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

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Outline

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Introduction

- Studying liquidity pool pricing dynamics is crucial for understanding decentralized finance mechanisms and gaining insights into the efficiency of price discovery processes.
- Centralized exchanges like Binance use order book pricing, displaying buy and sell orders, while UNISWAP-V2 employs a liquidity pool mechanism.
- This research investigates the difference in price dynamics and market efficiency in decentralized Ethereum (ETH) prices compared to centralized exchanges.
- The study employs Multi-fractal Detrended Fluctuation Analysis (MF-DFA) to analyze scaling exponents and multi-fractal properties of price data in Binance and UNISWAP-V2 markets for ETH priced in BTC, DAI, and USDT.
- The goal is to quantify and compare the efficiency levels in these markets, determining whether ETH exhibits greater efficiency on centralized or decentralized exchanges.
- To check whether efficiency manifests first, the study incorporates the Thermal Optimal Path (TOP) analysis, providing insights into the lead-lag relationships between the pricing mechanisms for each ETH.

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LP's Background

- Constant Function Market Makers (CFMMs) are smart contract-based algorithms designed to provide liquidity to decentralized exchanges and trading platforms.
- Unlike traditional market makers, CFMMs operate with a fixed pricing function, typically involving a linear relationship between quantities of two assets in a trading pair.

$$k = x \times y \quad \text{or} \quad k = x + y$$

- Users deposit assets into the Liquidity Pool (LP) and receive LP tokens representing their pool share.
- CFMMs enable decentralized liquidity provision, reducing slippage on decentralized exchanges but carrying risks like impermanent loss due to asset value fluctuations.

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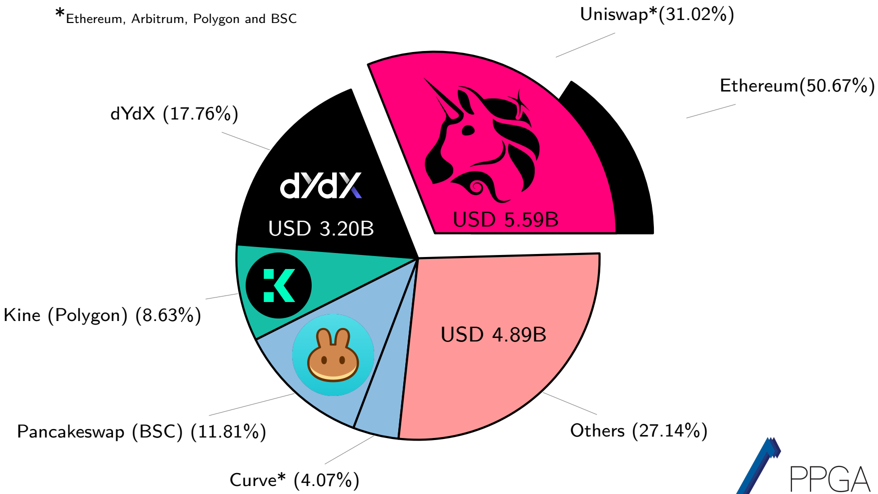
Data


*Ethereum, Arbitrum, Polygon and BSC
Uniswap*(31.02%)
Ethereum(50.67%)
dYdX (17.76%)
dYdX
USD 3.20B
USD 5.59B
Kine (Polygon) (8.63%)
USD 4.89B
Pancakeswap (BSC) (11.81%)
Others (27.14%)
Curve* (4.07%)

Data

- Data sourced from The Graph and Binance for ETH prices in BTC, DAI, and USDT.
- Dataset covers 1014 daily observations from August 11, 2020, to May 23, 2023. All time series in the dataset are stationary.
- Analyzed timeframe includes significant events such as the SARS-CoV-2 pandemic peaks, a U.S. presidential inauguration, global supply chain disruptions, BTC reaching an all-time high, Terra-Luna crash, FTX's bankruptcy, and Ethereum merge.

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Methodology

- Rolling window analysis was employed to perceive the pricing efficiency of ETH priced in BTC, DAI, and USDT.
- The MF-DFA approach is utilized with varying window sizes: 256 (Basel Committee minimum requirement), 512 (Aloui et al., Shrestha approach), and 384 days (average of the two).
- MF-DFA is a technique that allows us to compare and rank market efficiency between Constant Function Market Maker (UNISWAP-V2) and order book (Binance) pricing mechanisms efficiency.

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Multi-fractal Detrended Fluctuation Analysis

Step 1: Given a time series $\{x_t,\ t = 1, \cdots, N\}$, we convert the time series x_t white noise into random walk.

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

Step 2: $X(t)$ is divided into $N_s \equiv int(N/s)$ of non-overlapping segments of equal length s. The detrended time series $(X_s(t))$ is given by the difference between the actual value and its estimate (tendency):

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

Step 3: The variance is

$$F_{xx}^2(s, \upsilon) = \frac{1}{s} \sum_{t=1}^{s} \{X_s(t)\}^2 \text{ for } \upsilon = N_s + 1, ..., 2N_s.$$

Step 4: The q^{th} order fluctuations are obtained by averaging the variance over all sub-intervals

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

Multi-fractal Detrended Fluctuation Analysis

Step 5: 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.

- The MF-DFA technique provides a spectrum of generalized Hurst exponents - $h(q)$.
- Thus, we employ a market efficiency measure [Wang et al., 2009, Aloui et al., 2018, Al-Yahyaee et al., 2020]

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

- Consequently, if the market is perfectly efficient $D = 0$.
- The MF-DFA parameters:
  - $30 < s < N_s/5$ [Wang et al., 2009]
  - $q \in \{n \in \mathbb{Z} | -4 \leq n \leq 4\}$ [Kwapień and Drożdż, 2012, Aloui et al., 2018]

Thermal Optimal Path

- The Thermal Optimal Path (TOP) is a method used to analyze causal relationships and lagged dependencies between two time series [Sornette and Zhou, 2005, Trichilli and Boujelbène Abbes, 2023].
- It identifies the optimal path or direction of causality between two time series by considering their dynamic interactions over time.
- Specifically, the TOP analysis helps establish lead-lag relationships between the two time series.
- It determines which of the two series tends to manifest changes first, providing insights into the temporal order of causality.
- In this study, the TOP analysis is applied to explore lead-lag relationships between Binance and UNISWAP-V2 pricing efficiency mechanism considering ETH priced in BTC, DAI, and USDT.

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Results - MF-DFA

Table: MF-DFA method results for ETH/BTC, ETH/DAI, ETH/USDT on UNISWAP-V2 and Binance exchanges for three distinct rolling window sizes. Daily observations ranges 08-11-2020 to 05-21-2023.

	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)

- Lower values indicate higher market efficiency, while higher values suggest lower efficiency.
- Results are consistent with prior literature:
  - market transparency enhances price efficiency [Madhavan, 1996];
  - arbitrage opportunities reduce the profitability of market anomalies, thereby improving price efficiency [Shleifer and Vishny, 1997, Akbas et al., 2016].
- 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, improving price discovery and market efficiency.

Results - TOP

Table: This table present 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.

Lag (l)	ETH-DAI			ETH-USDT			ETH-BTC		
	256	384	512	256	384	512	256	384	512
$X(t) < 0$	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

- UNISWAP-V2 pricing efficiency leads against Binance regarding ETH-BTC pair for all three rolling window sizes.
- A plausible hypothesis for the leading position of UNISWAP-V2 is the association with ETH as the native token of the Ethereum blockchain.
- Rolling window of 256 observations, no relevant daily lag for ETH-DAI and ETH-USDT. For long-term investments, 512 observations, UNISWAP-V2 leads the pricing efficiency against Binance by around one day.

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Conclusions

- With an increase in the number of rolling window observations, there is a consistent increase in the market efficiency of all ETH prices.
- Two interconnected viewpoints discussion: market transparency and arbitrage opportunities.
- Cross-exchange arbitrage [Wang et al., 2022, Vakhmyanin and Volkovich, 2023] within the decentralized market, offer global accessibility, thus contributing to improved price discovery and market efficiency.
- Users employing algorithmic trading strategies adeptly capitalize on market inefficiencies.
- Fewer regulatory hurdles on the decentralized system enable implementing changes and innovations, contributing to a nimble adaptation to evolving market conditions.
- A culture of financial innovation and rapid adoption of novel concepts further accelerates responses to challenges in market efficiency.

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Thank You!

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