby measuring the presence of complex fractals precisely. Moreover, the MODWT complements the CWPS since some wavelet coefficients located in the latter's cone of influence may be estimated with bias due to the lack of a boundary condition. In contrast, MODWT models require one solution to be computed for solving convolutions at the endpoints (e.g., periodic), since the discrete wavelet



Time	Date
1	01/01/17
500	15/05/18
1000	27/09/19
1095	31/12/19
1166	11/03/20
1500	08/02/21
2000	23/06/22
2130	31/10/22

FIGURE 2 This figure presents the multiresolution analysis (MRA) of Bitcoin's (XBTC) log-return series from 1 January 2017 to 31 October 2022, using the maximal overlap discrete wavelet transform (MODWT). The y-axis denotes the multiscale movement of returns. The series is decomposed using the Daubechies wavelet filter with length of 8, at a scale level of $J = 1$ to 8 (or a period of 2–256). The periodic boundary condition is implemented as a solution for the wavelet coefficients at the endpoints.

transform assumes the data to have finite intervals and distribution. Lastly, MRA allows us to locate precise magnitudes (e.g., lowest or highest, positive or negative returns) at a specific time-frequency point. In comparison, the CWPS is solely based on colours, which makes it challenging for us to distinguish amplitudes and it does not reveal the direction of returns.

Moving to Bitcoin's returns at the D1 scale, it is clear that the highest crest and deepest trough occur somewhere around the 1170th observation, which happens to be in mid-March 2020, followed by a lingering wave of volatility. This shock reveals that Bitcoin's returns were mostly affected during the international onset of COVID-19 when news arose of lockdowns, deaths, market closures, and so forth. A memory of noise streams between the 1st and ~600th observation in all three short-term scales. These visuals confirm the corresponding volatility in the CWPS, where short-term returns are impacted by the introduction of Bitcoin futures, immediately followed by the infamous cryptocurrency crash in 2018. The short-term scales also confirm Bitcoin's third bull run, beginning from around the 1400th observation (October 2020). We see that both bull markets show some level of persistence in the medium-term scales (D4 and D5), which is thus in agreement with the CWPS events. Although the longer-term scales (D6 and D7) display these events, the amplitudes are significantly lessened, suggesting that impacts on Bitcoin's returns are minimal from the quarterly and semi-annual lenses. The D8 scale demonstrates unconditional volatility, and it is evident that Bitcoin's returns show annual cycles. These cycles hint at the presence of long memory due to the low-frequency trends. Moreover, the MODWT shows Bitcoin's returns indeed revealing persistent fluctuations within different market conditions–in essence, we see periods where small oscillations move together, and likewise periods of large swings. Hence, Bitcoin's fat-tailed distribution identified from the descriptive data, mixed with the self-similar and self-affine fractals from both wavelet models, implies that Bitcoin possesses multifractal volatility.

4.2.2 | Ethereum (XETM)

Figure 3 shows the movements in the log-return series of Ethereum, obtained using the CWT-CWPS. At first

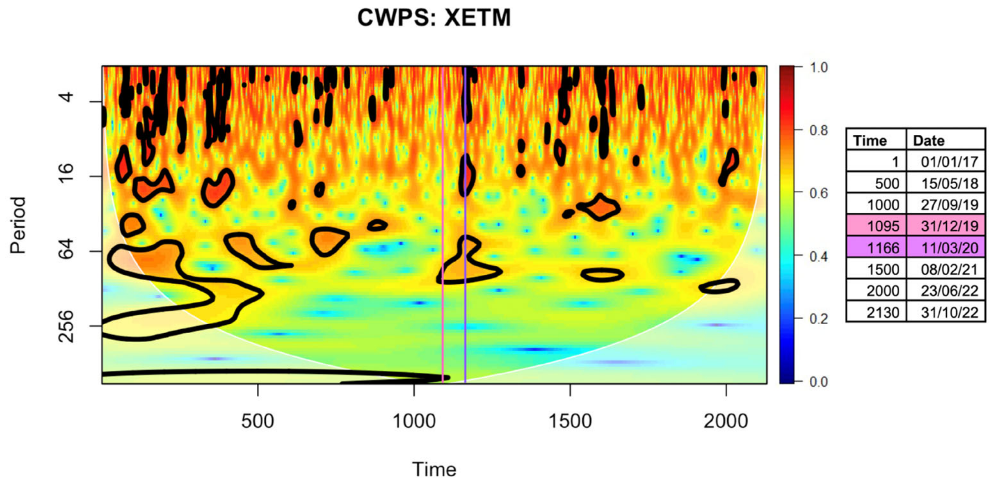


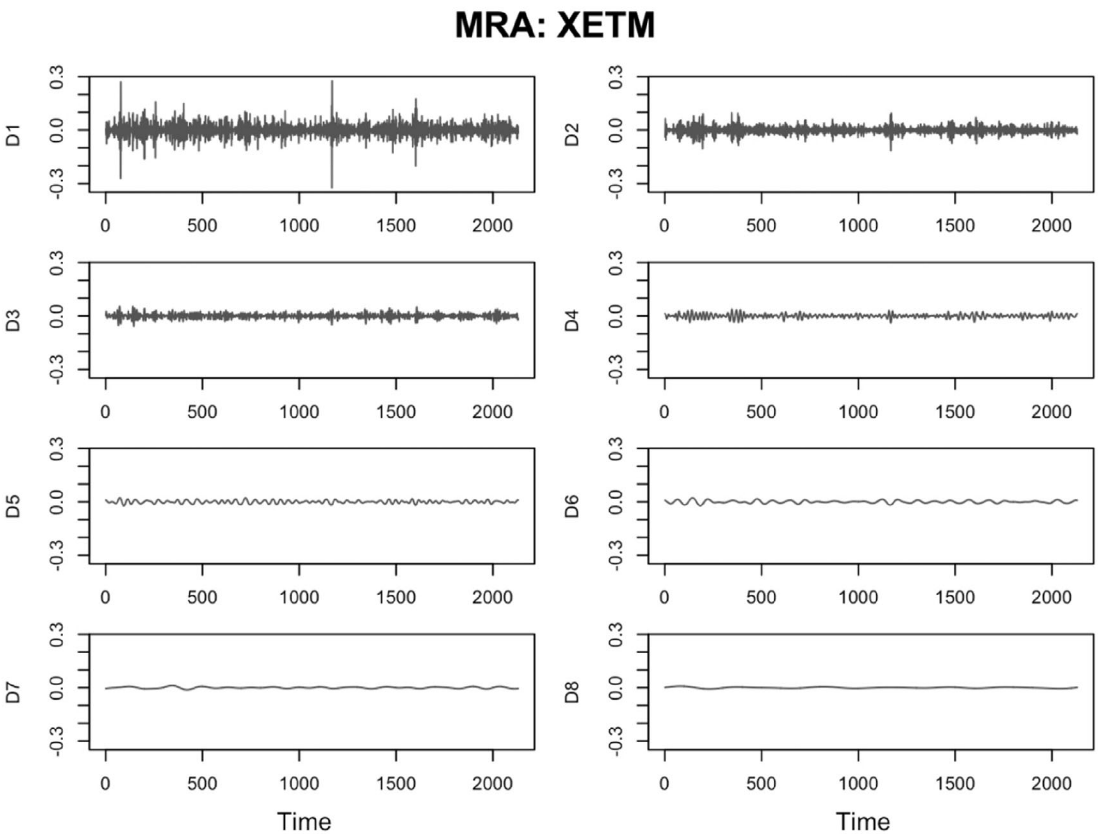
FIGURE 3 This figure shows the continuous wavelet power spectrum (CWPS) of Ethereum's (XETM) log-return series from 1 January 2017 to 31 October 2022, using the continuous wavelet transform (CWT) with Morlet wavelet application. The thick black contour indicates the 5% significance level against red noise (region of significance). The cone of influence (faded area) borders the region affected by edge effects. The code for power ranges from blue to red, as denoted in the colour bar (colours closer to 1.0 indicate higher power). Vertical lines mark the two significant WHO events on COVID-19—pink reveals the organization's awareness of the epidemic in China and purple represents the pandemic transition announcement. [Colour figure can be viewed at wileyonlinelibrary.com]

glance, it seems that Ethereum's returns mirror Bitcoin's to some degree. In 2017, many events regarding Bitcoin translated into scenarios that may have created volatility spillovers across the cryptocurrency market, especially for those that are also investment tokens. Ethereum is undoubtedly the second-largest cryptocurrency based on price history, length of existence, and market capitalization. If crypto-investors are optimistic about a market leader's performance (i.e., Bitcoin), it is logical that they will exude the same level of confidence in its major competitor by purchasing more Ether (i.e., a term used to refer to Ethereum tokens that are exchanged on the network). Beyond the currency that it is, Ethereum is well-known for its uniqueness in providing smart contract capabilities in its transactions. In March 2017, a non-profit organization called the Enterprise Ethereum Alliance (EEA) was established, comprising various blockchain startups and major corporations such as Accenture, JPMorgan Chase Bank, and Microsoft. The goal of the EEA is to promote the adoption and usage of Ethereum's technology as part of daily business operations for its members (Enterprise Ethereum Alliance, 2022). Belief in this cryptocurrency grew, resulting in Ethereum's first ever bull run. The asset peaked at approximately $1448 per token in January 2018, thus breaking the four-figure mark. This market exhibits similar purchasing patterns in 2017, when Bitcoin gained traction due to the release of Bitcoin futures at the year-end. However, the EEA's establishment would mainly have affected Ethereum's demand systematically, rather than Bitcoin's. In contrast, Ethereum suffers from the 2018 cryptocurrency crash when Bitcoin suddenly begins its descent, causing investors to short their Ether. Although the prices of Bitcoin and Ethereum differ massively, the CWPS demonstrates that their localized movements are mostly similar in the pre-epidemic sample. This phenomenon may be caused by a herding behaviour that persuades investors to enter other crypto-markets when Bitcoin performs well, while exiting when Bitcoin is turbulent, without inputting any fundamentals into their decision-making. Unlike for Bitcoin, the whole year of 2019 displays a period of stability for Ethereum, as the asset travels between $100 and $300. Bitcoin enters a bullish period, while Ethereum is in a harmonious phase at this time. This period explains the CWPS differences between the two tokens, whereby Bitcoin shows unconditional volatility, whereas Ethereum displays mild variation limited to the short run. In March 2020, Ether prices plummet quickly when the WHO announces the international contagion, which is similar to Bitcoin's immediate fall at the same time. It is evident that the pandemic and related macroeconomic news affected investors in other crypto-markets, and not merely in Bitcoin's. Nevertheless, Ethereum's price rebounds a few weeks after its rapid price drop and gains traction towards the second half of 2020–this is displayed at the 1166th observation, with the short, medium, and longer terms being significantly volatile. Following the Bitcoin futures era, it is evident that Ethereum's returns are tumultuous but only until period 128–we ignore the green bubble at period 512 due to its likely biased estimation. Moreover, the volatility seems to project constant fractals throughout the sample period as we increase the scale dimension from the short to the longer terms. In other words, Ethereum returns reveal more moments of self-similarity than do those of the prime cryptocurrency. This marvel is likely caused by traders who (1) time their trades seasonally based on calendar events, and (2) a *balanced* switch of horizons between active and passive investors, contrasting with Bitcoin's self-affine behaviour.

On 1 December 2020, the Beacon Chain was officially launched and announced on the Ethereum website. The Beacon Chain was essentially a prototype proof-of-stake blockchain engineered alongside its predecessor, the proof-of-work. The system was installed due to its efficient energy usage and eco-friendliness, contrasting with the detrimental proof-of-work. This date marked the beginning of Ethereum's second major bull market. The Beacon Chain was instructed to accept transactions from the original chain, package them into several blocks and lay them together by utilizing a consensus mechanism. Those forming this consensus, previously miners, eventually became validators on this new system. Validators would stake their own Ether tokens in the hope of getting the chance to write the new block, and hence receiving Ether as a reward. In 2021, we see the rise of Non-Fungible Tokens (NFTs). Fungible tokens such as cryptocurrencies are divisible and homogeneous, making them synonymous with regular fiat money. On the contrary, NFTs are unique tokens tied to a virtual asset which specifies ownership of that particular asset on the blockchain–unlike cryptocurrencies, these special tokens are not mutually interchangeable since they are heterogeneous. Content creation in the NFT space generally includes virtual artworks, music, and even virtual land on a metaverse network (e.g., Next Earth). The ERC-721 is a specific standard interface on the Ethereum network that allows users to transfer ownership of NFTs through buying and selling, as well as to trace and track these possessions through its advanced smart contract capabilities. Hence, NFTs are widely traded on Ethereum's platform where, in order to purchase an NFT, one would need to own an e-wallet that is denominated primarily in Ether. On 11 March 2021, Christie's auction house sold Mike Winkelmann's famous virtual artwork named 'Everydays: the First 5000 Days' for approximately $69.3 million, payment for which was accepted only in Ether currency (Christie's, 2021). Famous and remarkable sales of NFTs created an increased demand for Ether, which consequently led Ether's price to increase due, not necessarily only to crypto-investors, but *also* to NFT investors. Ether began its rapid climb in January 2021, passing $4000 for the first time in May. Hence, this bull run from December 2020 to May 2021 may have been caused by (1) Bitcoin's massive rise, (2) the launching of the efficient proof-of-stake mechanism, and (3) the increased demand for NFTs. The CWPS showcases that this period has significant short-, medium-, and longer-term volatilities due to those three factors. In 2022, Ethereum descends until July, and then reverts to similar prices to those seen in its first bullish period. As with Bitcoin's bear market, it is clear that the fall of TerraUSD, Luna, and 3AC negatively affected Ethereum's returns in the transitory scales. This plunge suggests that news regarding FinTech ventures does affect tokens other than Bitcoin, especially the one cryptocurrency that is supposedly Bitcoin's ultimate competitor. On 15th September, the Merge resulted from the now-defunct Beacon Chain, with the proof-of-stake completely replacing the proof-of-work on the Ethereum Mainnet, hence reducing energy consumption by 99.95% (Ethereum, 2022). However, this announcement does not seem to have impacted returns, despite representing a positive move regarding the environment, suggesting that investors in Ethereum were not boosted by the eco-friendly upgrade of the network.

Overall, Ethereum displays significant volatilities throughout the time-frequency spectrum. However, unconditional volatility is only evident in the pre-epidemic period when the EEA and Bitcoin futures were launched. This level of turbulence is non-existent after the 2018 cryptocurrency crash. Although this cryptocurrency may trend with Bitcoin in some shocks, fractal dynamics propose that Ethereum's returns are not solely due to the prime cryptocurrency's movement–policy-related events differ between the two assets and will thus impact each token differently. Despite both cryptocurrencies displaying multifractality, Ethereum's volatility patterns reveal more evidence of self-similarity, whereas Bitcoin shows more presence of self-affinity. Price discovery suggests that Ethereum traders are influenced by the news of the policy upgrades on the network, institutional investors, the pandemic transition, and the fall of other major cryptocurrencies. These factors affect Ethereum only until the longer term (periods 32–128). Unconditional volatility completely dissipates in the post-epidemic sample, in line with the CWPS.

Figure 4 presents the decomposition of Ethereum's log-return series, using the MODWT-MRA. At the D1 scale, we see three major events occurring around the 100th (April 2017), 1166th (March 2020) and 1600th (May 2021) observations. The EEA's establishment and continuous recruitment of members in 2017 likely sent an immediate shock towards Ethereum. The MRA affirms these events with a thick stream of noise, surpassing the Bitcoin futures announcement at the year-end. As with Bitcoin, it is also clear that the pandemic declaration in March 2020 stifled Ethereum temporarily, as the highest crest and lowest trough can be seen after this specific event. The MRA also



Time	Date
1	01/01/17
500	15/05/18
1000	27/09/19
1095	31/12/19
1166	11/03/20
1500	08/02/21
2000	23/06/22
2130	31/10/22

FIGURE 4 This figure presents the multiresolution analysis (MRA) of Ethereum's (XETM) log-return series from 1 January 2017 to 31 October 2022, using the maximal overlap discrete wavelet transform (MODWT). The y-axis denotes the multiscale movement of returns. The series is decomposed using the Daubechies wavelet filter with length of 8, at a scale level of $J = 1$ to 8 (or a period of 2–256). The periodic boundary condition is implemented as a solution for the wavelet coefficients at the endpoints.

confirms Ethereum's immediate rise in May 2021, when Bitcoin began its rapid climb, alongside the popular NFT craze. Regarding the other two short scales, D2 shows the impact of these events to be sustaining whereas D3 displays no interesting information. In the medium term, D4 interestingly mimics the D2 fractals regarding the aforementioned significant events, which aligns with the self-similarity in the CWPS. However, D5 reveals no new information. In the longer term, D6 displays certain areas of disruption in the pre- and post-epidemic samples, but harmony eventually followed. This scale reveals strong evidence of Ethereum's self-similar patterns, mirroring the volatility fractals of the D2 and D4. The D7 scale displays some impact during the Bitcoin futures announcement. However, volatility is non-existent from this event onwards, which corresponds to period 128 of the CWPS. Finally, the D8 scale demonstrates unconditional volatility regarding Ethereum. As this view presents annual cycles, if we inspect and compare them closely, Ethereum's trends are less pronounced than Bitcoin's. In fact, Ethereum takes longer to complete one cycle than the prime cryptocurrency does, as Bitcoin shows shorter "wavelengths" (i.e., the distance between two consecutive crests in a wave) than Ethereum in their respective D8 scales. Therefore, Ethereum is less volatile than Bitcoin from an annual perspective. This result confirms the CWPS regions in which significant volatility is absent in period 256 for Ethereum. Nevertheless, these cycles still signal the presence of long memory due to the low-frequency trends. Similar to Bitcoin, the MODWT displays that Ethereum's returns do reveal persistent fluctuations with different market regimes. Hence, Ethereum's fat-tailed distribution identified from the descriptive data, mixed with the complex fractals from both wavelet models, implies that Ethereum retains multifractal volatility.

4.2.3 | Tether (XTET)

Figure 5 reports the log-return series movement of Tether, obtained using the CWT-CWPS. The term USDT is commonly used to refer to Tether's currency. Unlike the previous two investment tokens, Tether is a stablecoin, which is a cryptocurrency designed to be pegged to

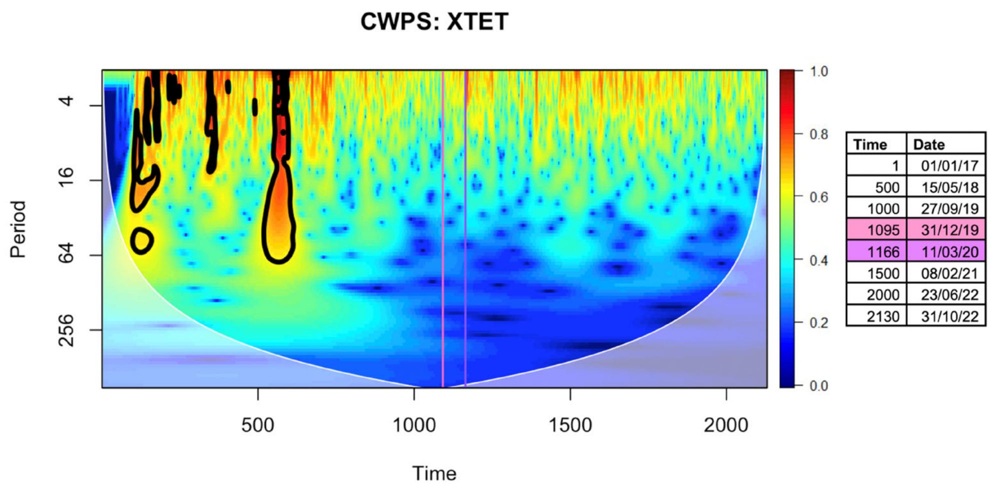


FIGURE 5 This figure shows the continuous wavelet power spectrum (CWPS) of Tether's (XTET) log-return series from 1 January 2017 to 31 October 2022, using the continuous wavelet transform (CWT) with Morlet wavelet application. The thick black contour indicates the 5% significance level against red noise (region of significance). The cone of influence (faded area) borders the region affected by edge effects. The code for power ranges from blue to red, as denoted in the colour bar (colours closer to 1.0 indicate higher power). Vertical lines mark the two significant WHO events on COVID-19—pink reveals the organization's awareness of the epidemic in China and purple represents the pandemic transition announcement. [Colour figure can be viewed at wileyonlinelibrary.com]

another asset (i.e., a fiat currency) and used as a medium of exchange. Originally existing through the Bitcoin blockchain, Tether currently exists on other networks. On the Ethereum blockchain, Tether primarily utilizes the Ethereum Request for Comment 20 token, or simply ERC-20. The ERC-20 is a standardized platform that allows fungible tokens to be created, used, transferred, and approved on the Ethereum network. Tether's main purpose is to follow a one-to-one ratio with the US dollar, and this pegging is achieved using various reserves held by the company. Essentially, the company needs to back every USDT unit minted with a portion of their assets, which mainly includes traditional currency and commercial papers. Tether Holdings Ltd. is owned by iFinex Inc., a Hong-Kong-based corporation that also owns the massive Bitfinex cryptocurrency exchange.

At first glimpse of its CWPS, there seems to be three different events during the pre-epidemic period, with no significant volatility in the post-epidemic era. These scenarios occur around the 100th (April 2017), 330th (November 2017) and 570th (July 2018) observations. In April 2017, iFinex Inc. and its subsidiaries filed a lawsuit against Wells Fargo for allegedly blocking international wire transfers (Higgins, 2017). The halt rendered Tether's banking partners unable to transfer funds outside of Taiwan. This event likely caused a major dive in Tether's currency, which dropped in value by 10% for a whole month before reverting back to its $1 equilibrium in May. USDT became turbulent as investors began panicking due to the fear that their funds might be frozen, while Tether simultaneously needed to ensure the coin's value did not collapse. The CWPS evinces that this period was volatile in the short, medium, and longer terms. On 21 November 2017, the company announced that an external hacker had breached one of its treasury wallets, stealing approximately $31 million worth of USDT (Tether, 2017). Investors panicked again but, this time, the volatility impact was only significant in the medium run, as seen around the 330th observation. Hence, not only were Tether investors afraid of their e-wallets freezing, but also that their assets might be misappropriated due to cybercrime attacks. Recall that, in December 2017, Bitcoin futures were announced. The USDT price increases slightly but the bullish period is minuscule compared to Bitcoin's surge. It is plausible to assume that investors were galvanized to purchase USDT because of confidence in Bitcoin or in the overall cryptocurrency market, fitting in with the investor demand theory. As discussed in the literature, the initial working paper of Griffin and Shams (2018) claims that Tether issuances/burns are timed exactly to match cryptocurrency downturns, so as to deliberately cause a hike in Bitcoin's price. In the first half of the infamous 2018 cryptocurrency crash, Bitcoin, and other investment tokens declined until mid-year. Coincidentally, Tether's price skyrocketed to $1.32 in July 2018, while Bitcoin's price suddenly stopped descending in this month. This phenomenon is shown in Tether's CWPS, where a thick stream of significant volatility hovers around the 570th observation, lasting until the longer term. Griffin and Shams (2018) further argue that new USDT are basically ‘unbacked digital money,’ while also suggesting that the company has inadequate reserves. On 7 November 2019, Tether rebutted a revised version of this study, claiming that the authors were unable to truly establish a proper sequence of events through which market manipulation could occur. The company makes the further clarification on its website:

> All Tether tokens are fully backed by reserves and are issued pursuant to market demand, and not for the purpose of controlling the pricing of crypto assets. It is reckless–and utterly false–to assert that Tether tokens are issued in order to enable illicit activity. Tether token issuances have quadrupled since December 2017. This growth is not a product of manipulation; it is a result of Tether's efficiency, acceptance and widescale utility within the cryptocurrency ecosystem. (Tether, 2019)

Agreeing with this statement, Wei (2018) proposes that there is no evidence to prove that Tether issuances were timed to increase Bitcoin's returns during the 2017 boom. However, these issuances could potentially increase the trading volumes of both cryptocurrencies during the short run. Assuming that market demand is what ultimately determines Tether's motives for minting and burning, then the desire for Bitcoin in 2017 likely led to investors wanting more USDT so as to make future cryptocurrency purchases. Hence, more USDT would have been minted, which explains Wei's (2018) reasoning about Tether issuances having autocorrelation that may increase both trading volumes. Eventually, Tether would then need to issue more tokens to increase supply and thus reduce its all-time-high price back to equilibrium. In August 2018 alone, the company released more than $500 million worth of USDT onto the market (Leising, 2018). The USDT market was unsettled during this mid-year period, with the CWPS showing that Tether had volatile returns until period 64.

Compellingly, Tether's post-epidemic sample does not display significant volatility in any of the horizons, with a majority of blue and green regions dominating the second half of the diagram. Many Tether-related events have occurred during the pandemic window, from its inception until now. Examples include a series of legal cases involving a US independent agency, regarding Tether's misleading usage of the term 'reserves' (Commodity Futures Trading Commission, 2021), and a recent September court order requesting it to disclose those reserves thoroughly (CourtListener, 2022). Yet, significant volatility is absent from this entire post-coronavirus sample. The announcement of lockdowns, deaths, and market closures did not disrupt USDT's returns in March 2020. The fall of TerraUSD and Luna in mid-2022, both of which were renowned cryptocurrencies, did not budge Tether's returns either. Hence, it is indisputable that Tether has become more effective in influencing its dollar-equilibrium dynamics, implying the company's maturity in monitoring price stability. As time passes, the company is gaining more experience in controlling the circulation of its tokens, and thereby reacting more quickly with new issuances and burns.

Overall, Tether's returns display significant volatility in the short, medium, and longer terms. However, these turbulences only existed during the pre-epidemic period, as revealed in the CWPS. Conditional dynamics suggest that previous events, such as cybercrime and the trading halt, affected Tether due to users quickly withdrawing from using USDT. Hence, price discovery uncovers that investors and consumers in this market were influenced by news of events pertaining to Tether as a currency, and as a company. The dynamics further suggest that USDT was marginally impacted by the rise of Bitcoin and Bitcoin futures, which may have resulted in a minor spillover onto Tether due to investor confidence. Moreover, the pandemic and related events do not seem to have distorted this token, as significant volatility remains evanescent in all time-frequency scales. Therefore, the likelihood of Tether being disrupted again by the pre-epidemic events, or events of similar types, is minimal. Unconditional volatility is non-existent throughout the entire sample, as evinced by the blue regions in the CWPS. The improvement in Tether's ability to quickly rebound towards the dollar-equilibrium suggests that returns are strongly mean-reverting, thus exhibiting zero random processes. Regarding multifractality, it is difficult to determine simple and complex fractals in this CWPS due to a deficiency of significant bubbles. Hence, the MRA will be needed to elucidate Tether's isotropy.

Figure 6 demonstrates the decomposition of Tether's log-return series, obtained using the MODWT-MRA. Glancing at this entire figure, it is obvious that stablecoins generally display far less noise than investment tokens. Unlike in the CWPS, the three short-term scales in the MRA reveal the presence of multifractality in Tether. In the D1 view, we notice the three pre-coronavirus events significantly impacting Tether's returns. The largest crest and trough occur around the 570th observation (July 2018), when Tether rapidly reached an all-time high before immediately dropping back to the dollar-equilibrium the next day. These spikes coincide with the thickest stream of red power in the CWPS. Strangely, we see that there is a minor disturbance around the 1170th observation (March 2020), when news of international contagion began to emerge.

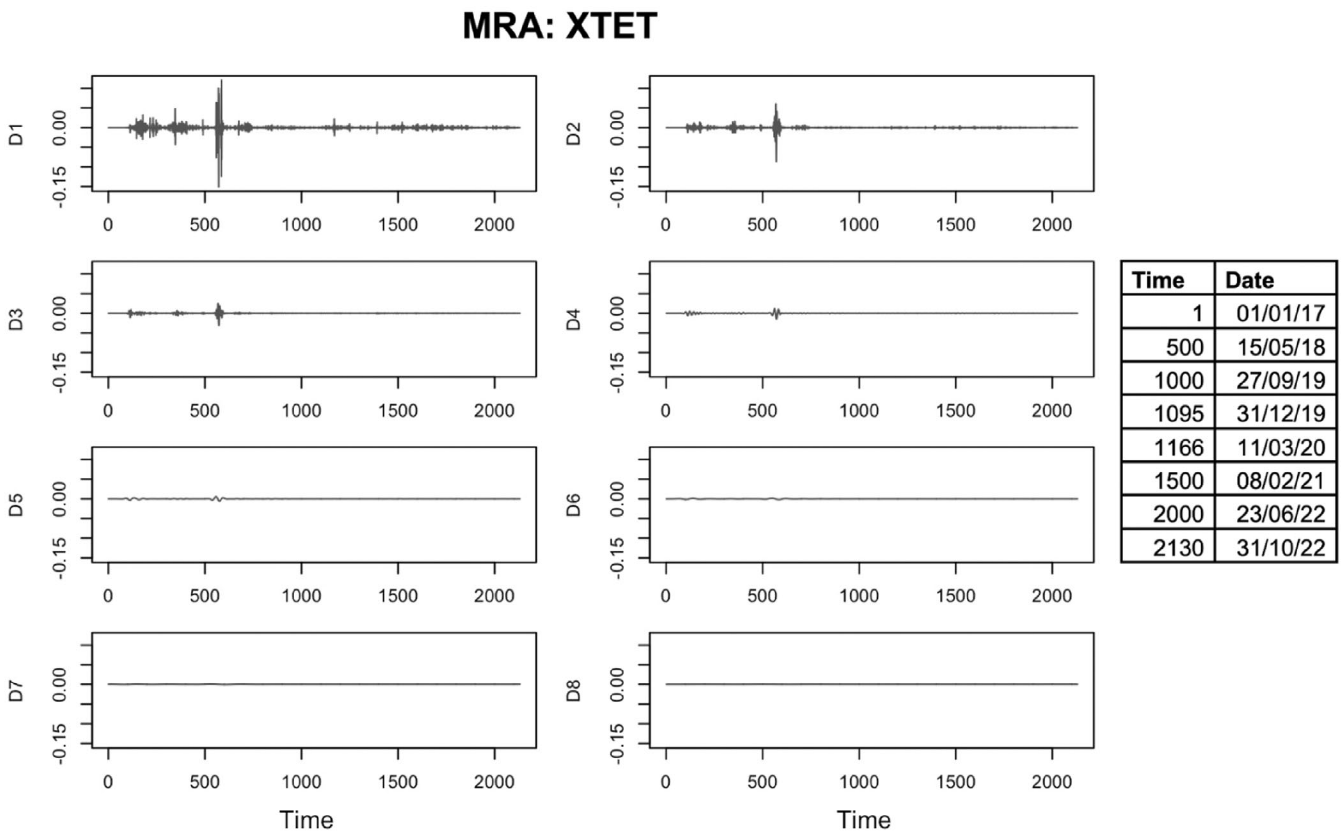


FIGURE 6 This figure presents the multiresolution analysis (MRA) of Tether's (XTET) log-return series from 1 January 2017 to 31 October 2022, using the maximal overlap discrete wavelet transform (MODWT). The y-axis denotes the multiscale movement of returns. The series is decomposed using the Daubechies wavelet filter with length of 8, at a scale level of $J = 1$ to 8 (or a period of 2–256). The periodic boundary condition is implemented as a solution for the wavelet coefficients at the endpoints.

Just as the CWPS reported no concrete significance at this time, the MRA suggests that there was indeed some level of distortion in Tether's short-term returns but too little for it to be considered a significant event. The remaining short scales in D2 and D3 show no additional information besides the three pre-epidemic incidents. The medium-term scales and D6 display that the Wells Fargo lawsuit and Tether's all-time record are likely to have impacted returns until the longer term. In contrast, Bitcoin's bullish period, Bitcoin futures, and the cyber-crime attack on Tether's treasury only affected Tether in the short and medium terms, which is in line with the CWPS. D7 unveils an extremely small wave of Tether's all-time high, but it is not easily noticeable. Finally, the D8 scale demonstrates unconditional volatility regarding Tether's annual cycles. Although USDT received shocks during the pre-epidemic period, the ramifications are nowhere near as persistent as those in Bitcoin's and Ethereum's markets. This result explains the overall nature of Tether, in that it is a stablecoin for consumers, rather than an investment asset aimed purely at traders wanting to participate in a single market. Showing complex fractals in the short run, Tether's returns signal the presence of strong reversions. These cycles exhibit pure zero-mean properties in the long run, as waves are completely absent from the D8 scale. This scale concurs with the dominating blue and green regions of Tether's CWPS. Nevertheless, Tether's fat-tailed distribution, determined from the descriptive data, mixed with the self-similar and self-affine fractals from the MODWT short scales, implies that Tether shows multifractal volatility.

4.2.4 | USD Coin (XUSC)

Figure 7 evinces the log-return series movement of USD Coin, obtained using the CWT-CWPS. USD Coin was founded by Coinbase and Circle Internet Financial Ltd. (i.e., Circle), issued by the latter, and managed by an institution named Centre. Like Tether, USD Coin utilizes the ERC-20 platform, and its sole purpose is to be a peer-to-peer payments system for consumers to use as an alternative medium. As USDT is the common term for

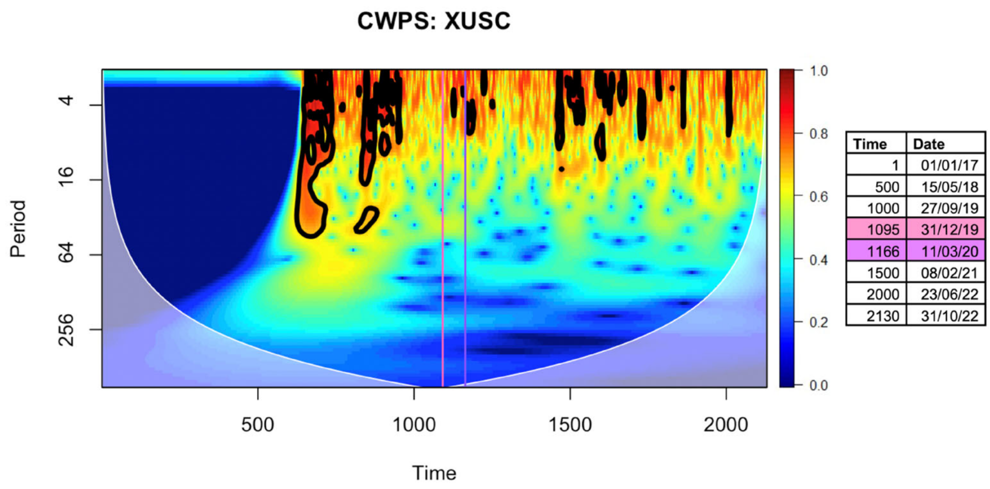
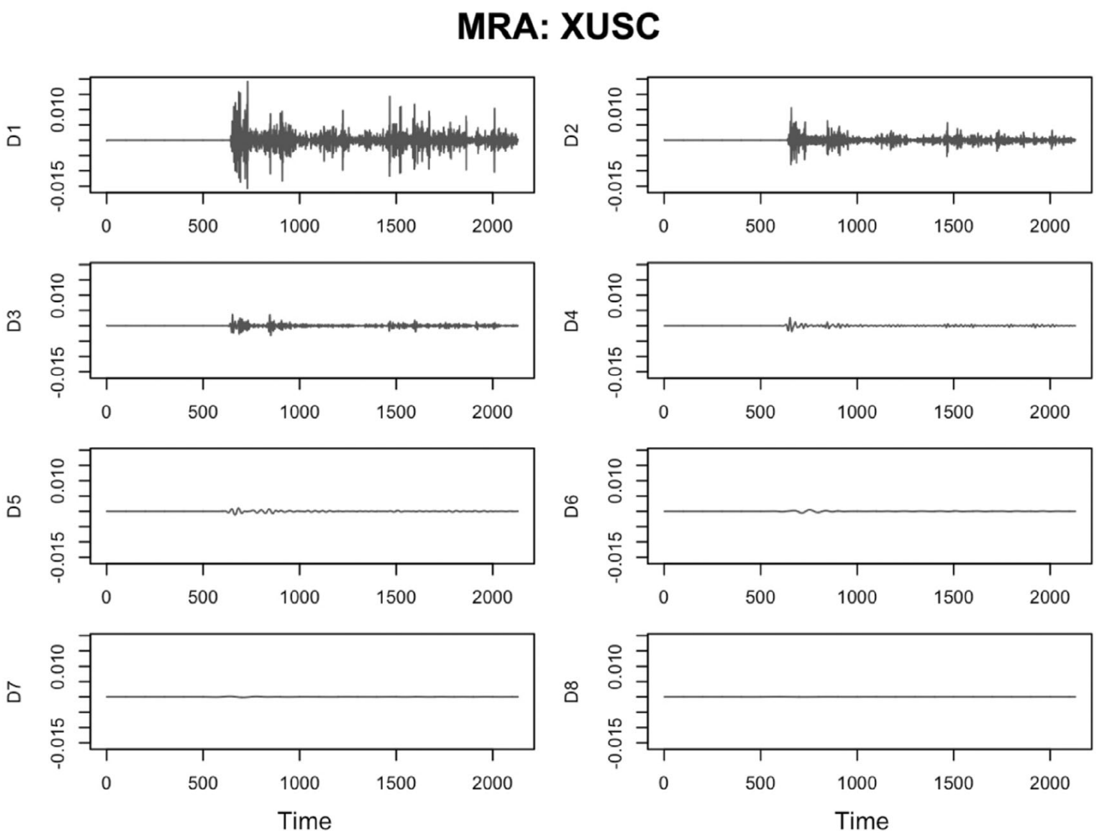


FIGURE 7 This figure shows the continuous wavelet power spectrum (CWPS) of USD Coin's (XUSC) log-return series from 6 October 2018 to 31 October 2022, using the continuous wavelet transform (CWT) with Morlet wavelet application. The thick black contour indicates the 5% significance level against red noise (region of significance). The cone of influence (faded area) specifies the region affected by edge effects. The code for power ranges from blue to red, as denoted in the colour bar (colours closer to 1.0 indicate higher power). Vertical lines mark the two significant WHO events on COVID-19—pink reveals the organization's awareness of the epidemic in China and purple represents the pandemic transition announcement. [Colour figure can be viewed at wileyonlinelibrary.com]

Tether's currency, USDC is commonly used to refer to USD Coin's currency. Although this cryptocurrency was launched in September 2018, our price data from CoinGecko date back only to 5 October 2018, the earliest point at which information was available. Hence, we begin our analysis at the 644th observation.

At first sight, USDC exhibits a tumultuous period when it first sprawled onto the cryptocurrency market prior to the epidemic. These disturbances seem to extend until around the 920th observation (July 2019). The significant volatility suggests that both investors and consumers may have been swift to make large purchases of USDC upon its release date and in the weeks that followed. The price upswing to $1.04 in October 2018 led to Centre bringing the USDC price down to the dollar-equilibrium immediately. Yet, the currency reached the same peak again in November, indicating high demand for the stablecoin. As the company receives more USD deposits, more USDC are issued. Therefore, market supply increases along with trading volume. Keeping up with market demand is perhaps the main reason for its volatile infancy period. By December 2019, Circle had already minted $519.6 million worth of USDC, while simultaneously having $520.5 million in reserves, thus possessing assets that exceeded its liabilities for collateralization (Lyons & Viswanath-Natraj, 2021). In USD Coin's CWPS, only during this pre-epidemic window is volatility shown persevering until the medium run, whereas in the post-epidemic era it displays short-term variation at the most. The gradual progression indicates that Centre becomes better at monitoring the movement of its currency, yet the token seems to be far from the mature stablecoin Tether is. In USD Coin's post-epidemic sample, significant short-term noise is evident during March 2020, which is likely due to investors being perturbed by news of the international COVID-19 outbreak. Traders were either (1) investing more into USD Coin as a safe haven or (2) exiting the USD Coin market due to anxiety about the global sentiment during this time. Harmony followed throughout the second half of 2020, but short-term volatility reappeared in January 2021 with consistency, demonstrating a contrast with Tether's market. This comparison is fascinating because, unlike USDT, USDC displays transitory shocks indefinitely, which are absent for the prime stablecoin. Nevertheless, we must note that Tether is a much older company than Centre, and therefore has more experience in influencing market-equilibrium dynamics through token issuances/burns, forecasting demand, and backing its respective asset.

Overall, USD Coin's returns display significant volatility in the short, medium, and longer terms. However, these disturbances were likely due to the inception of USDC as the ultimate competitor to USDT, resulting in market hype from investors. As the price increases due to surging demand, the major disruption to the returns may also have been due to rapid token issuances during USD Coin's infancy year, which would explain the constant disequilibrium. Conditional dynamics propose that these shocks have generally decreased since its youthful period, but



Time	Date
1	01/01/17
500	15/05/18
1000	27/09/19
1095	31/12/19
1166	11/03/20
1500	08/02/21
2000	23/06/22
2130	31/10/22

FIGURE 8 This figure presents the multiresolution analysis (MRA) of USD Coin's (XUSC) log-return series from 6 October 2018 to 31 October 2022, using the maximal overlap discrete wavelet transform (MODWT). The y-axis denotes the multiscale movement of returns. The series is decomposed using the Daubechies wavelet filter with length of 8, at a scale level of $J = 1$ to 8 (or a period of 2–256). The periodic boundary condition is implemented as a solution for the wavelet coefficients at the endpoints.

nevertheless recur in the short term. The dynamics further unveil that USD Coin was likely impacted by the global pessimism of lockdowns, deaths, and market closures due to COVID-19. These effects show significant volatility in USD Coin's CWPS, whereas Tether's diagram shows zero effects at this crucial moment. Although a stablecoin is used by investors and consumers for its price stability, our price discovery suggests that USDC is not as stable as USDT. The short-term volatility due to significant deviations from the dollar-equilibrium repeats throughout the entire sample, and hence is unlikely to become non-existent over time. The regular and irregular short-term variations also indicate the presence of multifractality. Like Tether, USD Coin's returns do exhibit mean reversions. However, the later efficiency tests will identify which of these stablecoins contains stronger mean-reverting cycles between successive returns. This result suggests that USD Coin is an inefficient market, but its returns are potentially more random than Tether's. Regardless, USD Coin's unconditional volatility is absent, with blue and green regions dominating the long scales of the CWPS.

Figure 8 presents the decomposition of the USD Coin's log-return series, using the MODWT-MRA. Starting from USD Coin's earliest available return (644th observation), we compare the D1 scale of USDC to the D1 scale of USDT. It is obvious that USD Coin exhibits far more short-term volatility in its returns than does Tether. In fact, its short-term returns are more akin to Bitcoin's and Ethereum's than to Tether's. This outcome is astonishing since we would expect USDC, a stablecoin, in its daily price changes, to follow another stablecoin such as Tether. Even looking at USD Coin's D2 and D3 scales, Tether's D1 scale is still more stable, which is eye-opening. Moreover, the D2 and D3 scales reveal that USDC contains a mixture of self-similar and self-affine fractals, thus confirming the presence of multifractality. The unceasing noise in the short-term scales highlights that USD Coin is far from being a mature stablecoin as Tether is. The peak and trough occur during its infancy year around the 720th observation, according with the thick volatility stream in the CWPS. Following a short period of tranquillity afterwards, returns become mildly turbulent with the announcement of the pandemic in March 2020. D4 and D5 reveal that medium-term volatility drops extraordinarily in magnitude. In fact, USD Coin's D4 and D5 are more similar to Tether's medium run, rather than those of the two investment tokens, as Bitcoin and Ethereum still exhibit persistent trends. The longer-term scales in D6 and D7 show no new information, besides a minimal slump during its emergence in 2018. Finally, the D8 scale demonstrates unconditional volatility regarding USD Coin's annual nature. Although USD Coin experienced deep shocks during the pre-coronavirus period, these impacts were likely due to its introduction onto the cryptocurrency market, whereupon investors became bullish regarding the stablecoin. Furthermore, these turbulences are nowhere near as aggressive as the shocks found in Bitcoin and Ethereum, yet this token is still not as stable as Tether. Remarkably, it is as if USD Coin falls in between these two cryptocurrency categories–possessing short-term volatility like investment tokens, but long-term volatility like stablecoins. Nevertheless, the returns signal the presence of volatility reversions. As with Tether, these cycles exhibit pure zero-mean properties in the long run, as waves are absent in the D8 scale. This scale concurs with the blue and green regions of its CWPS. USD Coin's fat-tailed distribution, determined from the descriptive data, mixed with the self-similar and self-affine fractals from the MODWT short scales, suggests that USD Coin has multifractal volatility.

4.3 | Market efficiency and dimension analyses

In this section, we briefly analyse the market efficiency and dimension level of the four cryptocurrencies during the post-epidemic period. The previous wavelet analysis explains how strong volatility is at a specific time-frequency point. However, unlike the wavelet transform, market efficiency tests can tell us how predictable a series is based on the probability of its successive movements. In essence, these tests describe how likely it is for a positive (negative) change to be *immediately* followed by the next positive (negative) change. If both are flowing in the same direction then they are persistent, while they are anti-persistent (i.e., mean-reverting) if they are flowing inversely.

Table 2 displays the efficiency and dimension tests used to measure the long-range dependence of the four cryptocurrencies. Panel A shows the R/S and V-statistic analyses, while Panel B summarizes the Hurst exponents and fractal dimensions. In Panel A, the subsamples are scaled based on the number of observations they contain–for example, a subsample of '2' splits the sample size of 1024 observations into halves (n = 512), one of '4' splits it into quarters ($n = 256$), and so on. The $log(R/S)_n$ shows that both investment tokens generally have higher values than the stablecoins, indicating large differences in mean rescaled returns. The V-statistic output converts the corresponding R/S values into meaningful solutions which yield expected trends–it will be discussed alongside Figure 9 in the next paragraph. In Panel B, Bitcoin reveals the highest Hurst exponent (0.62914), while Tether displays the lowest (0.36255). This result indicates that Bitcoin possesses the longest memory, while Tether has the greatest amount of mean reversion. Ethereum shows persistence, but less clustering than the prime cryptocurrency. USD Coin's Hurst approximation suggests that it is slightly more random than the prime stablecoin, but nevertheless mean-reverting. All Hurst exponents are significant at the 1% level based on the two-tailed t-distribution. The fractal dimension reveals that both investment tokens simulate one-dimensional lines and curves (i.e., smoother trends), whereas both stablecoins mimic two-dimensional planes and boxes (i.e., jagged edges).

Figure 9 presents the V-statistic diagrams of all four cryptocurrencies, corresponding to the values found in Panel A of Table 2. This figure reveals expected trends for the four assets, verifying their respective Hurst exponents, and hence providing robustness to the efficiency results. It is evident that both investment tokens project an upward trend, which indicates long memory. With Bitcoin having a steeper slope (0.1333), this outcome confirms that the prime cryptocurrency shows more persistence than Ethereum (0.0985). Conversely, both stablecoins project a downward trend, which validates mean reversion. With Tether having a steeper downward slope (−0.0766), this value confirms that the prime stablecoin presents more mean-reverting cycles than USD Coin (−0.0693), making the latter slightly more efficient than the former. Nevertheless, in the long run, none of the four cryptocurrencies is market-efficient, due to the absence of significant randomness. Investment tokens present volatility clusters where high (low) values are expected to be followed by subsequent high (low) values, whereas stablecoins present volatility reversals, such that high values attract low values and vice versa. These efficiency results are in line with and support the volatility findings of the wavelet models, particularly in the post-epidemic period. We expect these idiosyncratic trends to continue in the future.

TABLE 2 Market efficiency and dimension analyses

Panel A: Decomposition summary of R/S and V-statistic									
Subsamples		2	4	8	16	32	64	128	256
Observations (n)		512	256	128	64	32	16	8	4
Log (n)		6.23832	5.54518	4.85203	4.15888	3.46574	2.77259	2.07944	1.38629
Log $(R/S)_n$	XBTC	3.46860	3.02433	2.55155	2.17027	1.75462	1.36253	0.84986	0.35771
	XETM	3.27232	2.95597	2.61544	2.20570	1.79171	1.34487	0.86842	0.36418
	XTET	2.14362	1.95234	1.80646	1.59109	1.32240	1.06184	0.75530	0.34303
	XUSC	2.23973	2.07184	1.79480	1.55726	1.32548	1.06923	0.77466	0.34151
V-statistic	XBTC	1.41826	1.28627	1.13375	1.09509	1.02199	0.97651	0.82708	0.71503
	XETM	1.16551	1.20127	1.20855	1.13457	1.06061	0.95942	0.84257	0.71967
	XTET	0.37699	0.44032	0.53818	0.61364	0.66334	0.72292	0.75245	0.70461
	XUSC	0.41502	0.49621	0.53195	0.59323	0.66538	0.72828	0.76716	0.70354

Panel B: Summary of Hurst and fractal dimension				
Cryptocurrency	**XBTC**	**XETM**	**XTET**	**XUSC**
H	0.62914	0.60147	0.36225	0.38097
SE_H	0.00997	0.01824	0.02202	0.01692
t-statistic	12.95401	5.56322	−6.25672	−7.03631
p-value	0.00130%*	0.14285%*	0.07733%*	0.04118%*
Fractal dimension	1.37086	1.39853	1.63775	1.61903

Note: This table displays the market efficiency and dimension tests of Bitcoin (XBTC), Ethereum (XETM), Tether (XTET), and USD Coin (XUSC) during the post-epidemic era. The sample period covers from 12 January 2020 to 31 October 2022 (i.e., 1024 daily return-observations) for each token. Panel A overviews decomposition of returns using the R/S analysis and V-Statistic. Panel B summarizes the classical Hurst exponents and fractal dimensions. The * denotes the significant p-values (at 1% level) by using the two-tailed t-distribution when assessing major deviations from expected Hurst ($H = 0.5$).

4.4 | Summary of key findings

For the reader's ease, we tabulate the key takeaways from this article:

1. Tether and Bitcoin are the least and most volatile cryptocurrencies respectively.
2. Juxtaposing the two cryptocurrency categories, investment tokens exhibit greater significant volatility than stablecoins in all time-frequency scales. Investment tokens are extremely persistent, whereas stablecoins are highly anti-persistent.
3. Comparing the investment tokens, Bitcoin and Ethereum do not present the same level and direction of fractal volatility due to events that impact them uniquely. Bitcoin is more persistent and unconditionally volatile than Ethereum. The significant volatility fractals suggest that Bitcoin possesses greater self-affinity, while Ethereum contains more self-similarity.
4. Comparing the stablecoins, Tether and USD Coin do not show the same level and direction of fractal volatility either, due to the former's stability in the short run. Tether is more anti-persistent than USD Coin.
5. USD Coin displays short-term turbulence that is akin to that of the investment tokens, but simultaneously demonstrates unconditional volatility that is similar to that of stablecoins. Hence, its processes are generally more random than those of Tether's, but only marginally.
6. Based on the domestic epidemic window, none of the four return series shows evidence that investors overreacted when the WHO were initially informed of the disease's existence in China.
7. All cryptocurrencies, except Tether, absorbed significant disruption at the time of the WHO's announcement of COVID-19's pandemic transition.
8. All cryptocurrencies possess multifractal volatility. The self-similarity and self-affinity are scale-dependent, and heterogeneous across the tokens. While it is easier to identify multifractals in investment tokens due to their significant volatility, stablecoins also project these complex fractals but the amplitudes are diminutive.

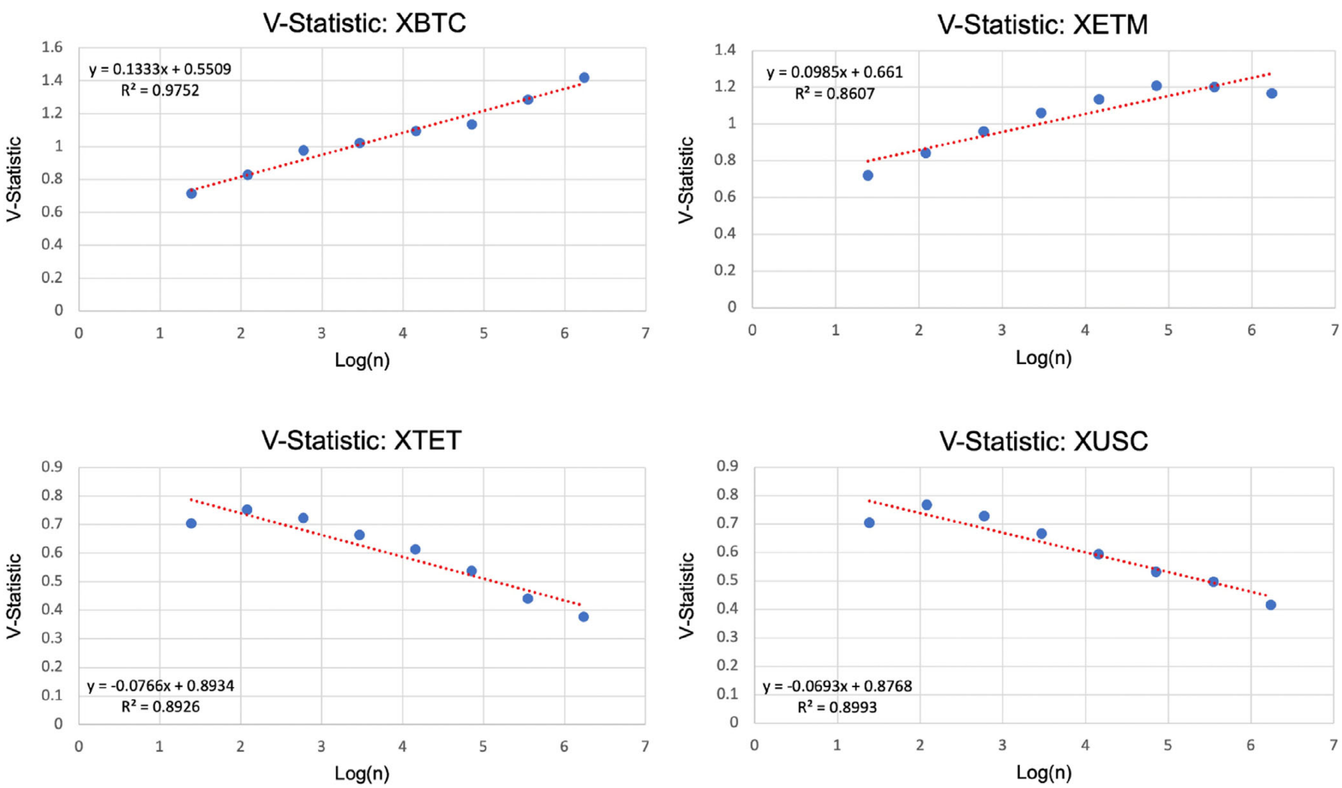


FIGURE 9 This figure presents the V-Statistic diagrams of Bitcoin (XBTC), Ethereum (XETM), Tether (XTET) and USD Coin (XUSC) during the post-epidemic period. An estimated line of best fit is deployed to examine the overall trend of each cryptocurrency. An upward trend confirms the Hurst approximation of long memory, vice versa a downward trend verifies mean reversion. A horizontal line would attest that the series follows a random walk. [Colour figure can be viewed at wileyonlinelibrary.com]

9. The fractal dimension reveals that investment tokens imitate one-dimensional lines and curves, which show smooth trends. In contrast, stablecoins mimic two-dimensional planes and boxes, which display jagged edges.

5 | DISCOURSE

5.1 | Extending the literature

Based on our results, it is axiomatic that most cryptocurrency traders are not rational, nor do they all possess the same level of information and horizon, especially when comparing retail and institutional investors. As Fang et al. (2020) elucidate regarding the factors that drive cryptocurrency prices, market sentiment plays a major role in investment decisions and more so than fundamentals, which our results confirm and agree with. These factors render the traditional EMH inapplicable and thus lead our analysis towards incorporating cognitive biases of investors (e.g., overconfidence, overreaction, confirmation bias etc.). Although the adaptive market hypothesis (AMH) also includes these biases, the AMH assumes that the primary objective of market participants is to survive, with the making of excess gains a second priority (Lo, 2005). Hence, the FMH is more favourable for explaining our study.

Published before Bitcoin's 2017 climb, early EMH papers on cryptocurrencies, such as Bartos (2015) and Urquhart (2016), claim that the prime cryptocurrency is becoming more efficient. However, these works may no longer be relevant due to the multitude of events that have occurred in the past 6 years, as our study has uncovered. Extending these works are Al-Yahyaee et al. (2020) and Noda (2021), analysing tokens' efficiency before the existence of COVID-19. Al-Yahyaee et al. (2020) claim that all investment tokens exhibit multifractality and long memory. In accordance with this, Bitcoin and Ethereum show no signs of developing efficiency and monofractality after 3 years of the epidemic. Noda (2021) claims that Bitcoin is generally more efficient than Ethereum, and we extend these results by contending that Bitcoin is less efficient than Ethereum based on our post-epidemic sample. Continuing on from these works, newer efficiency papers observe cryptocurrencies after the introduction of the coronavirus. Naeem et al. (2021) argue that inefficiency of cryptocurrencies was normal before COVID-19, but Bitcoin and Ethereum were deeply affected by the introduction of the disease. Our Hurst approximations concur, as we see that strong inefficiencies continue for both investment tokens. Kakinaka and Umeno (2022) posit that after the domestic COVID-19 outbreak, inefficiency was present in the short term for Bitcoin and Ethereum during 2020. However, they assert that efficiency is progressing in the long run. Extending this result with 2021 and 2022 data, our study in contrast shows that both investment tokens display inefficiency from a long-term perspective. While our CWPS models agree with those authors' claims of short-term herding behaviour, the presence of long memory in Bitcoin and Ethereum allows passive investors to occasionally hold positions (i.e., long entry and exit points). Hence, random walks are unconditionally absent. Fernandes et al. (2022) similarly claim that Bitcoin and Ethereum display efficiency, with a sample ending on 31st December 2021. Our findings oppose theirs, as the augmented pandemic sample demonstrates that long-term efficiency does not improve for either token as we head towards the year 2023. With respect to market efficiency, we add to these studies with our recent findings. Investment tokens (Bitcoin and Ethereum) trend greatly, whereas stablecoins (Tether and USD Coin) strongly switch directions when reverting to a baseline mean. These inefficiency results ultimately assert that cryptocurrencies, in general, are predictable and thus do not exhibit stochastic processes. The predictability allows investors to engage in arbitrage regardless of token category, and hence gain abnormal returns.

With regard to general volatility, it is apodictic that investment tokens explode while stablecoins maintain a fragmentation during mean-deviating cycles. As Gradojevic and Tsiakas (2021) propose, significant volatility tends to cascade from long to short horizons, but there is no evidence of the reverse causality. Consistent with this theory, our CWPS shows investment tokens on one timescale exhibiting both transient and prolonged clusters, but we rarely observe moments on another timescale where long volatility is present while short and medium turbulences are non-existent. Hence, not all transitory shocks will lead to significant unconditional volatility for Bitcoin and Ethereum. Lucey et al. (2022) describe how news of key events creates uncertainty in the overall cryptocurrency market, examples being China's ban and the introduction of Bitcoin futures in September and December 2017, respectively. In our wavelet analyses, these two events are clearly imperative for Bitcoin, Ethereum, and Tether, suggesting that returns were significantly unstable at this time. While young Tether was impacted, the effects were ephemeral, as the stablecoin rebounded between the two events, whereas Bitcoin and Ethereum showed long-term volatility with lingering shocks during this four-month window. Regarding COVID-19, Corbet et al. (2022) state that price volatility in cryptocurrencies was not perceptible during the epidemic in China, but only emerged when the international outbreak occurred. Our results agree with this–Bitcoin and Ethereum show no significant volatility during the inception of the domestic epidemic, but solely when the disease transitions into a pandemic. In addition, we extend by claiming that Tether displays no tumultuous behaviour during either COVID-19 era, whereas USD Coin presents short-term volatility after the pandemic announcement. This finding indicates that stablecoins show idiosyncratic properties and may not behave exactly like each other, thus following their own unique paths.

Finally, we end with fractal volatility. It is evident that multifractals of cryptocurrency returns exist and are dependent on various frequency scales. Delfin-Vidal and Romero-Meléndez (2016) suggest that Bitcoin displays recurring volatility patterns, and these patterns maintain regular and irregular shapes as the scales are shifted. Six-years later, our study is in line with them, and shows that Bitcoin reveals evidence of self-affine and self-similar fractals. However, Bitcoin seems to project more of the former monofractal than the latter type, indicating that patterns are marginally distorted with an unequal volatility distribution across each scale. Extending this outcome with Bitcoin's ultimate competitor, our Ethereum results unveil more self-similarity than do the Bitcoin results, as these patterns tend to retain their overall shape under scale invariance. Nonetheless, these significant fractals only persist until the medium and longer terms, thus not being unconditional. Lastly, Celeste et al. (2020) believe that Bitcoin's fractal dynamics evanesce over time. Adding to this with our post-coronavirus sample, we find the contrasting result that Bitcoin displays no signs of either monofractal ever dissipating.

5.2 | Avenues for future research

As we have thoroughly examined the fractal volatility of these cryptocurrencies, some suggestions can be considered which are beyond the scope of this research. Hence, two recommendations will now be made for future avenues pertaining to these four tokens. First, since this article solely analyzes returns and thus price changes, it does not examine changes in trading volume. In essence, this study does not measure the changes of liquidity within each investment token and stablecoin. With respect to trading volume, it would be interesting to see future research replicating the same variables and timeframe as this study–instead of volatility, focusing perhaps on

(1) liquidity of aggregating/segregating various cryptocurrency-to-fiat pairs, and (2) liquidity based on crypto-exchanges that distribute the token within and across different countries. While measuring price dynamics is a good indicator of demand, evaluating trading volume completes the former by revealing the friction of an asset during different market regimes. Hence, future studies that mirrored our chosen variables and sample length would add to our paper through providing an understanding of tokens based on their liquidity levels during pre- and extended post-epidemic periods.

Second, although this paper has briefly examined market efficiency with 3 years of post-epidemic data, it has solely observed long-range dependence and not multiple ranges. In other words, this paper does not focus on fractal efficiency but rather inspects predictability from a long-term point of view. As previous papers have discussed fractal efficiency (e.g., Al-Yahyaee et al., 2020; Kakinaka & Umeno, 2022; Naeem et al., 2021), it would be intriguing to update these works using the latest available data, enveloping a multitude of recent events not covered by those studies. Moreover, these fractal efficiency papers mainly (1) analysed the infancy periods of COVID-19 and (2) monitored investment tokens without considering true stablecoins. Since our paper assumes the simplicity of a converging monoscale process and thus a conditional Hurst, it would be interesting if future researchers observed cryptocurrency dependence through rolling fractal dimensions within each post-epidemic year. Essentially, it would provide an update on whether these investment tokens and stablecoins dynamically improve or deteriorate in efficiency across different market conditions, while highlighting moments of anisotropy.

6 | CONCLUSION

Our research is inspired by the notion that alternative assets can either be a medium of exchange, or a financial tool for investment. Cryptocurrencies, in essence, can fall into either one of the two categories but rarely ever both, due to their different mechanics and purposes. Bandwidths in stablecoins are intended to project fixed prices indefinitely from a governing entity, whereas unrestricted pricing in investment tokens is designed to be purely determined by the strength of market demand. In this paper, we examined two investment tokens, Bitcoin and Ethereum, as well as two stablecoins, Tether and USD Coin. As of today, these top four cryptocurrencies form the largest market share of their asset group. Specifically, we conducted fractal volatility analyses of these tokens by applying the continuous wavelet transform and the maximal overlap discrete wavelet transform to their daily returns. We then employed efficiency and dimension tests to examine their long memory properties and geometric patterns. Our paper did not scrutinize bivariate volatility spillovers, but rather undertook an approach to individual volatilities of distinguishable cryptocurrencies, thus discovering unique characteristics that we could learn from their past behaviour. The magnificence of the CWT therefore allowed us to compare these tokens' fractals, while the MODWT complemented with its ability to see distinctive amplitudes between frequency-varying timescales.

Our findings suggest that Tether exhibits the least overall volatility throughout the time-frequency spectrum, in comparison to its investment counterparts and USD Coin. As stablecoins are expected to closely replicate the movements of traditional fiat currencies, we can further segregate USD Coin and Tether based on their growth and inception. USD Coin presents short-term volatility for an indefinite period, in contrast to the largest and most mature stablecoin that is Tether. This distinction is likely due to the latter's long-term experience in influencing market equilibrium through token issuance and trade responses, and thus its better price stability. In the post-epidemic sample, both stablecoins show strong anti-persistence, with USD Coin showing marginally better efficiency. However, the statistical significance of the Hurst exponent suggests that these stablecoins are still deeply inefficient. Conversely, investment tokens display persistent volatility clusters due to the presence of long-term fundamental institutions and retail traders who have different investment horizons. Although these tokens illustrate multifractal volatility with scattered variation, Bitcoin exhibits more evidence of self-affinity, while Ethereum reveals a greater amount of self-similarity. Hence, there is no definitive proof that traders in Ethereum's market truly duplicate every Bitcoin move. Policy-related events that solely pertain to Ethereum (currency-wise and company-wise) differ to those affecting Bitcoin, and therefore these events will impact the two tokens differently. The fractal patterns demonstrate that both return series move incongruously, as Bitcoin is more turbulent than Ethereum. Conditional dynamics imply that none of the cryptocurrencies reacted when the WHO were informed of COVID-19's existence in China. However, all cryptocurrencies except Tether were affected by the pandemic transition of the virus and macroeconomic news regarding it. The unconditional volatility of the stablecoins evinces zero-mean errors, antithetical to investment tokens exhibiting yearly cycles. The fractal dimension suggests that investment tokens imitate one-dimensional lines and curves, whereas stablecoins mimic two-dimensional planes and boxes. The volatility differences between the two investment tokens are marginal, whereas the dissimilarities between the two stablecoins are highly noticeable. Nevertheless, the volatility difference between the two cryptocurrency categories is night and day.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no personal relationships or competing financial interests that could have influenced the results and conclusions of this study.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study can be retrieved from CoinGecko. The data is freely accessible on the website with no subscription requirement.

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ENDNOTE

[1] To correct for potential bias, CoinGecko uses a global volume-weighted average price for each cryptocurrency on each crypto-exchange. Crypto-exchanges are ranked based on their 'trust scores,' which include internet traffic, total trading volume, order book spread, trading frequency and checking for outliers. Therefore, priority is given to both (i) the liquidity reliability of each crypto-exchange, and (ii) the liquidity reliability of each cryptocurrency on the relevant exchange. This information can be found in the links below: https://www.coingecko.com/en/faq https://www.coingecko.com/en/methodology#:~:text=Market%20Data,1.,volume%2Dweighted%20average%20price%20formula Furthermore, the robustness of a reputable cryptocurrency data provider such as CoinGecko has been confirmed by Vidal-Tomás (2022), who states that this historical data source is reliable for conducting cryptocurrency research.

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