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Decoding multifractality in DeFi through governance tokens

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Abstract

This study investigates the multifractal characteristics of the decentralised finance (DeFi) market through the lens of governance tokens. We classify governance tokens into two categories: blockchain governance tokens and governance tokens for decentralised autonomous organisations (DAOs). Using daily returns of seven tokens Uniswap, Compound, Maker, Curve DAO, Aave, Dash, and Decred spanning May 2020 to June 2024, we apply Multifractal Detrended Fluctuation Analysis (MFDFA) to examine scaling behaviour and long-memory properties. Our findings confirm multifractality across all tokens, with blockchain governance tokens exhibiting greater multifractality and thus higher market inefficiency than DeFi tokens. We further introduce the Generalised Magnitude of Long Memory (GMLM), a novel measure of relative efficiency across return moments, which shows that DeFi tokens are more efficient at higher moments, while blockchain tokens are more efficient at lower moments. This suggests that risk assessment strategies in DeFi should account for moment-specific efficiency, with higher-order risk models being more appropriate for DeFi tokens and lower-order models being better suited for blockchain governance tokens. These findings offer actionable insights for investors, portfolio managers, and policymakers navigating the DeFi landscape.

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1. Introduction

Recent years have witnessed significant transformations in the global financial system, driven by innovative financial instruments, technological advancements, and evolving financial architectures. A prominent example is the Decentralised Financial System (DeFi), which leverages blockchain technology to remove intermediaries and decentralise financial operations (Makarov & Schoar, 2022). Broadly, financial systems can be categorised into Traditional Financial Systems (TradFi) and Decentralised Financial Systems (DeFi). TradFi operates through a centralised structure in which a central authority governs most operations and decision-making, limiting participant autonomy.

DeFi, as defined by Ozili (2022), encompasses financial services developed on open-source protocols and public blockchain networks, thereby eliminating the need for traditional intermediaries. Central to DeFi are various tokens, particularly governance tokens, which play a key role in managing decentralised applications (dApps) and Decentralised Autonomous Organisations (DAOs) (Mensi et al., 2023). Understanding governance tokens is crucial to comprehending DeFi's dynamics; however, not all governance tokens actively participate in DeFi operations.

Some governance tokens, such as DASH and DECRED, primarily serve as cryptocurrencies focused on blockchain governance rather than facilitating direct financial services. These tokens operate at the infrastructure layer, providing the foundational technology that supports the blockchain network; however, they are not involved in lending, trading, or other DeFi services. In contrast, governance tokens within DeFi protocols are directly linked to financial applications or organisations, granting holders the right to participate in decisions regarding the protocol's or organisation's financial operations. This distinction highlights the broad distinction between governance tokens in the broader blockchain ecosystem; one is used for maintaining the underlying infrastructure, while the other is used to drive the financial activities in DeFi

Despite DeFi's growing relevance, empirical studies remain limited due to its novelty. Zhang et al. (2023) explored market efficiency using the Dominguez and Lobato (DL) test, uncovering complex market dynamics. Mensi et al. (2023) examined asymmetric multifractality in DeFi tokens using Asymmetric Multifractal Detrended Fluctuation Analysis (A-MFDFA), identifying significant multifractal characteristics indicative of market inefficiency. These studies primarily focus on DeFi tokens, which combine utility and governance features (Harvey et al., 2021).

Research has also examined DeFi's interconnectedness with traditional financial assets, highlighting its integration within broader financial markets (Bejaoui et al., 2023; Karim et al., 2022; Yousaf et al., 2022; Nekhili et al., 2024). Specifically, Nekhili et al. (2024) reported substantial links between DeFi and traditional financial markets, suggesting an increasingly integrated financial landscape.

This study distinguishes itself by utilising governance tokens as proxies for decentralised finance (DeFi) markets. We differentiate between governance tokens actively involved in DeFi services and those used solely for blockchain governance. Our comparative analysis focuses on multifractal properties, which are critical in financial time series as they indicate varying degrees of market efficiency (Cajueiro et al., 2009). Following Fama (1965), a market is considered informationally efficient if asset prices fully reflect available information and accurately reflect the fundamental value. By analysing multifractality, this study aims to deepen the understanding of DeFi market efficiency and dynamics.

Multifractality in financial time series reflects heterogeneous scaling behaviours, typically arising from autocorrelation, fat tails, or both (Kantelhardt et al., 2002). The degree of multifractality is commonly measured using the generalised Hurst exponent, $h(q)$. When $h(q)=0.5$ across all moments, the market exhibits random, uncorrelated behaviour and can be considered efficient. Values of $h(q)>0.5$ indicate persistence or long memory, whereas $h(q)<0.5$ suggests anti-persistence or mean-reverting tendencies. The presence of persistence or mean reversion implies predictable patterns in returns, which should not exist under the weak form of the Efficient Market Hypothesis (EMH), where price changes follow a random walk and cannot be predicted from past information. According to Mensi et al. (2023)The existence of multifractality validates long-range memory and return predictability while refuting the efficient market hypothesis (random walk hypothesis).

Conventional efficiency tests, such as the variance ratio test, are limited because they rely solely on variance (a single moment). In contrast, Multifractal Detrended Fluctuation Analysis (MF-DFA) evaluates efficiency across multiple time scales and higher-order moments, reducing the likelihood of misclassifying a market as efficient when hidden inefficiencies exist beyond the second moment (Jayasankar, 2025).

MF-DFA has been applied extensively across financial markets. Studies document multifractality in stock markets (Niere, 2013; Lee et al., 2017; Ikeda, 2018; Khurshid et al., 2024), foreign exchange markets (Han et al., 2020; Diniz et al., 2023), and cryptocurrencies (da Silva Filho et al., 2018; Gunay & Kaşkaloğlu, 2019; Kakinaka & Umeno, 2022), highlighting its versatility as a tool for detecting inefficiencies across diverse financial systems. MF-DFA has also been used for measuring the sustainability of debt (see Brou& Bouoiyour, 2023).

This study makes significant contributions. Analytically, it is the first to compare DeFi tokens with blockchain governance tokens and test for distinct patterns. Methodologically, it introduces a new measure, the Generalized Magnitude of Long Memory (GMLM), extending the Magnitude of Long Memory of Khuntia and Pattanaik (2020). GMLM enables estimation of relative efficiency or inefficiency across moments and identification of distinct patterns across higher and lower moments.

The remainder of the paper is structured as follows: Section 2 details the data and methodology, Section 3 presents the results, and Section 4 concludes.

2. Data and Methods

We chose five major DeFi governance tokens: Uniswap (UNI), Compound (COMP), Maker (MKR), Curve DAO Token (CRV), and Aave (AAVE) based on market capitalization and Total Value Locked (TVL) from CoinMarketCap as of June 30, 2024. Leading decentralized exchange, lending, stablecoin, and liquidity protocols that are mostly implemented on Ethereum are governed by these tokens, which are distinguished by high protocol usage, significant TVL, and active on-chain governance. Decred (DCR) and Dash (DASH), native blockchain governance tokens with integrated voting and treasury mechanisms that represent non-DeFi, chain-level governance models, were also included for comparison. The time period has been chosen per data availability from 10-05--2020 to 06-30-2024 (1361 observations), with daily data

Daily data was used for reliability, and balancing informativeness with reduced noise, whereas high-frequency data, though richer, can introduce substantial noise, making daily data a practical choice. We have calculated the returns based on the closing prices. In the following equation, $\hbar$ denotes the time period.

$$\text{Ret}\,(\hbar) = \log\left(\frac{\text{Close Price}_{\hbar}}{\text{Close Price}_{\hbar-1}}\right) \qquad (1)$$

2.1 Multifractal Detrended Fluctuation Analysis

We employed the Multifractal Detrended Fluctuation Analysis (MF-DFA) method proposed by Kantelhardt et al. (2002). For a nonstationary time series x_n, with length L, the cumulative deviation from its mean is calculated as:

$$X(t) = \sum_{n=1}^{t} (x(n) - \bar{x}), \quad t = 1,2, \dots, L \tag{2}$$

This cumulative series X(t) is partitioned into $L_s = \text{int}\left(\frac{L}{s}\right)$ segments of equal length s. If L is not divisible by s, the segmentation is executed from both ends of the series, yielding $2L_s$ segments.

Local trends in each segment ϑ are identified using polynomial least-squares fitting $x_\vartheta(m)$, and the segment variances are computed as:

$$F^2(s, \vartheta) = \frac{1}{s} \sum_{n=1}^{s} \{[X(\vartheta - 1)s + n] - x_\vartheta(n)\}^2 \tag{3}$$

Averaging these variances provides the q^{th}-order fluctuation function:

$$F_q(s) = \left\{ \frac{1}{2L_s} \sum_{\vartheta=1}^{2L_s} [F^2(\vartheta, s)]^{\frac{q}{2}} \right\}^{\frac{1}{q}}, \quad q \neq 0 \tag{4}$$

When $q = 0$, we calculate:

$$F_0(s) = \exp \left\{ \frac{1}{4L_s} \sum_{\vartheta=1}^{2L_s} \ln [F^2(s, \vartheta)] \right\} \tag{5}$$

Scaling behavior is represented as $F_q(s) \sim s^{h(q)}$, with chosen scale intervals ranging from 10 to 100.

The Renyi exponent $\tau(q)$ relates to the generalized Hurst exponent $h(q)$ as $\tau(q) = qh(q) - 1$.There are two methods for the formulation of $\tau(q)$ using the multifractal spectrum to detect whether the series is monofractal or multifractal. On the one hand, the first method is based on the generalized Hurst exponent (GHE), which is calculated as follows:

$$h(q) = \frac{1 + \tau(q)}{q} \quad (6)$$

On the other hand, the second method follows the generalized fractal dimension (GFD):

$$d(q) = \frac{\tau(q)}{q - 1} \quad (7)$$

Further, the Hölder exponent (α) can be obtained by employing the Legendre transformation; it shows the singularity strength:

$$\alpha = h(q) + q\frac{dh_q}{d_q} \quad (8)$$

The singularity spectrum $f(\alpha)$ *which shows the dimension of the subset* calculated as

$$f(\alpha) = q\alpha - \tau_q \quad (9)$$

To evaluate the robustness of the estimated Generalised Hurst exponent, we tested its significance across different moments using Monte Carlo simulations. Specifically, we generated 1,000 synthetic time series from a Generalised Brownian Motion, ensuring that each series followed a normal distribution with the same length, mean, and standard deviation as the selected governance tokens. For each simulated series, we computed the Generalised Hurst exponent. The resulting simulated values formed an empirical distribution of the exponent under the null hypothesis of randomness, from which we derived the upper and lower critical values at the 5% significance level.

2.2. Generalised Magnitude of Long Memory (GMLM)

The Magnitude of Long Memory (MLM) proposed by Khuntia and Pattnayak (2020) shows the degree of deviation of the asset prices from the efficiency level. In equation (10), ǵ indicates the Generalised Hurst Exponent. If the returns are efficient or long memory is absent, MLM will be equal to 0.

$$MLM = \frac{1}{2}(|\acute{g}(-10) - 0.5| + |\acute{g}(10) - 0.5|) \quad (10)$$

We have extended the Magnitude of Long Memory(MLM) . The traditional MLM only captures the deviation of efficiency from the smallest fluctuation /moment and the largest fluctuation. It fails to capture the fluctuations between the other moments.

In GMLM, we estimate the MLM across all moments, which helps capture the efficiency deviation across moments. We estimate this for all moments except 0, as there is no fluctuation in that moment. As in MLM, a value of zero indicates efficiency, and a larger value than 0 indicates a higher level of inefficiency in the selected tokens. This estimate can help investors understand the deviations holistically, prompting them to make better decisions.

$$GMLM = \frac{|(\acute{g}(-q_i) - 0.5) + (\acute{g}(q_j) - 0.5)|}{2} \tag{11}$$

for j=1,2… $q_{maximum}$ and i=,-1,-2,….. $q_{minimum}$, and $|q_{maximum}| = |q_{minimum}|$. For i=$q_{minimum}$ and j=$q_{maximum}$, GMLM reduces to MLM. Using GMLM, we can observe how the nature of efficiency/inefficiency changes across the moments.

This study introduces the Generalised Magnitude of Long Memory (GMLM) as an extension of the traditional Magnitude of Long Memory (MLM) framework. Unlike existing measures that assess efficiency deviations using only extreme moments, GMLM aggregates scaling deviations across the full range of admissible moments, thereby capturing the entire multifractal structure of financial return series.

By jointly incorporating positive and negative moment orders, the measure accounts for asymmetric and nonlinear scaling responses that commonly arise during periods of market stress. Because GMLM is constructed from scaling properties rather than volatility levels, it remains robust to transitory volatility spikes and isolates persistent departures from random-walk behaviour. This generalized formulation provides a more comprehensive and stable characterization of market inefficiency, particularly under extreme events and high-volatility regimes.

3. Results and Discussion

In Table I, we show the Generalised Hurst exponent of DeFi governance tokens and governance tokens used in blockchain governance over the moments(q). IfΔfi is 0.5, the process is a random walk, indicating efficiency; if Δfi is greater than 0.5, it indicates a long memory; and if it is less than 0.5, it indicates anti-persistence or a stationary nature. In case the series shows long memory, large fluctuations in this series are likely to be followed by large fluctuations and small fluctuations, indicating strong autocorrelation. In the case of anti-persistence, large fluctuations are likely to be followed by small fluctuations and vice versa.

Moments used in the study range from -10 to 10. Δfi was calculated using Hmax − Hmin, and the scale is 10:100. Our results show that only DECRED has a value greater than 0.5, indicating long memory. In contrast, DeFi governance has a value of less than 0.5, which indicates anti-persistence. None of the tokens have a value equal to 0.5, confirming that all the tokens lack efficiency.

In Table I, the values in the brackets show the 95% confidence intervals constructed. For governance tokens used for blockchain governance, we see that DECRED has significant value both in positive and negative moments

Table I also shows the multifractal spectrum of the selected governance tokens. The value of $\Delta\alpha$ is derived by $\alpha_{max} - \alpha_{min}$. A high $\Delta\alpha$ indicates a high degree of multifractality. In our case, we observe high multifractality in DECRED and DASH, governance tokens used for blockchain governance.

Hence, we observe that, compared to governance tokens used in DeFi, blockchain governance tokens exhibit a higher degree of multifractality. Among governance tokens used in DeFi, MAKER is the highest, followed by CURVE-DAO-TOKEN. The presence of multifractal characteristics in a market signals a departure from efficiency, as they reflect long-range autocorrelations, heavy-tailed distributions, or both, introducing exploitable patterns that violate the efficient market assumption (Shrestha, 2021). Hence, we can establish that the selected governance tokens lack efficiency

Table I: Generalised Hurst Exponent of Governance Tokens

q	DASH	DCR	MKR	COMP	CRV	UNI	AAVE
-10	0.76* (0.48,0.70)	0.71* (0.49,0.70)	0.78* (0.49,0.69)	0.76* (0.49,0.69)	0.61 (0.49,0.69)	0.61 (0.50,0.70)	0.70* (0.49,0.69)
-9	0.75* (0.48,0.69)	0.71* (0.49,0.69)	0.78* (0.48,0.68)	0.75* (0.49,0.68)	0.60 (0.49,0.68)	0.60 (0.49,0.69)	0.69* (0.48,0.68)
-8	0.74* (0.47,0.67)	0.70* (0.48,0.68)	0.77* (0.48,0.67)	0.74* (0.48,0.67)	0.60 (0.49,0.67)	0.60 (0.49,0.68)	0.69* (0.48,0.67)
-7	0.73* (0.47,0.66)	0.69* (0.48,0.66)	0.76* (0.48,0.65)	0.73* (0.48,0.66)	0.59 (0.48,0.66)	0.59 (0.48,0.67)	0.68* (0.48,0.66)
-6	0.72* (0.47,0.64)	0.68* (0.47,0.65)	0.74* (0.47,0.64)	0.72* (0.48,0.64)	0.59 (0.48,0.65)	0.59 (0.48,0.65)	0.67* (0.48,0.65)
-5	0.70* (0.47,0.63)	0.66* (0.47,0.63)	0.72* (0.47,0.62)	0.71* (0.47,0.63)	0.59 (0.47,0.63)	0.59 (0.47,0.64)	0.66* (0.47,0.63)
-4	0.68* (0.47,0.61)	0.64* (0.46,0.61)	0.70* (0.46,0.61)	0.69* (0.46,0.62)	0.58 (0.46,0.62)	0.58 (0.47,0.62)	0.65* (0.47,0.61)
-3	0.66* (0.46,0.60)	0.62* (0.46,0.60)	0.68* (0.46,0.60)	0.67* (0.46,0.60)	0.57 (0.46,0.60)	0.57 (0.46,0.61)	0.64* (0.46,0.60)

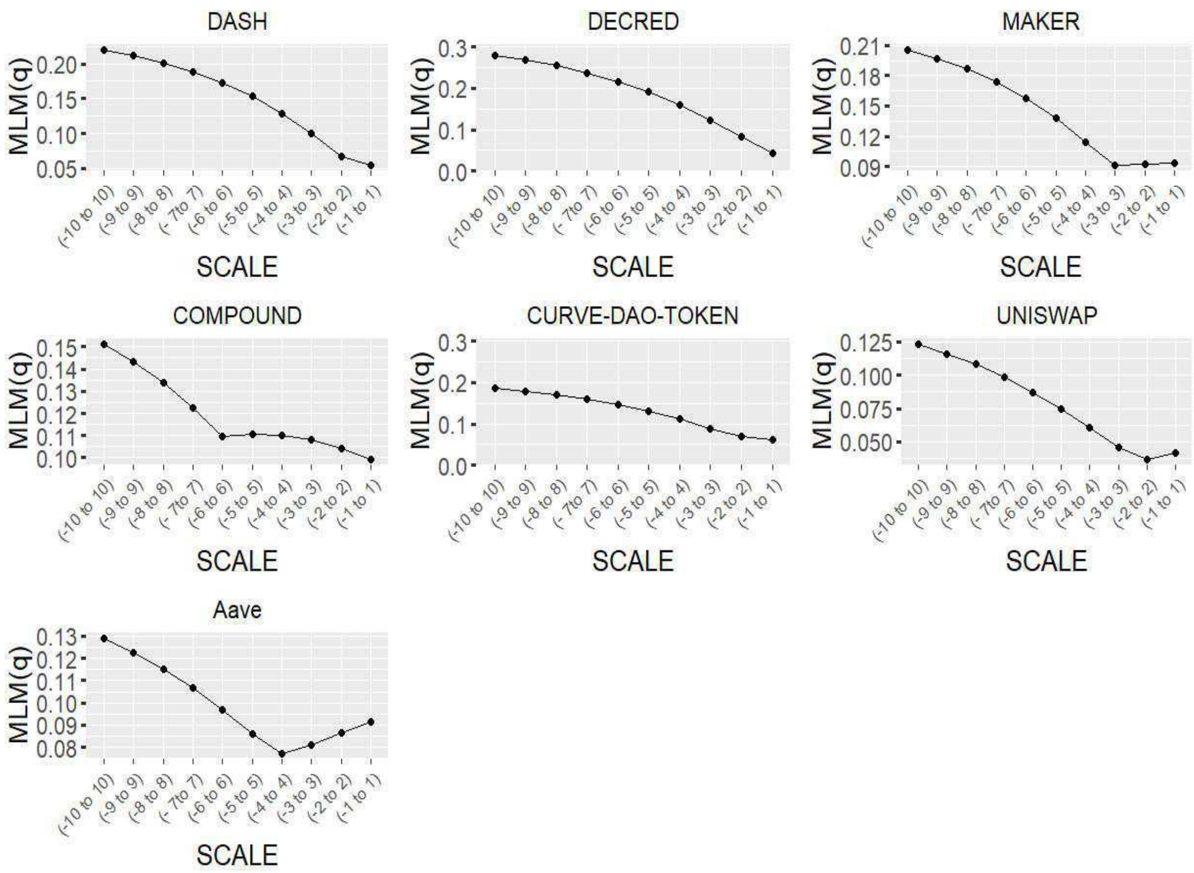
-2	0.62* (0.46,0.60)	0.59 (0.45,0.59)	0.65* (0.46,0.59)	0.64* (0.45,0.59)	0.57 (0.45,0.59)	0.57 (0.46,0.60)	0.63* (0.46,0.59)
-1	0.59 (0.45,0.59)	0.56 (0.45,0.58)	0.62* (0.45,0.59)	0.62* (0.45,0.59)	0.56 (0.45,0.58)	0.56 (0.45,0.59)	0.61* (0.45,0.58)
0	0.55 (0.45,0.58)	0.52 (0.44,0.58)	0.59* (0.44,0.59)	0.60* (0.44,0.59)	0.54 (0.44,0.58)	0.54 (0.45,0.58)	0.59* (0.44,0.58)
1	0.52 (0.44,0.58)	0.47 (0.43,0.58)	0.57 (0.43,0.58)	0.58 (0.43,0.59)	0.53 (0.43,0.59)	0.53 (0.44,0.58)	0.57 (0.44,0.57)
2	0.49 (0.43,0.58)	0.43 (0.42,0.58)	0.54* (0.43,0.59)	0.57 (0.43,0.58)	0.51 (0.43,0.59)	0.51 (0.43,0.58)	0.54 (0.43,0.57)
3	0.46 (0.42,0.58)	0.38* (0.42,0.58)	0.51 (0.42,0.59)	0.55 (0.42,0.59)	0.48 (0.42,0.59)	0.48 (0.42,0.58)	0.52* (0.42,0.58)
4	0.43 (0.41,0.59)	0.33* (0.40,0.58)	0.48 (0.41,0.59)	0.53 (0.41,0.59)	0.46 (0.40,0.59)	0.46 (0.41,0.58)	0.50 (0.41,0.58)
5	0.40 (0.40,0.59)	0.28* (0.39,0.59)	0.45 (0.40,0.59)	0.52 (0.39,0.59)	0.44 (0.39,0.59)	0.44 (0.39,0.59)	0.49 (0.40,0.59)
6	0.37 (0.39,0.59)	0.24* (0.38,0.59)	0.43 (0.39,0.59)	0.50 (0.38,0.59)	0.42 (0.38,0.60)	0.42 (0.38,0.59)	0.48 (0.39,0.59)
7	0.35 (0.38,0.59)	0.21* (0.37,0.59)	0.41 (0.38,0.59)	0.49 (0.37,0.59)	0.40 (0.37,0.59)	0.40 (0.37,0.59)	0.47 (0.37,0.59)
8	0.34 (0.37,0.59)	0.19* (0.36,0.58)	0.39 (0.37,0.59)	0.47 (0.36,0.59)	0.38 (0.36,0.59)	0.38 (0.35,0.59)	0.46 (0.37,0.59)
9	0.33 (0.36,0.59)	0.17* (0.35,0.58)	0.38 (0.35,0.59)	0.46 (0.35,0.59)	0.37 (0.35,0.59)	0.37 (0.34,0.59)	0.45 (0.36,0.58)
10	0.32 (0.35,0.59)	0.15* (0.34,0.58)	0.37 (0.35,0.59)	0.45 (0.34,0.59)	0.36 (0.35,0.59)	0.36 (0.34,0.59)	0.44 (0.35,0.58)
Δﬁ	0.43	0.55	0.41	0.30	0.37	0.24	0.25
Δα	0.59	0.76	0.57	0.45	0.52	0.38	0.37

*Values in () show the critical values at 5% significance , * indicates significance

Figure 1 shows the GMLM plots; the x-axis shows the scale, and the y-axis shows the GMLM values. We see that the deviations from efficiency vary across moments. Furthermore, a downward trend is observed for most of the tokens, except for AAVE and UNISWAP. For larger fluctuations, such as -10 to 10, we observe that the deviation from 0 is greater for the blockchain governance tokens than for the DeFi governance tokens. The results show that the blockchain governance tokens are relatively inefficient compared to the DeFi Governance tokens in higher moments. The downward trend in GMLM is absent for AAVE and UNISWAP in the smaller time intervals. Furthermore, in the smaller moments, the GMLM values of the blockchain governance tokens are closer to 0 than those of the DeFi governance tokens, suggesting that they are more efficient in these instances. We provide the GMLM values at each moment in the appendix.

From a portfolio perspective, GMLM provides the investors with certain insights; it helps identify assets whose returns deviate from efficiency at various scales, guiding hedging strategies, asset allocation, and tactical rebalancing. By observing inefficiency across moments, investors can reduce risk, exploit predictable patterns, or optimise diversification in token portfolios.

Figure 1: Generalised MLM plots



4. Conclusion

We analysed the multifractal behaviour of DeFi governance tokens against Blockchain Governance tokens using MF-DFA analysis. Our study shows that the degree of multifractality is higher for governance tokens that serve in blockchain than for DeFi governance tokens, indicating that a governance token backed by a financial service is more efficient than governance tokens that do not provide one. We also propose a new measure, GMLM, which is a generalisation of the MLM estimate proposed by Khuntia and Pattanaik (2020). The GMLM results show that the relative efficiency across moments changes, and it decreases as we approach lower moments. Further, we identified distinct patterns in relative efficiency in higher and lower moments, with DeFi tokens being more efficient in the higher moments and Blockchain tokens being more efficient in the lower moments.

The results presented in this study can benefit stakeholders, as they can use multifractal models to formulate strategies and forecast volatility for their portfolios. The GMLM measure can be useful for investors and fund managers, for example, if an asset shows high GMLM at certain moments, it may have predictable autocorrelations, which can be hedged against using options, futures, or complementary assets, also by looking at the GMLM under small and large fluctuations portfolio managers can get deeper insights on the risk of the asset than the standard mean-variance methods. It is clear from the analysis that models assuming homogeneity across scales may be inadequate, as all the tokens examined in this study exhibit multifractality. Future studies in this domain could focus on the reason for the multifractal nature seen among these governance tokens and the determinants of efficiency.

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Appendix

Figure A1: Plots of the Generalised Hurst Exponents

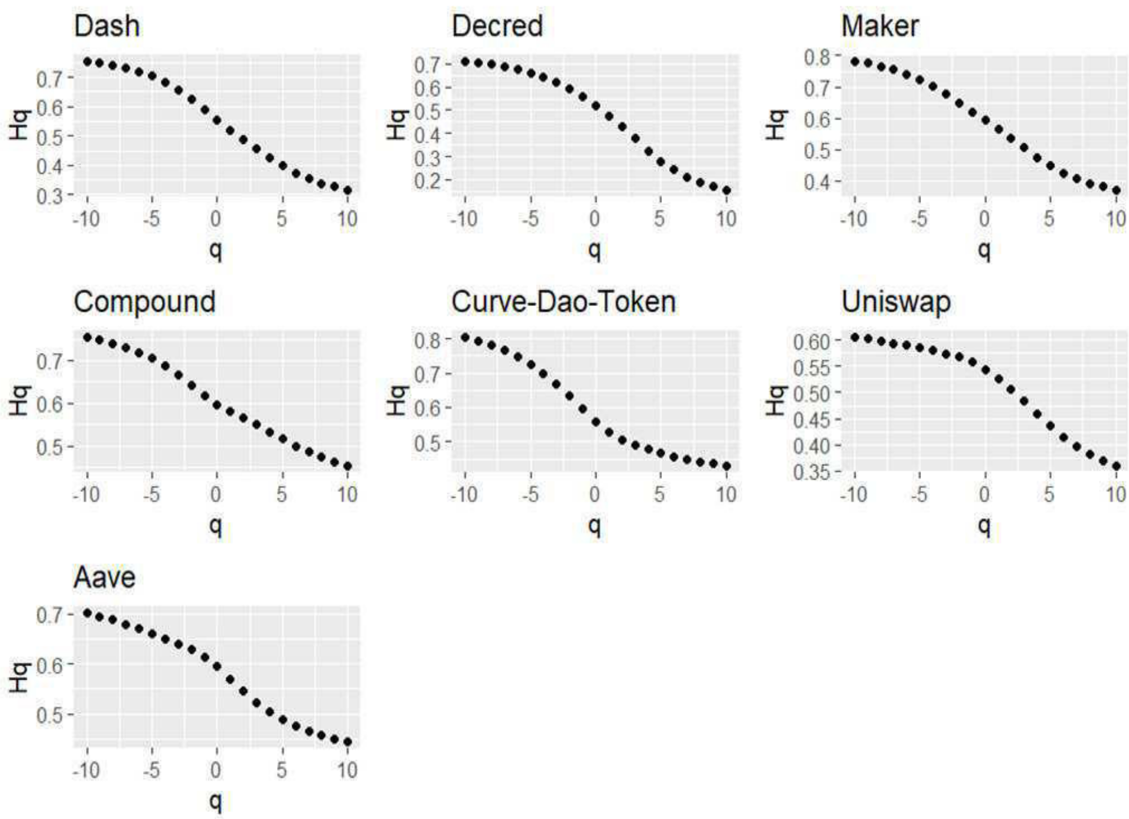

Figure A2: Plot of Multifractal Spectrum

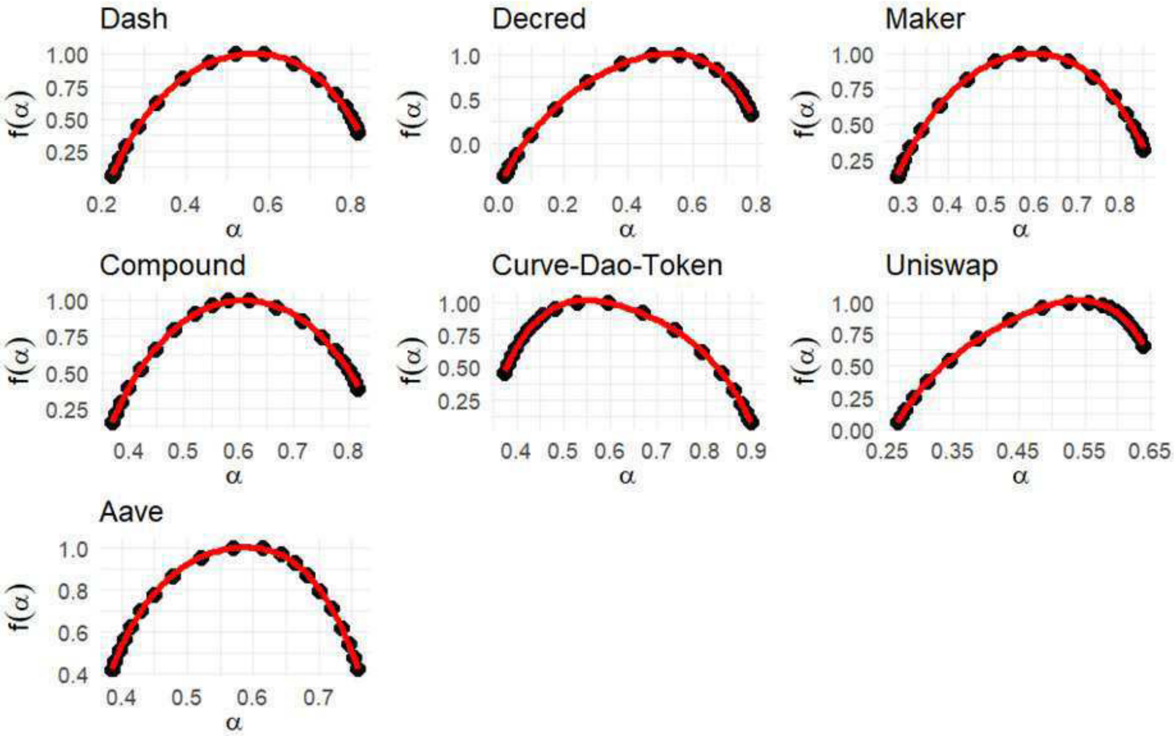

Table A1: Generalised MLM Values

SCALE	DASH	DECRED	MAKER	COMPOUND	CURVE-DAO-TOKEN	UNISWAP	AAVE
(-10 to 10)	0.21995	0.27915	0.20550	0.15125	0.18770	0.12345	0.12900
(-9 to 9)	0.21135	0.26785	0.19685	0.14315	0.17955	0.11630	0.12255
(-8 to 8)	0.20100	0.25425	0.18640	0.13370	0.17005	0.10810	0.11515
(- 7to 7)	0.18830	0.23740	0.17370	0.12265	0.15885	0.09845	0.10670
(-6 to 6)	0.17260	0.21650	0.15785	0.10970	0.14545	0.08730	0.09695
(-5 to 5)	0.15295	0.19045	0.13810	0.11045	0.12960	0.07455	0.08585
(-4 to 4)	0.12875	0.15855	0.11375	0.11025	0.11080	0.06050	0.07720
(-3 to 3)	0.09990	0.12175	0.09140	0.10820	0.08875	0.04565	0.08115
(-2 to 2)	0.06785	0.08240	0.09290	0.10405	0.06915	0.03680	0.08655
(-1 to 1)	0.05470	0.04175	0.09335	0.09930	0.06240	0.04205	0.09165

Ethics Statement

The authors have nothing to report.

Data Availability Statement

The data supporting this study's findings are available from the corresponding author upon reasonable request.