Pricing efficiency in cryptocurrencies: the case of centralized and decentralized markets

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Abstract

This article presents a comparative analysis of Ethereum (ETH) market efficiency priced in Bitcoin (BTC), Dai (DAI), and Tether (USDT). The investigation encompasses data obtained from both UNISWAP-V2, a decentralized app utilizing liquidity pools for cryptocurrency pricing, and Binance, a centralized exchange. The study employs a rolling window procedure to apply the MF-DFA, utilizing 256, 384, and 512 observation window sizes. The efficiency of exchange pairs is ranked using the market deficiency measure (MDM). Our findings align with existing literature, revealing an efficiency increase with larger rolling window sizes across centralized and decentralized exchanges. Notably, ETH priced in BTC, DAI, and USDT in decentralized exchanges demonstrates greater efficiency than centralized exchanges for window sizes of 384 and 512 observations. At 256 observations, this efficiency is exclusive to BTC pricing. To delve deeper into this phenomenon and explore the dynamics between distinct pricing mechanisms, the Thermal Optimal Path is employed. The analysis highlights a lead-lag relationship between ETH prices in centralized and decentralized exchanges. The results suggest that market efficiency emerges first in the decentralized exchange, particularly when ETH is priced in BTC. This analysis is crucial for enhancing our understanding of evolving financial ecosystems, guiding regulatory considerations, and empowering market participants to navigate the complexities of both decentralized and centralized trading environments.

Keywords: Ether (ETH), market efficiency, centralized and decentralized exchanges, price dynamics.

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1. Introduction

In recent years, cryptocurrency market efficiency has sparked considerable debates, concerning both Bitcoin (BTC) (Urquhart, 2016; Nadarajah & Chu, 2017; Vidal-Tomás & Ibañez, 2018; Nan & Kaizoji, 2019; Zargar & Kumar, 2019) and Ether (ETH) (Naeem et al., 2021; Kakinaka & Umeno, 2022). Significant consequences are at stake for both market participants and governmental decision-makers. This is largely due to the rise of cryptocurrencies, which can be considered an alternative to conventional government-backed currencies and a novel digital asset for investment purposes. Bitcoin is the leading cryptocurrency in market capitalization and trading volume, closely followed by Ethereum in the second position. These two digital forms of currency hold considerable appeal for researchers and investors alike.

However, majority of research's rely solely on data obtained from centralized exchanges or price aggregators. Cryptocurrencies, by design, are often based on decentralized principles, aiming to eliminate the need for central intermediaries. Relying solely on centralized data sources can provide a skewed view of how these systems operate and evolve. Moreover, blockchain, as a highly dynamic environment, can change rapidly. Thus, depending solely on centralized data sources may result in inaccuracies when seeking information about the impacts of modifications to the Ethereum blockchain, including forks and updates implemented in smart contracts within Decentralized Exchanges (DEX) and Efficient Market Hypothesis (EMH) in cryptocurrencies

Furthermore, studying the formation of pricing dynamics in liquidity pools holds significant importance as it unveils the intricate mechanisms governing decentralized finance ecosystems. Delving into these dynamics elucidates how these pools respond to supply and demand fluctuations, thus offering insights into the efficiency and accuracy of price discovery processes (Pani, 2021). Understanding these dynamics aids in evaluating risks associated with impermanent loss and empowers investors with informed decision-making tools (Heimbach et al., 2022). It provides crucial data for designing resilient DeFi protocols, detecting market manipulation, and fostering regulatory transparency (Bellare & Rogaway, 1993; Chohan, 2021). Investigating pricing dynamics in liquidity pools is a cornerstone for comprehending the evolving landscape of decentralized finance and shaping its future development. Moreover, it allows policymakers to adopt a deliberate strategy when addressing a market founded on innovative principles.

Researchers typically focus on comprehending the evolution of security prices (Belaire-Franch & Opong, 2005). Investors and practitioners, including arbitrageurs, hedgers, and speculators, are more inclined to identify market inefficiencies that can potentially be capitalized upon. On the other hand, the primary objective of policymakers and regulators [1] in the case of Binance and blockchain-based financial institutions (such as UNISWAP) is to elevate the pricing efficiency of financial assets by enhancing the velocity at which information circulates within the financial markets where ETH (alongside other cryptocurrencies) is exchanged.

Information velocity can also be enhanced, alongside Decentralized Finance (DeFi) pricing mechanism distinctions, by market transparency (O'hara, 1998; Malinova & Park, 2017), which is a fundamental trait inherent in the concept of the decentralized financial sector. According to Biais (1993), the transparency of quotations may lead to higher market efficiency and liquidity. Within centralized systems, the integration of markets could lead to implementing

[1] In the US the Security and Exchange Commission (SEC), Financial Crimes Enforcement Network (FinCEN) and Commodity Futures Trading Commission (CFTC).

regulations that compel dealers to make their past trades public (Madhavan, 1995, 1996). This level of transparency is already accomplished in public blockchains. UNISWAP platform is established upon confidence in their code and smart contracts, in contrast to the conventional trust-dependent financial system that leans on institutions and human engagement. In order to emphasize the role of market transparency, it is worth noting that the stablecoin Dai (DAI) operates under the governance of MakerDAO (Sun & Stasinakis, 2021), a Decentralized Autonomous Organization (DAO) Chohan (2017); Wang et al. (2019); Hassan & De Filippi (2021) responsible for both creating and managing this stablecoin cryptocurrency.

The difference between price dynamics and the presence or absence of market efficiency in decentralized prices of ETH is investigated in this research. The hypothesis was instigated from the difference between centralized (Binance) and centralized (UNISWAP-V2 (Adams et al., 2020)) exchange pricing mechanisms. The order book pricing mechanism is adopted in centralized exchanges. It displays buy and sell orders for an asset, creating a bid side (buyers' prices) and an ask side (sellers' prices). Trades occur when these prices match, determining the market price. The order book updates in real-time, reflecting supply and demand changes. In contrast, a liquidity pool in UNISWAP-V2 is a smart contract-based mechanism that enables users to provide funds for trading pairs of cryptocurrencies. It involves depositing equal values of two different tokens into the pool. These funds are used to facilitate instant trades by automated algorithms (constant function market making). Users who contribute to the liquidity pool earn a share of the trading fees proportional to their contribution. Hence, apart from the evident contrasts in pricing mechanisms, the distinct incentives associated with each platform attract diverse profiles of investors, resulting in a broad and varied user base.

In this study, we employ a method from the field of econophysics, known as Multifractal Detrended Fluctuation Analysis (MF-DFA) (Kantelhardt et al., 2002). By analyzing the scaling exponents and multifractal properties of price data, MF-DFA provides a way to quantify the efficiency level in a market. Our aim is to examine the variations in market efficiency and dynamics between centralized (Binance) and decentralized (UNISWAP-V2) markets, both of which involve ETH priced in BTC, DAI, and Tether (USDT). This approach enables us to not only rank the efficiency of the ETH price within BTC, DAI, and USDT, but also to evaluate the efficiency of ETH within the contexts of Binance and UNISWAP-V2. Put differently, we will have the ability to determine whether ETH priced in BTC (using it as an example) exhibits greater efficiency on decentralized or centralized exchanges.

We opted to adopt ETH as our focal cryptocurrency, given its status as the native currency on the Ethereum blockchain and its standing as the second-largest cryptocurrency by market capitalization. The decision to value ETH in BTC stems from its prominence as one of the most actively traded cryptocurrency pairs across various DEX and CEX. Additionally, pricing ETH in stablecoins like DAI and USDT, both characterized by substantial transaction volumes, introduces a perspective of traditional FIAT currencies into the decentralized ecosystem.

In economics and finance, time series data often lacks constant stability. Changing factors like regime shifts and evolving expectations can alter lagged correlation and causality between series. The Thermal Optimal Path (TOP) (Sornette & Zhou, 2005; Zhou & Sornette, 2006) is a procedure used to analyze the causal relationships and lagged dependencies between two time series. It aims to identify the most optimal path or direction of causality between the series by considering their dynamic interactions over time. In addition to the findings from the MF-DFA analysis, we extended our research contribution to the domain of market efficiency by integrating the TOP (Sornette & Zhou, 2005), which allows to establish the lead-lag relationship between Binance and UNISWAP-V2 for each ETH pricing scenario. This enables us to determine whether, for instance, market efficiency for ETH priced in BTC tends to manifest first on average in Binance or Uniswap-V2.

As previously mentioned, our research contrasts the market efficiency of Binance and UNISWAP-V2 for specific pairs. This stands in contrast to existing literature that exclusively relies on centralized data. As a market efficiency tool indicator, MF-DFA has been employed in various studies related to Bitcoin and other cryptocurrencies. For instance, it was utilized to compare the efficiency of Bitcoin and gold markets (Al-Yahyaee et al., 2018a). Additionally, Garnier et al. (2019) shows that the price behavior of BTC demonstrates a correlation structure across multiple time scales. Gunay et al. (2019) indicates that cryptocurrency returns deviate from randomness and instead follow a chaotic pattern, and in (Vaz et al., 2021), the evidence indicates that while Bitcoin maintains its popularity and experiences long-term value growth, its behavior can be rather unstable in the short term.

This research is organized into 4 distinct sections. The introduction, Section 1, sets the stage by outlining the significance of evaluating market efficiency in the context of ETH pricing across both centralized (Binance) and decentralized (Uniswap-V2) platforms. Section 2 delves into the data collection process, detailing the sources and types of data utilized for analysis and, elucidates the implementation of the MF-DFA and TOP technique, elaborating on its applications to assess market efficiency and compare the pricing mechanisms of order books and liquidity pools. Section 3, presents the findings derived from the analysis, shedding light on the market efficiency disparities between the two platforms and the performance of the distinct pricing mechanisms. Finally, Section 4, concludes the research by synthesizing the key findings, discussing their implications, offering insights into the broader implications for decentralized financial ecosystems and market efficiency enhancements, and discussing potential avenues for future research in the field.

2. Data and Methodology

In this section, the dataset from The Graph decentralized protocol and Binance is introduced, accompanied by the essential procedures for computing both MF-DFA and the TOP.

2.1. Data

Data was gathered from The Graph (`https://thegraph.com/`) and Binance for ETH prices in BTC, DAI, and USDT. The UNISWAP-V2 [2] subgraph is accessible for queries at `https://api.thegraph.com/subgraphs/name/uniswap/uniswap-v2`. Regarding both Binance and UNISWAP-V2, the dataset encompasses 1014 daily observations spanning from August 11, 2020, to May 23, 2023. All the time series within our dataset exhibit stationarity according to ADF (Dickey & Fuller, 1979) and KPSS (Kwiatkowski et al., 1992) tests. The analyzed time frame encompasses a challenging period marked by significant events, including peaks in SARS-CoV-2 pandemic infections, a United States presidential inauguration, disruptions in the global supply chain, BTC reaching an all-time high price, the crash and contagion of Terra-Luna, FTX's bankruptcy, and the Ethereum merge.

Analyzing the price efficiency of ETH across BTC, DAI, and USDT trading pairs is a robust parameter to gain comprehensive insights into the broader cryptocurrency market dynamics. Each of these currency pairs represents

[2] UNISWAP-V2's launch date is in May 2020, with transactions for some pools commencing in August 2020

distinct aspects of the cryptocurrency landscape: BTC signifies the relationship between two major cryptocurrencies, DAI represents a stablecoin tethered to the value of the US dollar, and USDT is a widely used stablecoin with a direct peg to the USD.

2.2. Methodology

We conduct a rolling window analysis to observe the local market efficiency trend. We propose an approach where the MF-DFA, see Section 2.3, window size varies among three different numbers of observations: 256, which is the explicit minimum requirement set by the Basel Committee on Banking Supervision (Basel Committee on Banking Supervision, 2013), we also consider 512 following the approach of Aloui et al. (2018) and Shrestha (2021), while 384 denotes the average between the other two values. This permits us to compare and rank market efficiency between the Constant Function Market Maker (UNISWAP-V2)[3] and order book (Binance) pricing mechanisms.

Constant Function Market Makers (CFMM's) are fundamental in DeFi ecosystems. They are smart contract-based algorithms designed to provide liquidity to decentralized exchanges and trading platforms (Szabo, 1996; Hanson, 2003; Krishnamachari et al., 2021). Unlike traditional market makers who adjust their prices based on external factors like supply and demand, CFMM's operate with a fixed pricing function (Angeris & Chitra, 2020). This function typically involves a linear relationship between the quantities of two assets in a trading pair. As users deposit assets into the Liquidity Pool (LP), they receive LP tokens in return (Adams et al., 2020), representing their share of the pool. These LP tokens can later be used to withdraw their portion of the liquidity and any accumulated trading fees. This innovative mechanism enables users to contribute to liquidity in a decentralized manner, facilitating smoother trading and minimizing slippage on decentralized exchanges. It is important to note that while CFMM's offer liquidity, they also come with risks such as impermanent loss, where the value of deposited assets can change relative to holding them outside the pool due to price fluctuations (Aigner & Dhaliwal, 2021; Loesch et al., 2021).

In accordance with Wang et al. (2017),Aloui et al. (2018) and Al-Yahyaee et al. (2020) we employ a market efficiency measure (D[45]), Equation 1. This measure allows us to systematically assess and rank the inefficiency levels exhibited by the same trading pair on both centralized and decentralized exchanges. In contrast to other market efficiency measures that simply indicate whether a period was efficient or not - such as the variance ratio test Lo & MacKinlay (1988) and the Wild Bootstrap Automatic Variance Ration (WBAVR) test Kim (2009) - the MF-DFA approach furnishes us with more comprehensive insights. This methodology is pivotal to our research, allowing for a comprehensive analysis of market efficiency for ETH against BTC, DAI, and USDT on both Binance and UNISWAP-V2.

$$D = \frac{1}{2}(|h(-q) - 0.5| - |h(q) - 0.5|). \tag{1}$$

It is important to highlight that, in a cryptocurrency market, efficiency is indicated when all price dynamics, encompassing both large ($q = 4$) and small ($q = -4$) fluctuations, conform to a random walk behavior. Consequently, if the market is perfectly efficient, the calculated value of the market efficiency measure (Equation 1) would be zero - where $h(q)$ is the generalized Hurst exponent, and q its order, $q > 0$ represents large fluctuations and $q < 0$ small

[3]UNISWAP-V2 uses a constant product market maker structure.

[4]In Al-Yahyaee et al. (2018b),Al-Yahyaee et al. (2020) and Aloui et al. (2018) it is called Market Deficiency Measure (MDM), but in Mnif et al. (2020) and Mnif & Jarboui (2021) it is magnitude of long memory (MLM).

[5]We have chosen to adopt the nomenclature presented in the study by Wang et al. (2009).

fluctuations. Otherwise, the market might exhibit inefficiency. Subsequently, the thermally optimal path, see 2.4, is employed on the outcomes of the MF-DFA across the three window sizes in both Binance and UNISWAP-V2 datasets.

2.3. Multifractal Detrended Fluctuation Analysis

In this subsection, we present details about the parameter specifications utilized in the procedure. To perform MF-DFA (Multifractal Detrended Fluctuation Analysis), we adhere to the five-step approach introduced by Kantelhardt et al. (2002), which has been widely replicated in the literature (Aloui et al., 2018; Wang et al., 2009). For a more comprehensive understanding of the procedure and its steps, we suggest Kantelhardt et al. (2002).

Following the methodology proposed by Peng et al. (1994), let's us assume that $\{x_t,\ t = 1, \cdots, N\}$ is a time series with N observations. Initially, it is necessary to generate a new series:

$$X(t) = \sum_{i=1}^{t}(x_i - \overline{x}), \ \ t = 1, \ \cdots, N$$

where $\overline{x}$ is the average of the entire time series, and the profile y_k is the cumulative sum of the deviations from the sample mean - this procedure converts the time series x_t white noise into random walk.

Then $X(t)$ is divided into $N_s \equiv int(N/s)$ of non-overlapping segments of equal length s. However, we modify the lower limit to ensure that there are at least 30 observations within each segment. As a result, the scales for segment length, denoted as s, fall within the range of $30 < s < N_s/5$, following Wang et al. (2009). Following the procedure, we need to determine the local trend for each of the $2N_s$ segments, using a least square fit for each sub-interval. Thus, the corresponding detrended time series ($X_s(t)$) is given by by the difference between the actual value and its estimate (tendency):

$$X_s(t) = X[(\upsilon - N_s)s + 1] - x_\upsilon(t) \text{ for } \upsilon = 1, \cdots, N_s,$$
$$X_s(t) = X[N - (\upsilon - N_s)s + 1] - x_\upsilon(t) \text{ for } \upsilon = N_s + 1, \cdots, 2N_s$$

where x_υ indicates the polinomial fit for the υth sub-interval. We are required to choose the order of the fitting polynomial. The available options include linear, quadratic, cubic, or higher orders. Based on the literature (Penzel et al., 2003; Gu et al., 2010; Zheng & Lai, 2010), we have opted to utilize a quadratic polynomial. This choice allows us to determine the variance, effectively eliminating second-order trends in the profile[6] and first-order trends in the original record (Zheng & Lai, 2010).

The variance is determined as follows:

$$F^2_{xx}(s,\upsilon) = \frac{1}{s}\sum_{t=1}^{s}\{X[(\upsilon - N_s)s + 1] - x_\upsilon(t)\}^2 \text{ for } \upsilon = 1, ..., N_s,$$
$$F^2_{xx}(s,\upsilon) = \frac{1}{s}\sum_{t=1}^{s}\{X[N - (\upsilon - N_s)s + 1] - x_\upsilon(t)\}^2 \text{ for } \upsilon = N_s + 1, ..., 2N_s.$$

The q^{th} order fluctuations are obtained by averaging the variance over all sub-intervals,

[6] For a more comprehensive understanding of the MF-DFA, we suggest referring to the work of Kantelhardt et al. (2002). Their paper provides further insights and in-depth explanations regarding the MF-DFA methodology.

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

Thus, the scaling behavior of the fluctuation functions ($F_q(s)$) is determined by analyzing their log-log plots against s for each value of q. If the series exhibits long-range power-law correlation, $F_q(s)$ increases as a power-law for large values of s,

$$F_q(s) \approx s^{h(q)}. \tag{3}$$

The MF-DFA technique provides a spectrum of generalized Hurst exponents, which play a crucial role in determining the nature of the time series being analyzed, whether it exhibits random walk behavior or stationarity. In the literature, there are various suggested ranges for the order of fluctuation (q). For instance, Wang et al. (2009) and Laib et al. (2018) propose an interval of -10 to 10. Cajueiro & Tabak (2007) and Shrestha (2021) suggest -6 to 6, while Khuntia & Pattanayak (2020) use a range of -5 to 5. On the other hand, Ali et al. (2018), Aloui et al. (2018) and Naeem et al. (2021) utilize -4 to 4, small and large fluctuations respectively. For our analysis, we will use the interval [-4, 4] as the range for the order of fluctuations. This choice is motivated by the ”inverse-cubic” power law, which describes the thickness of the tails of financial fluctuations Gopikrishnan et al. (1998); Kwapień & Drożdż (2012); Aloui et al. (2018).

The exponent $h(q)$, in Equation 3, represents the generalized Hurst exponent, which may vary with different values of q. For stationary time series, $h(2)$ corresponds to the well-known Hurst exponent H. The family of generalized exponents $h(q)$ can be obtained by observing the slope of the log-log plot of $F_q(s)$ versus s using the least squares method.

In the context of the analysis, if the Hurst exponent $h(s)$ falls within the range $0.5 < H < 1$, it indicates that the series exhibits long-range dependence or the property of long memory. If the Hurst exponent $h(s)$ is not related to the moment of order q, then the process can be characterized as monofractal; otherwise, if related, it is called multifractal. According to the literature present in section 1, the market portrays efficiency if and only if all of its fluctuations follow a random walk behavior. This is equal to say that for all $h(q)$ related to different q should be equal to 0.5.

Additionally, the MF-DFA method facilitates the ranking of markets based on their efficiency levels. By employing the MF-DFA approach, the stationarity or random walk characteristics of financial time series can be determined by examining a spectrum of generalized Hurst exponents. This technique, which explores multifractal properties in non-stationary time series, offers greater to Detrended Fluctuation Analysis (DFA) Peng et al. (1994, 1995).

2.4. Thermal Optimal Path

The TOP method takes into account the evolving structure of causality and is particularly responsive to regime shifts and changing agent expectations. It has demonstrated its versatility across a range of applications within the finance literature, encompassing tasks such as testing dependencies between pairs of economic time series ((Guo et al., 2011; Jia et al., 2016), examining lead-lag relationships between stock indices and their futures (Gong et al., 2016), and investigating lead-lag connections between economic variables and stock markets (Guo et al., 2017; Trichilli et al., 2020; Yao & Li, 2020). While its application to cryptocurrencies remains relatively limited, a handful of studies have employed this methodology (Trichilli & Boujelbéne, 2023; Trichilli & Boujelbène Abbes, 2023). Utilizing the TOP method for analyzing data from both Binance and UNISWAP-V2 across diverse ETH price pairs (BTC, DAI, and USDT) assists in establishing the precedence of market efficiency in centralized versus decentralized finance. This lead-lag validation method contributes to a deeper comprehension of the intrinsic pricing mechanisms unique to these approaches.

Consider two time series denoted as $\{x(t_1), ; t_1 = 1, .., N_1\}$ and $\{y(t_2), ; t_2 = 1, .., N_2\}$, where N_1 and N_2 represent the number of observations, which may vary between the two series. While the thermal optimal path is not limited to time series with an equal number of observations, in the context of economic and financial data, it is common for N_1 to be equal to N_2. However, it is important to note that the two time series can have distinct characteristics, such as varying scales and meanings. To address this, both time series are normalized by their respective standard deviations. From this point forward, $X(t_1)$ and $Y(t_2)$ will refer to the normalized versions of the original time series.

A distance matrix, denoted as $E_{X,Y}$, is constructed using the normalized series $X(t_1)$ and $Y(t_2)$. The elements of this matrix are defined as follows:

$$\varepsilon(t_1, t_2) = |X(t_1) - Y(t_2)|^q. \tag{4}$$

Although the TOP method can be applied with any appropriate distance measure (Equation 4), it is important to consider the nature of the time series under analysis when selecting the most suitable choice. For instance, using a value of $q > 1$ would place greater emphasis on larger discrepancies in the data. Therefore, the choice of the distance measure can be tailored to the specific characteristics and requirements of the time series being studied. In this research, however, we have specifically set $q = 1$ (Sornette & Zhou, 2005; Zhou & Sornette, 2006; Xu et al., 2017; Yao & Li, 2020).

Moving forward, there are two situations concerning the minimization of the path in the thermal optimal path method. The first situation involves searching for the absolute minimum, aiming to identify the most precise and accurate path between the time series (Halpin-Healy & Zhang, 1995). However, in the second situation, the path is relaxed, taking into consideration that the distance matrix $E_{X,Y}$ may contain noise or irrelevant patterns. In this case, the focus is on finding a path that captures the essential patterns while allowing for some level of tolerance to noise. This path is determined by minimizing the energy or cost function associated with the TOP method across the entire range of starting and ending points.

In the studies conducted by Sornette & Zhou (2005) and Zhou & Sornette (2006), they introduced the concept of "thermal" excitations or fluctuations around the optimal path. This means that path configurations with slightly higher global energies are permitted, but their probabilities decrease as their energy increases. This approach allows for a more flexible exploration of path configurations and considers the influence of thermal-like fluctuations in the analysis.

The temperature, often referred to as the "thermal" factor, plays a significant role in the TOP method and has been subject to exploration in various research studies. In the literature, the temperature value ranges from T=2 (as found in studies by Wang et al. (2017); Yao & Li (2020); Yuan et al. (2021)) to T=0.05 (as observed in the study by (Yan & Lai, 2019)). The temperature, represented by T, is an element of the Boltzmann weight factor used to reduce noise in the analysis.

If two time series exhibit a perfect causal relationship, the optimal path in the TOP method would correspond to the diagonal of the distance matrix. This is because the diagonal represents the points where $X(t_1)$ and $Y(t_2)$ are equal, indicating a direct mapping from one time point to the corresponding time point in the other series. If the optimal path deviates from the diagonal, it indicates a lead-lag relationship between the two time series. The extent and direction of the deviation reveal the lead or lag between the two series, providing insights into the temporal relationship and potential causal interactions.

Considering the number of observations in our data, as mentioned in section 2.1, and the computational resources required by the thermal optimal path method, we have decided to use a temperature value of $T = 0.05$. This choice allows us to maintain the full set of observations without compromising the inclusion of relevant periods that could be lost if the number of observations was reduced.

3. Results

Table 1 presents the rankings of ETH values as assigned by four different cryptocurrencies using Equation 1. The rankings of Centralized Exchanges (CEX) and DEX for ETH prices are influenced by the rolling window length. However, the market efficiency comparison between CEX and DEX only differs from the dynamic at $n = 256$ for the ETH price assigned in BTC, with DEX exhibiting higher efficiency than CEX at this window size. It can also be observed that ETH market efficiency changes from Binance to UNISWAP-V2; however, it has a fixed rank - represented by the roman algarisms - through all rolling window lengths. The findings presented in Table 1 align with observations in existing literature (Kakinaka & Umeno, 2022; Mnif et al., 2020; Naeem et al., 2021), indicating that over the long term, the level of multifractality, as determined by Equation 1, diminishes. This phenomenon is not limited to centralized exchanges; it is also evident in the daily data of UNISWAP-V2.

The disparity in market efficiency between UNISWAP-V2 and the centralized environment (Binance), as indicated by the findings in Table 1, is consistent with prior literature. We delve into two complementary perspectives that are inherent to the structure of decentralized exchanges within public blockchains like Ethereum. The first viewpoint asserts that an increase in market transparency - which is one of the pillars of decentralized finance (Qin et al., 2021) - enhances price efficiency (Madhavan, 1996). The second perspective contends that arbitrage opportunities reduce the profitability of market anomalies, thereby improving price efficiency (Akbas et al., 2016; Shleifer & Vishny, 1997).

From the results of Madhavan (1996), transparency reduces price volatility and increases market liquidity if the market is sufficiently large and there is sufficient noise trading. Observing Table 1 with a rolling window size of 256 observations, it is reasonable to deduce that ETH pricing in DAI and USDT indicates that Binance may be more liquidy than in DEX. Thus, in line with Chordia et al. (2008), by virtue of transitive properties, market efficiency can be enhanced.

An explanatory framework for the ETH priced in BTC being more efficient in UNISWAP-V2 at the 256 rolling window observations may have its foundation placed in the argument that arbitrage drives more informed trading activity in UNISWAP-V2 thus, corroborating with the literature finds Ibikunle et al. (2020). The notion that arbitrage plays a significant role in enhancing market efficiency is heightened by the attributes of the Ethereum blockchain and the pricing mechanisms within decentralized exchanges, particularly UNISWAP-V2. Given the multitude of decentralized exchanges on the Ethereum blockchain, price disparities naturally increase as an inherent aspect of the ecosystem. This, in turn, facilitates the establishment of cross-exchange arbitrage within the market (Wang et al., 2022; Vakhmyanin

& Volkovich, 2023). Overall, DEX's - such as UNISWAP-V2 - offer global accessibility, enabling users from anywhere in the world to access and trade digital assets. This unrestricted access may foster a more diverse market, which, in turn, contributes to improved price discovery and market efficiency.

The outcomes derived from employing the TOP approach to assess and contrast the lead-lag relationship between market efficiencies in Binance and UNISWAP-V2 are presented in Table 2. When lag values, l, are negative, it indicates that UNISWAP-V2 is taking the lead over Binance regarding market efficiency. Among the cryptocurrency pairs, the ETH price in BTC exhibited market efficiency across all three rolling window sizes in 1, while also concurrently indicating a lead for UNISWAP-V2 - as it is observed in the *Average* lag value of the last two rows of Table 2. One plausible hypothesis for the leading position of UNISWAP-V2 is the association with ETH as the native token of the Ethereum blockchain, used for covering gas fees. Another valid conjecture is that ETH and BTC, ranking as the second and first cryptocurrencies by market capitalization, respectively, could potentially act as safe havens within the realm of cryptocurrencies.

Table 2 illustrates the fluctuating correlation between ETH prices denominated in DAI and USDT, stablecoins. When analyzing 256 data points, it becomes apparent that there is no significant daily lead-lag relationship between Binance and UNISWAP-V2; any lags observed are shorter than a 24-hour period. When considering a long-term investment time frame with 512 data points, it becomes evident that ETH-DAI and ETH-USDT exhibit comparable lag durations. Notably, in both of these cryptocurrencies, UNISWAP-V2 consistently leads the ETH price by one day compared to Binance.

Decentralized exchanges, exemplified by Uniswap-V2, may demonstrate early market efficiency by a synergy of influential factors. Users employing algorithmic trading strategies adeptly capitalize on market inefficiencies, responding swiftly to variations in price. These platforms lead the way in figuring out fair prices, attracting traders who skillfully make the most of differences between decentralized exchanges. Uniswap-V2's decentralized nature, characterized by fewer regulatory hurdles, enables the expeditious implementation of changes and innovations, contributing to a nimble adaptation to evolving market conditions. Within the dynamic decentralized finance (DeFi) ecosystem linked to these exchanges, a culture of financial innovation and rapid adoption of novel concepts further accelerates responses to challenges in market efficiency.

4. Conclusion

This research presents a comprehensive comparative analysis of market efficiency, focusing on ETH pricing in BTC, DAI, and USDT. The investigation incorporates data collected from both UNISWAP-V2, a decentralized application utilizing liquidity pools for cryptocurrency pricing, and Binance, a centralized exchange. Employing a rolling window procedure with window sizes of 256, 384, and 512 observations, the study applies the MF-DFA methodology to rank the efficiency of exchange pairs using the market deficiency measure (MDM). Moreover, for a more profound exploration of this phenomenon and to delve into the dynamics inherent to distinct pricing mechanisms, we employed the Thermal Optimal Path method, allowing us to derive the lead-lag relationship of the investigated ETH prices.

The MF-DFA results indicate that with an increase in the number of rolling window observations, there is a consistent increase in the market efficiency of all ETH prices. This observed pattern gains additional weight because this is also acknowledged in existing literature. The high level of market efficiency observed in UNISWAP-V2 is

	256		384		512	
Pair	CEX	DEX	CEX	DEX	CEX	DEX
ETH-BTC	0.2685308 (III)	**0.2264989** (III)	0.1713707 (III)	**0.1365076** (III)	0.1435508 (III)	**0.117233** (III)
ETH-DAI	**0.1844849** (I)	0.1875527 (II)	0.1339416 (I)	**0.1237944** (II)	0.1131219 (I)	**0.09958054** (II)
ETH-USDT	**0.1849068** (II)	0.186141 (I)	0.1346383 (II)	**0.1234804** (I)	0.113539 (II)	**0.09916427** (I)

Notes: Market efficiency is assessed using the MF-DFA (Multifractal Detrended Fluctuation Analysis) method. Lower values indicate higher market efficiency, while higher values suggest lower efficiency. The ranking of cryptocurrency pairs within each exchange is based on their calculated efficiency scores. Bolded values indicates in which exchange (decentralized or centralized) the pair is more efficient.

Table 1: Results of market efficiency analysis using the MF-DFA method for various cryptocurrency pairs (ETH/BTC, ETH/DAI, ETH/USDT) on decentralized (UNISWAP-V2) and centralized (Binance) exchanges for three distinct rolling window sizes. Daily observations ranges 08-11-2020 to 05-21-2023.

consistent with prior literature. We also explored two interconnected viewpoints, Section 3, inherent to decentralized exchanges within public blockchains like Ethereum, which could potentially aid in comprehending the results that point to a higher market efficiency observed in UNISWAP-V2, as they might either offer an understanding of the phenomenon or be the underlying cause of it.

Concerning the ETH price in BTC, the data highlights a lead favoring UNISWAP-V2. This trend is noticeable through the Average lag value. Upon analyzing 256 data points, it becomes evident that there is no substantial lead-lag relationship between Binance and UNISWAP-V2; observed lags are within a 24-hour timeframe. However, when examining a longer-term investment horizon with 512 data points, it becomes clear that ETH-DAI and ETH-USDT display similar lag durations. Importantly, in both of these cryptocurrencies, UNISWAP-V2 consistently maintains a lead of one day over Binance in terms of the ETH price.

The nuanced factors contributing to these dynamics were explored, drawing from market transparency and arbitrage opportunities. Gaining a more in-depth comprehension of digital assets holds the advantage of guiding investors toward making well-founded choices when buying or selling. This enhanced understanding also empowers institutions and developers to devise superior products and solutions that contribute to the growth of the industry. Opportunities for future research lie in exploring the different distance metrics within the Thermal Optimal Path, investigating the repercussions of regulatory changes on market efficiency, and studying the effects of tokenomics - encompassing staking mechanisms, rewards, and governance structures - on market efficiency within decentralized ecosystems.

Lag (l)	ETH-DAI			ETH-USDT			ETH-BTC		
	256	384	512	256	384	512	256	384	512
-10< l ≤-9	0.528	0	0.399	0.396	0.318	0.399	0.925	0.477	0.998
-9< l ≤-8	0.925	0.159	0.399	1.189	0	0.798	0.925	1.431	0.599
-8< l ≤-7	1.585	0.318	0.998	1.717	0.795	0.798	0	1.431	1.397
-7< l ≤-6	1.982	0.477	0.399	0.925	0.795	0.798	1.453	0.795	2.595
-6< l ≤-5	1.982	0.795	0.998	2.510	0.636	0.798	1.453	1.431	3.393
-5< l ≤-4	3.699	1.113	1.996	3.699	0.636	2.595	2.114	1.590	3.792
-4< l ≤-3	2.906	1.908	4.990	3.170	1.590	2.794	4.888	3.975	4.591
-3< l ≤-2	5.020	4.293	7.784	5.284	3.657	8.184	6.869	7.790	5.788
-2< l ≤-1	11.361	11.924	14.571	10.964	12.401	18.363	9.775	11.924	9.381
-1< l <0	13.210	25.437	23.752	11.8891	27.504	18.962	20.343	16.057	14.571
0< l ≤1	11.229	17.170	17.964	12.417	17.806	19.361	15.588	14.944	13.573
1< l ≤2	4.359	7.949	9.980	5.945	6.836	11.377	7.133	7.790	4.990
2< l ≤3	4.888	5.246	4.391	3.963	4.452	4.591	4.888	3.657	2.994
3< l ≤4	6.341	1.590	2.395	5.152	3.339	2.196	4.888	2.703	3.194
4< l ≤5	3.963	2.385	0.798	4.359	2.385	0.798	1.849	2.067	2.595
5< l ≤6	3.170	2.226	0.599	4.359	1.113	1.198	1.717	1.113	2.196
6< l ≤7	2.510	0.954	1.198	3.038	1.431	0	0.793	0.477	1.597
7< l ≤8	1.321	1.908	0.200	1.585	1.272	0	0.793	0.636	1.198
8< l ≤9	0.528	1.908	0	1.849	1.749	0	0.661	0.477	1.597
9< l ≤10	1.321	1.431	0	1.585	1.590	0	0.132	0.477	0.798
$X(t) < 0$	52.048	46.741	61.876	50.594	48.967	59.880	59.445	64.388	59.880
Average	0.188	2.063	-1.357	-0.106	1.699	-1.371	-2.100	-5.465	-2.755

Table 2: This table presents the TOP method results across time lags from -10 to +10 days, highlighting temporal relationships between decentralized and centralized exchange pairs. It includes the percentage of lags under 1 day, indicating instances where decentralized pairs lead, and the average lags/leads per day, offering insights into temporal dynamics and synchronization patterns.

Acronyms

BTC Bitcoin

CEX Centralized Exchanges

CFMM's Constant Function Market Makers

CFTC Commodity Futures Trading Commission

DAO Decentralized Autonomous Organization

DeFi Decentralized Finance

DEX Decentralized Exchanges

DFA Detrended Fluctuation Analysis

EMH Efficient Market Hypothesis

ETH Ether

FinCEN Financial Crimes Enforcement Network

LP Liquidity Pool

MDM Market Deficiency Measure

MF-DFA Multifractal Detrended Fluctuation Analysis

SEC Security and Exchange Commission

TOP Thermal Optimal Path

USDT Tether

WBAVR Wild Bootstrap Automatic Variance Ration

References

Adams, H., Zinsmeister, N., & Robinson, D. (2020). Uniswap v2 core. 2020. *URL: https://uniswap. org/whitepaper. pdf*, .

Aigner, A. A., & Dhaliwal, G. (2021). Uniswap: Impermanent loss and risk profile of a liquidity provider. *arXiv preprint arXiv:2106.14404*, .

Akbas, F., Armstrong, W. J., Sorescu, S., & Subrahmanyam, A. (2016). Capital market efficiency and arbitrage efficacy. *Journal of Financial and Quantitative Analysis*, *51*, 387–413.

Al-Yahyaee, K. H., Mensi, W., Ko, H.-U., Yoon, S.-M., & Kang, S. H. (2020). Why cryptocurrency markets are inefficient: The impact of liquidity and volatility. *The North American Journal of Economics and Finance*, *52*, 101168.

Al-Yahyaee, K. H., Mensi, W., & Yoon, S.-M. (2018a). Efficiency, multifractality, and the long-memory property of the bitcoin market: A comparative analysis with stock, currency, and gold markets. *Finance Research Letters*, . doi:10.1016/j.frl.2018.03.017.

Al-Yahyaee, K. H., Mensi, W., & Yoon, S.-M. (2018b). Efficiency, multifractality, and the long-memory property of the bitcoin market: A comparative analysis with stock, currency, and gold markets. *Finance Research Letters*, *27*, 228–234.

Ali, S., Shahzad, S. J. H., Raza, N., & Al-Yahyaee, K. H. (2018). Stock market efficiency: A comparative analysis of islamic and conventional stock markets. *Physica A: Statistical Mechanics and Its Applications*, *503*, 139–153.

Aloui, C., Shahzad, S. J. H., & Jammazi, R. (2018). Dynamic efficiency of european credit sectors: A rolling-window multifractal detrended fluctuation analysis. *Physica A: Statistical Mechanics and Its Applications*, *506*, 337–349.

Angeris, G., & Chitra, T. (2020). Improved price oracles: Constant function market makers. In *Proceedings of the 2nd ACM Conference on Advances in Financial Technologies* AFT '20 (p. 80–91). New York, NY, USA: Association for Computing Machinery.

Basel Committee on Banking Supervision (2013). Fundamental review of the trading book: A revised market risk framework. *Consultative Document, October*, .

Belaire-Franch, J., & Opong, K. K. (2005). A variance ratio test of the behaviour of some ftse equity indices using ranks and signs. *Review of Quantitative Finance and Accounting*, *24*, 93–107.

Bellare, M., & Rogaway, P. (1993). Random oracles are practical: A paradigm for designing efficient protocols. In *Proceedings of the 1st ACM Conference on Computer and Communications Security* (pp. 62–73).

Biais, B. (1993). Price formation and equilibrium liquidity in fragmented and centralized markets. *The Journal of Finance*, *48*, 157–185.

Cajueiro, D. O., & Tabak, B. M. (2007). Long-range dependence and multifractality in the term structure of libor interest rates. *Physica A: Statistical Mechanics and its Applications*, *373*, 603–614.

Chohan, U. W. (2017). The decentralized autonomous organization and governance issues. *Available at SSRN 3082055*, .

Chohan, U. W. (2021). Decentralized finance (defi): an emergent alternative financial architecture. *Critical Blockchain Research Initiative (CBRI) Working Papers*, .

Chordia, T., Roll, R., & Subrahmanyam, A. (2008). Liquidity and market efficiency. *Journal of financial Economics*, *87*, 249–268.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*, 427–431.

Garnier, J., Garnier, J., Garnier, J., & Sølna, K. (2019). Chaos and order in the bitcoin market. *Physica A-statistical Mechanics and Its Applications*, . doi:10.1016/j.physa.2019.04.164.

Gong, C.-C., Ji, S.-D., Su, L.-L., Li, S.-P., & Ren, F. (2016). The lead–lag relationship between stock index and stock index futures: A thermal optimal path method. *Physica A: Statistical Mechanics and its Applications*, *444*, 63–72.

Gopikrishnan, P., Meyer, M., Amaral, L. N., & Stanley, H. E. (1998). Inverse cubic law for the distribution of stock price variations. *The European Physical Journal B-Condensed Matter and Complex Systems*, *3*, 139–140.

Gu, R., Chen, H., & Wang, Y. (2010). Multifractal analysis on international crude oil markets based on the multifractal detrended fluctuation analysis. *Physica A: Statistical Mechanics and its Applications*, *389*, 2805–2815.

Gunay, S., Gunay, S., Gunay, S., Kaşkaloğlu, K., Kaskaloglu, K., & Kaskaloglu, K. (2019). Seeking a chaotic order in the cryptocurrency market. *Mathematical & Computational Applications*, . doi:10.3390/mca24020036.

Guo, K., Sun, Y., & Qian, X. (2017). Can investor sentiment be used to predict the stock price? dynamic analysis based on china stock market. *Physica A: Statistical Mechanics and its Applications*, *469*, 390–396.

Guo, K., Zhou, W.-X., Cheng, S.-W., & Sornette, D. (2011). The us stock market leads the federal funds rate and treasury bond yields. *PLoS One*, *6*, e22794.

Halpin-Healy, T., & Zhang, Y.-C. (1995). Kinetic roughening phenomena, stochastic growth, directed polymers and all that. aspects of multidisciplinary statistical mechanics. *Physics Reports*, *254*, 215–414.

Hanson, R. (2003). Combinatorial information market design. *Information Systems Frontiers*, *5*, 107–119.

Hassan, S., & De Filippi, P. (2021). Decentralized autonomous organization. *Internet Policy Review*, *10*, 1–10.

Heimbach, L., Schertenleib, E., & Wattenhofer, R. (2022). Risks and returns of uniswap v3 liquidity providers. *arXiv preprint arXiv:2205.08904*, .

Ibikunle, G., McGroarty, F., & Rzayev, K. (2020). More heat than light: Investor attention and bitcoin price discovery. *International Review of Financial Analysis*, *69*, 101459.

Jia, R.-L., Wang, D.-H., Tu, J.-Q., & Li, S.-P. (2016). Correlation between agricultural markets in dynamic perspective—evidence from china and the us futures markets. *Physica A: Statistical Mechanics and its Applications*, *464*, 83–92.

Kakinaka, S., & Umeno, K. (2022). Cryptocurrency market efficiency in short-and long-term horizons during covid-19: An asymmetric multifractal analysis approach. *Finance Research Letters*, *46*, 102319.

Kantelhardt, J. W., Zschiegner, S. A., Koscielny-Bunde, E., Havlin, S., Bunde, A., & Stanley, H. E. (2002). Multifractal detrended fluctuation analysis of nonstationary time series. *Physica A: Statistical Mechanics and its Applications*, *316*, 87–114.

Khuntia, S., & Pattanayak, J. (2020). Adaptive long memory in volatility of intra-day bitcoin returns and the impact of trading volume. *Finance Research Letters*, *32*, 101077.

Kim, J. H. (2009). Automatic variance ratio test under conditional heteroskedasticity. *Finance Research Letters*, *6*, 179–185.

Krishnamachari, B., Feng, Q., & Grippo, E. (2021). Dynamic curves for decentralized autonomous cryptocurrency exchanges. *arXiv preprint arXiv:2101.02778*, .

Kwapień, J., & Drożdż, S. (2012). Physical approach to complex systems. *Physics Reports*, *515*, 115–226.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of econometrics*, *54*, 159–178.

Laib, M., Golay, J., Telesca, L., & Kanevski, M. (2018). Multifractal analysis of the time series of daily means of wind speed in complex regions. *Chaos, Solitons & Fractals*, *109*, 118–127.

Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. *The review of financial studies*, *1*, 41–66.

Loesch, S., Hindman, N., Richardson, M. B., & Welch, N. (2021). Impermanent loss in uniswap v3. *arXiv preprint arXiv:2111.09192*, .

Madhavan, A. (1995). Consolidation, fragmentation, and the disclosure of trading information. *The Review of Financial Studies*, *8*, 579–603.

Madhavan, A. (1996). Security prices and market transparency. *Journal of Financial Intermediation*, *5*, 255–283.

Malinova, K., & Park, A. (2017). Market design with blockchain technology. *Available at SSRN 2785626*, .

Mnif, E., & Jarboui, A. (2021). Covid-19, bitcoin market efficiency, herd behaviour. *Review of Behavioral Finance*, *13*, 69–84.

Mnif, E., Jarboui, A., & Mouakhar, K. (2020). How the cryptocurrency market has performed during covid 19? a multifractal analysis. *Finance research letters*, *36*, 101647.

Nadarajah, S., & Chu, J. (2017). On the inefficiency of bitcoin. *Economics Letters*, *150*, 6–9.

Naeem, M. A., Bouri, E., Peng, Z., Shahzad, S. J. H., & Vo, X. V. (2021). Asymmetric efficiency of cryptocurrencies during covid19. *Physica A: Statistical Mechanics and its Applications*, *565*, 125562.

Nan, Z., & Kaizoji, T. (2019). Market efficiency of the bitcoin exchange rate: Weak and semi-strong form tests with the spot, futures and forward foreign exchange rates. *International Review of Financial Analysis*, *64*, 273–281.

O'hara, M. (1998). *Market microstructure theory*. John Wiley & Sons.

Pani, S. (2021). Liquidity in high resolution in limit order markets. *International Journal of Financial Markets and Derivatives*, *8*, 23–49.

Peng, C.-K., Buldyrev, S. V., Havlin, S., Simons, M., Stanley, H. E., & Goldberger, A. L. (1994). Mosaic organization of dna nucleotides. *Physical review e*, *49*, 1685.

Peng, C.-K., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1995). Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. *Chaos: an interdisciplinary journal of nonlinear science*, *5*, 82–87.

Penzel, T., Kantelhardt, J. W., Grote, L., Peter, J.-H., & Bunde, A. (2003). Comparison of detrended fluctuation analysis and spectral analysis for heart rate variability in sleep and sleep apnea. *IEEE Transactions on biomedical engineering*, *50*, 1143–1151.

Qin, K., Zhou, L., Afonin, Y., Lazzaretti, L., & Gervais, A. (2021). Cefi vs. defi–comparing centralized to decentralized finance. *arXiv preprint arXiv:2106.08157*, .

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of finance*, *52*, 35–55.

Shrestha, K. (2021). Multifractal detrended fluctuation analysis of return on bitcoin. *International Review of Finance*, *21*, 312–323.

Sornette, D., & Zhou, W.-X. (2005). Non-parametric determination of real-time lag structure between two time series: the 'optimal thermal causal path'method. *Quantitative Finance*, *5*, 577–591.

Sun, X., & Stasinakis, C. (2021). Decentralization illusion in defi: Evidence from makerdao. *Available at SSRN 3971791*, .

Szabo, N. (1996). Smart contracts: building blocks for digital markets. *EXTROPY: The Journal of Transhumanist Thought,(16)*, *18*, 28.

Trichilli, Y., Abdelhédi, M., & Boujelbène Abbes, M. (2020). The thermal optimal path model: does google search queries help to predict dynamic relationship between investor's sentiment and indexes returns? *Journal of asset management*, *21*, 261–279.

Trichilli, Y., & Boujelbéne, M. (2023). Regime specific spillover between dow jones islamic market world index, islamic gold-backed crypto currencies and the blockchain halal index. *International Journal of Islamic and Middle Eastern Finance and Management*, *16*, 464–481.

Trichilli, Y., & Boujelbène Abbes, M. (2023). The impact of covid-19 on the portfolio optimization. *EuroMed Journal of Business*, *18*, 207–228.

Urquhart, A. (2016). The inefficiency of bitcoin. *Economics Letters*, *148*, 80–82.

Vakhmyanin, I., & Volkovich, Y. (2023). Price arbitrage for defi derivatives. In *2023 IEEE International Conference on Blockchain and Cryptocurrency (ICBC)* (pp. 1–4). doi:10.1109/ICBC56567.2023.10174884.

Vaz, C., Pascoal, R., Sebastião, H., & Sebastião, H. (2021). Price appreciation and roughness duality in bitcoin: A multifractal analysis. *Mathematics*, . doi:10.3390/math9172088.

Vidal-Tomás, D., & Ibañez, A. (2018). Semi-strong efficiency of bitcoin. finance res lett 27: 259–265.

Wang, D., Tu, J., Chang, X., & Li, S. (2017). The lead–lag relationship between the spot and futures markets in china. *Quantitative Finance*, *17*, 1447–1456.

Wang, S., Ding, W., Li, J., Yuan, Y., Ouyang, L., & Wang, F.-Y. (2019). Decentralized autonomous organizations: Concept, model, and applications. *IEEE Transactions on Computational Social Systems*, *6*, 870–878.

Wang, Y., Chen, Y., Wu, H., Zhou, L., Deng, S., & Wattenhofer, R. (2022). Cyclic arbitrage in decentralized exchanges. In *Companion Proceedings of the Web Conference 2022* (pp. 12–19).

Wang, Y., Liu, L., & Gu, R. (2009). Analysis of efficiency for shenzhen stock market based on multifractal detrended fluctuation analysis. *International Review of Financial Analysis*, *18*, 271–276.

Xu, H.-C., Zhou, W.-X., & Sornette, D. (2017). Time-dependent lead-lag relationship between the onshore and offshore renminbi exchange rates. *Journal of International Financial Markets, Institutions and Money*, *49*, 173–183.

Yan, D., & Lai, K. K. (2019). An analysis of china's onshore and offshore exchange rates—adjusted thermal optimal path approach based on pruning and path segmentation. *Entropy*, *21*, 499.

Yao, C.-Z., & Li, H.-Y. (2020). Time-varying lead–lag structure between investor sentiment and stock market. *The North American Journal of Economics and Finance*, *52*, 101148.

Yuan, X., Jin, L., & Lian, F. (2021). The lead–lag relationship between chinese mainland and hong kong stock markets. *Physica A: Statistical Mechanics and its Applications*, *574*, 125999.

Zargar, F. N., & Kumar, D. (2019). Informational inefficiency of bitcoin: A study based on high-frequency data. *Research in International Business and Finance*, *47*, 344–353.

Zheng, F., & Lai, B. (2010). A research on the fractal properties of aluminum future market. In *2010 WASE International Conference on Information Engineering* (pp. 288–291). IEEE volume 2.

Zhou, W.-X., & Sornette, D. (2006). Non-parametric determination of real-time lag structure between two time series: The "optimal thermal causal path" method with applications to economic data. *Journal of Macroeconomics*, *28*, 195–224.