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Ethereum 2.0 Hard Fork: Consensus Change and Market Efficiency

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Abstract

This study investigates the impact of consensus mechanism changes on cryptocurrency markets within the framework of the efficient market hypothesis, focusing on Ethereum's transition from Proof-of-Work to Proof-of-Stake consensus, known as the Ethereum 2.0 'The Merge' update. Two main hypotheses guide the enquiry: (i) 'The Merge' update will significantly enhance market efficiency and (ii) Ethereum's updates will have a greater impact on market efficiency compared to other cryptocurrencies. Using the Hurst exponent's R/S statistic, changes in Ethereum's long-term memory characteristics before and after major hard forks are quantified. The analysis reveals substantial improvements in Ethereum's market efficiency following the Ethereum 2.0 hard fork, attributed to the introduction of Proof-of-Stake, which enhanced transaction speed and built trust. These findings suggest a positive trajectory towards improved efficiency in Ethereum's market, particularly with 'The Merge' update. In conclusion, this study contributes to understanding the role of consensus mechanisms in cryptocurrencies and provides insights into future market trends resulting from such changes.

Keywords: *Ethereum, Cryptocurrency, Hard Fork, Consensus Algorithm, Proof-of-Stake*

JEL Classifications: *C58 – Financial Econometrics, G14 – Information and Market Efficiency; Event Studies, G15 – International Financial Markets, G17 – Financial Forecasting and Simulation, D53 – General Equilibrium and Disequilibrium*

1. Introduction

1.1 History and Forks of Ethereum

Ethereum, introduced by Vitalik Buterin in 2014, is an open-source, blockchain-based platform that utilises decentralised technology to address challenges like high transaction costs and information disparities [1]. Smart contracts are central to this transformation, streamlining asset transactions and reducing reliance on intermediaries [2]. Ethereum requires computational resources for transactions and 'smart contract' execution, with fees denominated in Ether (ETH) [3]. Unlike traditional cryptocurrencies like Bitcoin, Ethereum enables the creation and execution of decentralised applications (DApps) [4]. While Bitcoin has consistently utilised the Proof-of-Work (PoW) consensus mechanism since its inception [5], Ethereum was designed to transition from PoW to a more energy-efficient Proof-of-Stake (PoS) consensus mechanism. Table 1 provides definitions of key terms used in this article.

The Ethereum network was launched on 30 July 2015. In June 2016, a security breach led to the unlawful appropriation of about 3.6 million ETH. The Ethereum community chose a hard fork to rectify the transactions and restore affected investors' assets. A 'hard fork' signifies a substantial modification to a blockchain's operations, leading to a significantly different protocol. These changes may generate conflicts, potentially causing a division within the blockchain. In contrast, a 'soft fork' denotes a less drastic alteration [6]. The decision faced resistance, causing a schism in the Ethereum ecosystem, resulting in Ethereum Classic and the restructured Ethereum, which differ in consensus mechanisms and governance.

Ethereum achieved a market capitalisation of over $20 billion in June 2017. The Byzantium hard fork in October 2017 improved smart contract security and reduced mining rewards. The Constantinople update in February 2019 optimised the EVM and delayed difficulty bombs, paving the way for Ethereum's transition from PoW to PoS. PoW assigns network participants the challenge of solving complex mathematical puzzles, where individuals with more computational power have a greater chance of forming new blocks [7]. In PoS, participants validate transactions and create blocks based on their cryptocurrency holdings. Validators stake a predetermined amount of coins and gain the privilege to authenticate new blocks, receiving rewards in the same cryptocurrency [7]. 'The Merge' occurred on 15 September 2022, a focal point of this study. Table 2 summarises key Ethereum network updates and their objectives [5, 8, 9].

1.2 Consensus Mechanisms of Cryptocurrency

The consensus algorithm within a cryptocurrency is pivotal for maintaining the blockchain's integrity and reliability in the context of technological evolutions and social acceptance [10]. See Table 3 for types of popular consensus algorithms.

Table 1. Definitions of key terms used in this article.

Key Term	Definition
ETH	Abbreviation for Ethereum, the native cryptocurrency of the Ethereum platform.
DApps	Decentralised Applications that run on a blockchain network, not controlled by any single entity.
DAO	Decentralised Autonomous Organisation, a type of organisation controlled by members and not influenced by a central government.
DDoS	Distributed Denial of Service, a cyber-attack aiming to disrupt the availability of a resource.
PoW	Proof-of-Work, a consensus mechanism where complex computations validate transactions.
PoS	Proof-of-Stake, a consensus mechanism determining block validation by coin holdings.
EVM	Ethereum Virtual Machine, the runtime environment for Ethereum smart contracts.
ASIC	Application-Specific Integrated Circuit, hardware designed for specific tasks like mining.
EMH	Efficient Market Hypothesis, a theory stating that asset prices reflect all available information.
Block	A unit of data storage on a blockchain, recording transactions.
Difficulty Bomb	Mechanism in Ethereum to increase mining difficulty over time, encouraging a transition to PoS.
Gas Cost	The computational effort required to execute operations on the Ethereum network.
Hard Fork	A significant change to the blockchain protocol requiring all users to upgrade.
Soft Fork	A backward-compatible change to the blockchain protocol.
The Merge	Ethereum's transition from Proof-of-Work to Proof-of-Stake.
Stake	Holding cryptocurrency in a wallet to support blockchain network operations.
Validator	Responsible for storing data and adding new blocks in a PoS blockchain.
Economic Layer	The layer in blockchain architecture where economic incentives are defined.

It fosters agreement among network participants, ensuring the legitimacy of each block [11].

Consensus algorithms serve essential roles in blockchain networks. They support decentralisation by enabling collaborative interactions among nodes, preserve data integrity without relying on central authorities, and maintain trust by safeguarding against tampering [12]. They also function as governance and participation mechanisms, empowering cryptocurrency holders to engage in network activities and receive rewards, fostering community ownership [7, 13].

Efficient consensus algorithms offer benefits like improved transaction processing, enhanced performance, and increased scalability. The choice of consensus mechanism depends on the network's purpose and characteristics [11]. PoW is the most popular, followed by PoS and Delegated Proof-of-Stake (DPoS) [14].

Table 2. The major forks and updates to the Ethereum blockchain (https://ethereum.org/en/history/ and https://github.com/ethereum, accessed on 7 August 2023).

Date	Fork Name	Summary
30 Jul 2015	Ethereum (Frontier)	Ethereum blockchain launch.
7 Sep 2015	Ice Age (Frontier Thawing)	First (unplanned) fork, providing security and speed updates. Introduced the difficulty bomb to ensure a future PoS hard fork.
14 Mar 2016	Homestead	Enabled ETH transactions and smart contract deployment.
20 Jul 2016	The DAO	US $50 million stolen. Community hard forked to recover funds, leading to Ethereum Classic formation.
2016 ~	Ethereum Classic	Ethereum Classic split due to the DAO controversy.
18 Oct 2016	Tangerine Whistle	Response to DDoS attacks.
22 Nov 2016	Spurious Dragon	Response to DDoS attacks.
16 Oct 2017	Byzantium	Reduced mining rewards, delayed difficulty bomb, added non-state-changing contract calls.
28 Feb 2019	Constantinople	Ensured blockchain functionality pre-PoS, optimised gas costs, added interaction with non-existent addresses.
8 Dec 2019	Istanbul	Optimised the gas cost.
2 Jan 2020	Muir Glacier	Delayed the difficulty bomb (by increasing the block difficulty of the PoW consensus mechanism).
15 Apr 2021	Berlin	Optimised gas costs for certain EVM actions. Increased support for multiple transaction types.
5 Aug 2021	London	Reformed transaction fees (EIP-1559), changed gas refunds and Ice Age schedule.
9 Dec 2021	Arrow Glacier	Pushed back difficulty bomb.
30 Jun 2022	Gray Glacier	Pushed back difficulty bomb.
6 Sep 2022	Bellatrix	Prepared Beacon Chain for 'The Merge', updated fork choice rules.
15 Sep 2022	Paris (The Merge)	Switched from PoW to PoS.
12 Apr 2023	Shanghai	Enabled staking withdrawals on the execution layer.
12 Apr 2023	Capella	Enabled staking withdrawals and automatic account sweeping on the consensus layer (Beacon Chain).

Ethereum initially adopted PoW but was designed to transition to PoS [1]. After a series of upgrades, 'The Merge' successfully completed the transition on 15 September 2022.

Table 3. Types of popular consensus mechanism (https://crypto.com/university/consensus-mechanisms-explained, accessed on 2 October 2023).

Types of Consensus Mechanism	Description
Proof-of-Work (PoW)	Miners solve complex mathematical problems to add blocks, rewarded for being first. Used in Bitcoin and Ethereum.
Proof-of-Stake (PoS)	Validators stake cryptocurrency as collateral, chance to create blocks based on amount staked. Energy-efficient. Used in Ethereum 2.0, Cardano, Polkadot.
Delegated Proof-of-Stake (DPoS)	Similar to PoS, but with voted delegates creating blocks. Enhances scalability and speed. Used in EOS, Tron, Lisk.
Proof of Importance (PoI)	Considers transaction quality and reputation to determine block creation ability. Prevents centralisation. Used in NEM.
Proof of Capacity (PoC)	Uses storage capacity for mining. Miners plot nonce and block hashes before mining. Used in Burstcoin, Chia, Storj.
Proof of Elapsed Time (PoET)	Assigns random waiting times to miners, first to wake up creates a block. Used in Hyperledger Sawtooth.
Proof of Activity (PoA)	Combines PoW and PoS. Miners create empty blocks through PoW, holder with most coins adds transactions through PoS.
Proof of Authority (PoA)	Used in private/permissioned blockchains. Relies on participant reputation. Used in VeChain.
Proof of Burn (PoB)	Miners burn cryptocurrency, higher burn amount increases block creation chance. Used in Slimcoin.
Byzantine Fault Tolerance (BFT)	Focuses on consensus with malicious nodes. Regulates communication using cryptography. Used in Hyperledger Fabric, Zilliqa.

The shift from PoW to PoS carries profound technical, social and economic implications. Technically, it enhances scalability and energy efficiency by allowing users to participate in block creation through deposits [12]. Socially, it amplifies decentralisation by fostering wider participation, making the network more inclusive [15, 16]. Economically, PoS significantly reduces hardware and energy expenses compared to PoW, improving profitability for participants [15]. Moreover, the transition reshapes the token economy, an economic system where tokens serve as a versatile medium of exchange [17]. The token economy model design, which incentivises user participation, is crucial for sustainable business growth [18, 19]. PoS incentivises stakers who uphold network security and create blocks, altering token distribution dynamics and encouraging broader involvement [20, 21].

However, the potential market impact of Ethereum's consensus change through the hard fork must be acknowledged. Hard forks can result in new networks due to community disagreements, challenging compatibility with the existing virtual asset ecosystem and potentially impacting investor confidence and market stability [22].

1.3 Research Structure

This study delves into Ethereum's history of major hard forks, providing context for the Ethereum 2.0 transition and establishes the theoretical foundations of EMH and long-term memory. The research objectives and hypotheses are outlined, focusing on empirically validating the impact of Ethereum 2.0's consensus change, comparing it with other major updates, and examining the repercussions on other cryptocurrency markets. Data sources and analytical methods used to assess the impact of consensus changes on cryptocurrency markets using the EMH framework are explained. A comparative analysis of market trends before and after the Ethereum 2.0 hard fork is conducted to advance our comprehension of cryptocurrency dynamics and evolution. The findings are consolidated, emphasising the implications of the consensus change on cryptocurrency markets, and offering insights for policymakers and practitioners. Study limitations and potential avenues for future research are acknowledged.

2. Theoretical Background

2.1 Efficient Market Hypothesis and Long-Term Memory of Virtual Asset Markets

EMH posits that market prices rapidly integrate all available information, making it nearly impossible for investors to consistently outperform the market average return. EMH has been rigorously examined in various financial contexts, including stock markets, financial forecasting, capital markets, foreign exchange markets and cryptocurrency markets [23–30]. EMH offers three forms: (i) Strong form EMH assumes that all information, both public and private, is reflected in a security's current market price. This means that even insider information cannot be used to consistently generate abnormal returns. (ii) Semi-strong form EMH assumes that all publicly available information is reflected in a security's current market price. This includes not only past prices and trading volumes but also news announcements, financial statements and other publicly available data. In other words, fundamental analysis cannot be used to consistently generate abnormal returns. (iii) Weak form EMH assumes that all past prices and trading volumes of security are reflected in its current market price. In other words, technical analysis cannot be used to consistently generate abnormal returns [26]. Our study follows the weak form EMH assumption.

In time series analysis, long-term memory refers to a property where, following a disturbance, the autocorrelation function gradually diminishes but retains a lasting impact [31]. Identifying long-term memory in asset price changes implies historical shocks that persistently influence an asset's price, indicating market inefficiency. The presence of long-term memory in cryptocurrency price fluctuations suggests potential predictability of future returns, uncovering inefficiencies. Recent studies have probed these aspects in virtual assets:

Bartos (2015) initially observed that Bitcoin's price promptly responds to public information, implying market efficiency in swiftly reflecting known data. This observation suggests that Bitcoin behaves like a standard economic commodity, with its price determined through market supply and demand dynamics, a hallmark of efficient markets [32]. Urquhart (2016) scrutinised the efficiency of the Bitcoin market and noted its evolution from inefficiency to efficiency [33]. Bariviera (2017) also suggested that the Bitcoin market is not entirely efficient but has improved over time [34]. Nadarajah (2017) proposed a power transformation of Bitcoin returns satisfying EMH [35]. Khuntia and Pattanayak (2018) found Bitcoin's efficiency with exceptions during specific periods [36]. Mnif (2020) detected a positive impact of the COVID-19 pandemic on the cryptocurrency market efficiency [37]. López-Martín et al. (2021) investigated the efficiency of various cryptocurrencies and concluded that Bitcoin and Ethereum markets' inefficiency tends to diminish over time evolving to more efficient markets [38].

Comparatively, Mensi et al. (2019) discovered Bitcoin and Ethereum markets to be inefficient, with Bitcoin exhibiting slightly greater inefficiency overall, though the efficiency varies across subperiods [39]. Zargar and Kumar (2019) found informational inefficiency in Bitcoin returns at higher frequencies [40]. Gregoriou (2019) attributed cryptocurrency market inefficiency to investors obtaining significant returns [41]. Fidrmuc et al. (2020) suggested that Bitcoin, Ethereum and Litecoin markets displayed short-term inefficiency in 2017–2018 [42]. Fousekis and Grigoriadis (2021) proposed volume-to-returns predictability which indicates informational inefficiency in major cryptocurrencies' markets [43]. Yi et al. (2022) suggested Bitcoin's efficiency is lower than gold, USD and stock indices but not significantly different long-term [44].

The study of Ethereum forks holds pivotal importance in the cryptocurrency domain. Hard fork is anticipated to bolster Ethereum's network scalability and decentralisation, potentially yielding positive effects not only for Ethereum but also for the broader cryptocurrency market. However, consensus is lacking on cryptocurrency market efficiency [45]. In the field of capital market research, the EMH bears significance that extends beyond geographical and currency boundaries [46, 47] and remains relevant regardless of study time frames [48–50]. Notably, there is a shortage of research that delves into the precise implications of alterations in cryptocurrency consensus mechanisms on market efficiency.

2.2 Research Hypothesis

Decentralisation has a relationship with liquidity [51], and it can be inferred that liquidity and the number of active users may have a positive impact on market efficiency [52]. Extending EMH to the technical and intrinsic aspects of cryptocurrencies, our hypothesis suggests that the degree of decentralisation in a cryptocurrency, as determined by factors like liquidity and the number of active users, correlates with market efficiency.

Hypothesis 1: The efficiency enhancement effect induced by the Ethereum 2.0 'The Merge' update will be particularly pronounced. *This hypothesis aims to confirm that as Ethereum progresses towards achieving its decentralisation objectives, the associated efficiency gains will be notably pronounced.*

Hypothesis 2: Ethereum will exhibit a greater degree of efficiency improvement following updates compared to other cryptocurrencies. *If it is true, this hypothesis suggests that cryptocurrencies moving closer to decentralisation goals will see notable increases in market efficiency.*

3. Methods and Data

To assess the impact of decentralisation enhancements through changes in cryptocurrency consensus mechanisms, the analysis encompasses five cryptocurrencies: Ethereum, Bitcoin, Ethereum Classic, Ripple and Tether. These selections were based on criteria such as user base, market capitalisation, trading volume and general popularity.

Ripple functions as an international remittance currency aimed at expediting cross-border transactions involving traditional currencies. Unlike decentralised cryptocurrencies that permit broad participation as validators, Ripple adopts a more centralised approach, restricting validation authority to a limited number of pre-verified entities. This strategy enhances transaction verification speed. Ripple operates as a for-profit company, setting it apart from cryptocurrencies that adhere more closely to decentralisation ideology [53].

Tether, introduced in 2014, functions as a blockchain platform facilitating the digital spending of fiat money. Tether is a stablecoin, a type of cryptocurrency, with its value directly tied to real-world fiat currencies and tangible assets like gold, crude oil and legal tender. Tether serves as a foundational currency for acquiring other cryptocurrencies on various exchanges [54].

- Bitcoin and Ethereum Classic adhere to PoW, characterised by high energy consumption, limitations in scalability and transaction speed.
- Ripple deviates from decentralisation principles due to constraints on validators.
- Tether, in contrast to the overarching cryptocurrency philosophy of decentralisation, serves as a foundational currency tightly linked to centralised traditional finance.

3.1 Research Methods

This study employed the Hurst exponent, calculated through rescaled range (R/S) analysis, to assess the long-term memory of time series data. The Hurst exponent, developed by Hurst (1951) and evolved into a fundamental tool in fractal geometry, has found successful applications in various domains, including financial analysis [29, 44, 55], hydrological and climatological sciences [56–58], material science [59–61], control performance assessment [62–64], meteorology [65–67] and biosciences [68–

70]. The Hurst exponent's versatility and effectiveness make it invaluable for investigating time series data, including our examination of cryptocurrency market efficiency.

R/S analysis is robust to heavy tails in the underlying process and does not need strict assumptions about probability distributions, supporting its adaptability across domains concerning long-term dependencies and complexity. We utilised the Python Hurst package to measure the degree of long-term memory in our data. R/S analysis has broad applicability, extending to fields like finance, environmental studies and signal processing. It is resilient to heavy-tailed distributions and doesn't require stringent assumptions about probability distributions [71], making it suitable for analysing long-term dependencies and complexity in various domains.

The R/S statistic calculates the range of values that average the deviation from the mean for each time series, rescaled by the standard deviation of the returns, and can be measured as follows [72]:

$$(R/S)_n = \frac{1}{S_n}\left[\max_{1\le t\le n}\left(\frac{1}{n}\sum_{k=1}^{t}(r_k-\overline{r_n})\right)-\min_{1\le t\le n}\left(\frac{1}{n}\sum_{k=1}^{t}(r_k-\overline{r_n})\right)\right]$$

where $\{r_1, r_2, r_3, \cdots, r_t\}$ is the return of the cryptocurrency at each point in time, $\overline{r_n}$ is its average $\left(\frac{1}{n}\sum_{t=1}^{n} r_t\right)$ and n represents the length of the time series. And S_n is the standard deviation of the return, which is calculated as follows:

$$S_n = \left[\frac{1}{n}\sum_{t}(r_n-\overline{r_n})^2\right]^{\frac{1}{2}}$$

Hurst (1951) found that the statistic is proportional to the H(Hurst's exponent) power of n. This relationship can be expressed as follows:

$$\left(\frac{R}{S}\right)_n = c \times (n)^H,$$

where c is some constant. Taking logarithms on both sides and summing them up, the following relationship is obtained:

$$\log\left(\frac{R}{S}\right)_n = \log c + H\log(n),$$

where a simple regression model with the calculated $\log\left(\frac{R}{S}\right)_n$ as the dependent variable and $\log(n)$ as the explanatory variables can be estimated using least squares to obtain a slope estimate, the Hurst index. Interpretation of the Hurst exponent is contingent on its values:

• $H > 0.5$: Signifies a persistent trend in the time series. This implies that either the existing uptrend will continue upward or the existing downtrend will persist downward.
• $H = 0.5$: Represents a completely random walk. In this scenario, no discernible predictive pattern for future volatility exists, aligning with the principles of the EMH.
• $H < 0.5$: Indicates an anti-persistent tendency in the time series. This suggests that the previous uptrend will lead to a subsequent downtrend, and conversely, the previous downtrend will lead to an ensuing uptrend.

This study employs changes in the Hurst index to assess Ethereum's updates in terms of their long-term memory effects and impact on market efficiency. By examining these changes before and after each Ethereum update, we aim to provide evidence regarding how each update has influenced the market efficiency of virtual assets.

3.2 Data

The study uses daily closing price data for Bitcoin, Ethereum, Ethereum Classic, Ripple and Tether, spanning from 1 January 2016 to 31 May 2023, obtained from coinmarketcap.com (https://coinmarketcap.com, assessed on 6 June 2023). These daily closing prices were then subjected to log-difference transformation to calculate daily returns. For the analysis, we utilised data from 26 July 2016 (the split between Ethereum and Ethereum Classic) to 31 May 2023, a total of 2,501 data points for each cryptocurrency.

The average log-differential returns for Bitcoin, Ethereum, Ethereum Classic, Ripple and Tether are 0.0015, 0.0028, 0.0014, 0.0017 and 0.0000, respectively. All of these values are positive, suggesting that these cryptocurrency markets exhibited an overall upward trend during the study period. The standard deviation is notably higher than the rate of return, indicating that the volatility in these cryptocurrency markets was significant throughout the study period. Both skewness and kurtosis values indicate that the returns of all five markets do not conform to a normal distribution, implying that they exhibit non-normal behaviour in their return patterns [73]. Refer to Table 4 for descriptive statistics of log-difference rate returns of five virtual assets. Figure 1 shows the price of these assets during the entire period, while Figure 2 illustrates their log-difference rate of return.

Table 4. Descriptive statistics of log-difference rate return of five virtual assets.

	Bitcoin	**Ethereum**	**Ethereum Classic**	**Ripple**	**Tether**
Count	2707	2707	2501	2707	2707
Mean	0.0015	0.0028	0.0014	0.0017	0.0000
Median	0.0018	0.0008	−0.0005	−0.0015	0.0000
Maximum	0.2251	0.3041	1.4443	1.0274	0.0566
Minimum	−0.4647	−0.5507	−0.5064	−0.6163	−0.0526
Std.	0.0385	0.0556	0.0708	0.0659	0.0047
Skewness	0.0018	0.0008	−0.0005	−0.0015	0.0000
Kurtosis	11.3393	7.8201	74.4897	36.4056	37.6493

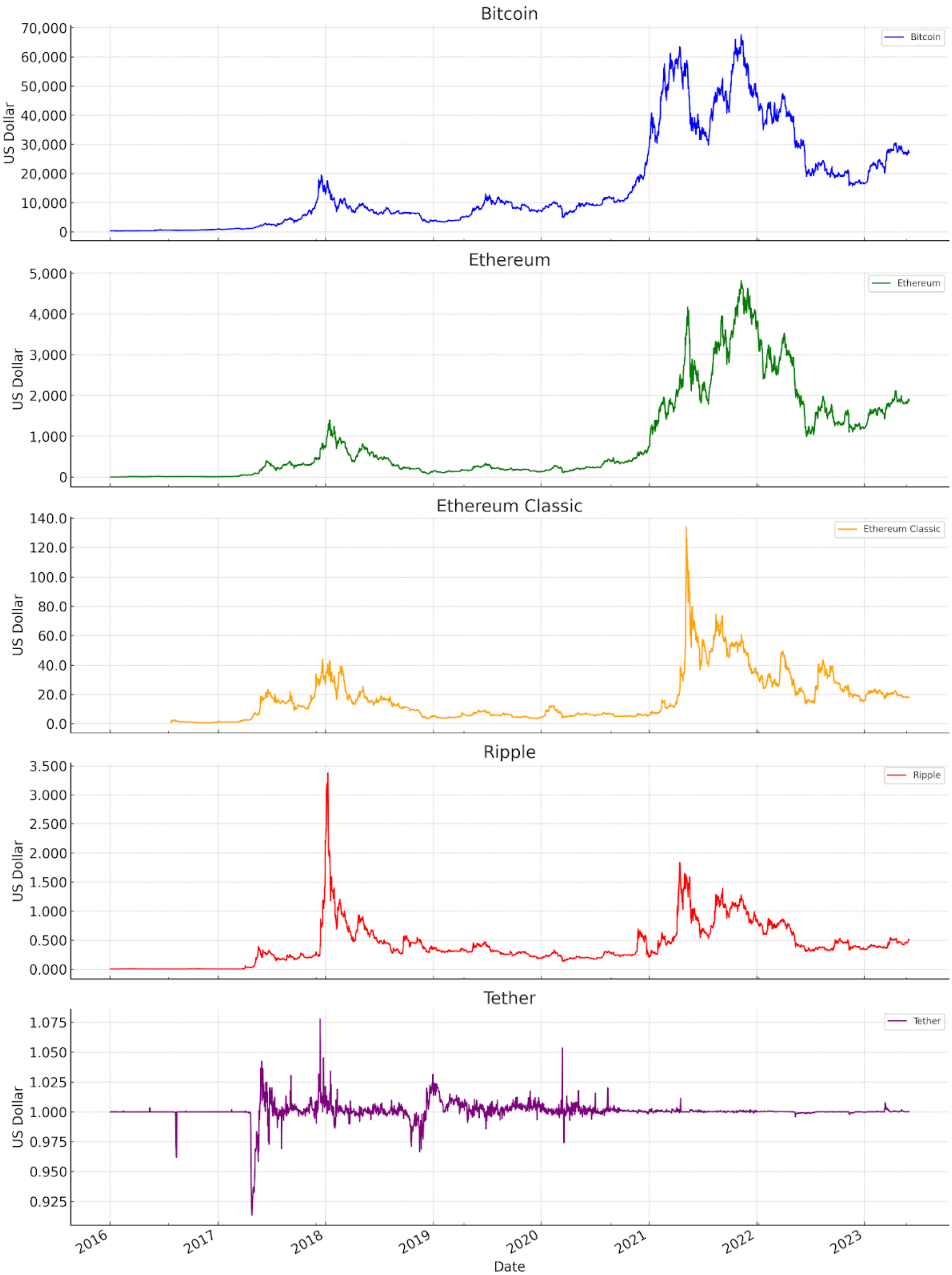

Figure 1. Price of five virtual assets during the entire period.

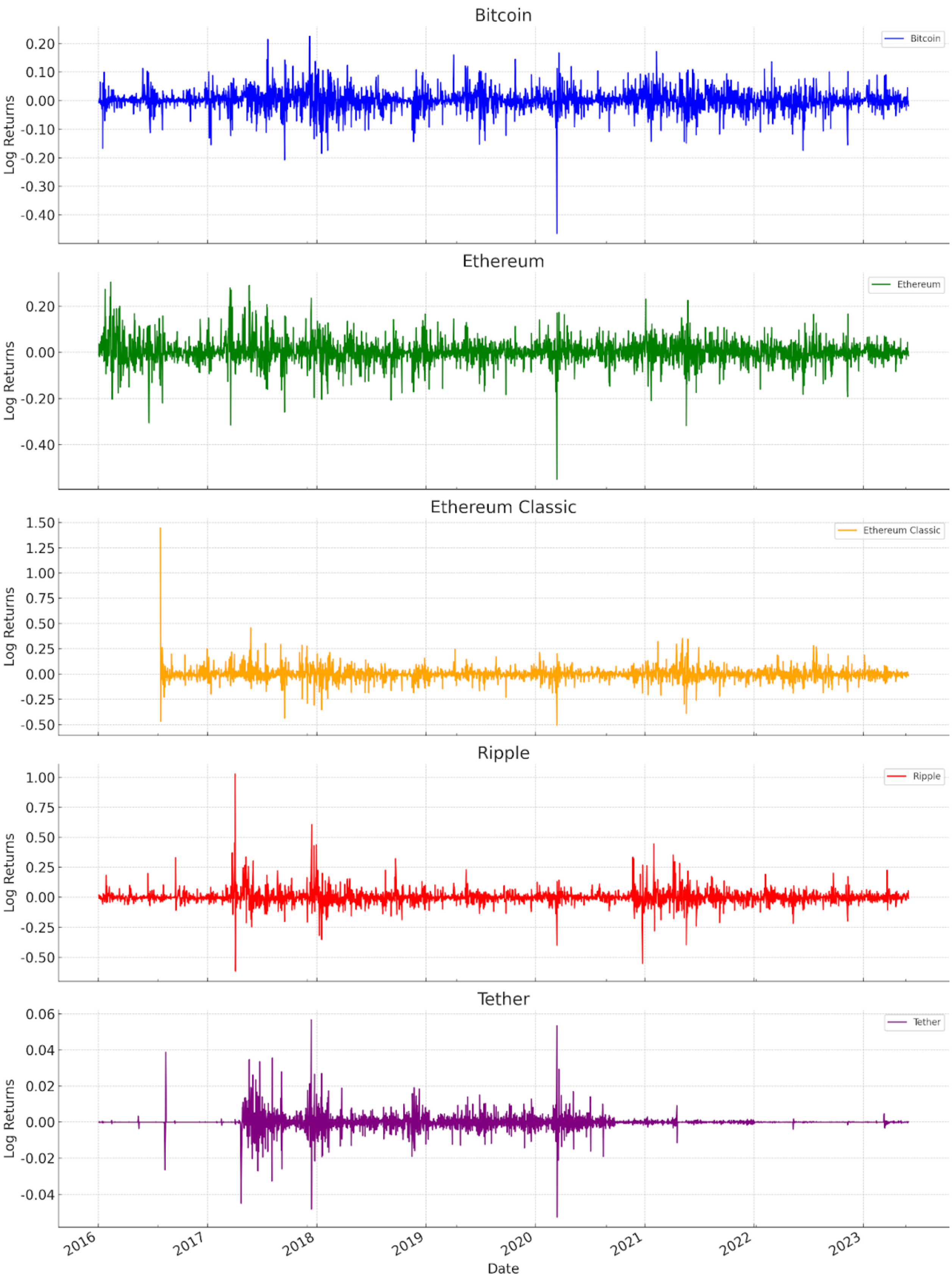

Figure 2. Log-difference rate of return of five virtual assets during the entire period.

4. Results and Discussion

4.1 Normality and Unit-Root Test

Table 5. Normality test of five virtual assets' log-difference rate return.

Normality Test	Bitcoin	Ethereum	Ethereum Classic	Ripple	Tether
Jarque-Bera	1.4680e4***	0.6901e4***	58.0677e4***	15.0836e4***	15.9404e4***
Kolmogorov-Smirnov	0.4482***	0.4319***	0.4265***	0.4334***	0.4888***
Anderson-Darling	59.5668***	50.4348***	92.3943***	134.7214***	311.2848***

* p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01

Table 5 presents the outcomes of the Jarque-Bera, Kolmogorov-Smirnov and Anderson-Darling tests used to assess the normality of return probability distributions. The Jarque-Bera test checks if data follows a normal distribution based on skewness and kurtosis. The Kolmogorov-Smirnov test is nonparametric and compares data's distribution to the normal distribution. The Anderson-Darling test, based on cumulative distribution, detects departures from normality [74]. The results consistently reject the null hypothesis of normality for all five cryptocurrencies return time series. A high kurtosis in a distribution often suggests the presence of more extreme values or 'fat tails' compared to a normal distribution. These fat-tailed distributions may exhibit long memory characteristics, implying a persistent dependency over time in the data series [75, 76].

Table 6. Unit-root test results of five virtual assets' log-difference rate return.

Unit-root Test	Bitcoin	Ethereum	Ethereum Classic	Ripple	Tether
Augmented Dickey-Fuller (ADF)	-36.0853***	-9.7025***	-8.7511***	-11.1166***	-12.3097***
Phillips-Perron (PP)	-53.4699***	-53.6693***	-57.6344***	-54.5986***	-92.8047***
Kwiatkowski-Phillips-Schmidt-Shin (KPSS)	0.2578*	0.5432**	0.1825*	0.1979*	0.0075*

* p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01

Table 6 summarises the findings from unit-root tests. The ADF test involves regressing the first difference of the time series on its lagged values and then examining the t-statistic of the coefficient on the lagged value. The PP test, similar to the ADF test, addresses serial correlation differently and employs a robust variance estimator for handling heteroskedasticity. The KPSS test is a two-sided assessment testing stationarity against a unit-root [77, 78]. The results indicate the absence of a unit-root in all five cryptocurrencies return time series. Both the ADF and PP test statistics yield significantly negative values, allowing us to reject the null hypothesis of a unit-root at the 1% significance level. Furthermore, the KPSS test statistics align with these results. Consequently, we can conclude that all five cryptocurrencies market return time series analysed can be considered stationary.

4.2 Hurst Exponent (R/S)

Table 7. Hurst exponent of five virtual assets according to test subperiods.

Event (Period)	Bitcoin	Ethereum	Ethereum Classic	Ripple	Tether
After Ethereum hard fork (26 Jul 2016 ~ 16 Oct 2017)	0.5887	0.7088	0.5950	0.6980	0.5850
After Byzantium update (17 Oct 2017 ~ 28 Feb 2019)	0.6311	0.6753	0.5487	0.6765	0.4718
After Constantinople update (01 Mar 2019 ~ 15 Sep 2022)	0.6021	0.6042	0.5976	0.5448	0.4404
After 'The Merge' update (16 Sep 2022 ~ 31 May 2023)	0.5781	0.5083	0.5694	0.5381	0.6275

Table 7 illustrates that Ethereum's updates generally influence the Hurst index of the cryptocurrency market. Right after Ethereum's split, the Hurst index of Ethereum stands at 0.7088, marking the highest within the entire observation period. However, as updates progress, Ethereum's Hurst index consistently declines. After 'The Merge' update, it experiences the most significant reduction, plummeting from 0.6042 to 0.5083, thus approaching a value close to 0.5.

Following the Ethereum split, all virtual assets display a persistent trend, with Ethereum exhibiting the highest index. Subsequent to the Byzantine update, the indices of Ethereum, Ethereum Classic and Ripple experienced slight decreases but still indicated a degree of persistence. Conversely, for Bitcoin, the index increased from 0.5887 to 0.6311, signifying a reinforced continuation trend.

Notably, after 'The Merge' update, Ethereum's Hurst exponent dropped from 0.6042 to 0.5083, indicating a reduction in long-term memory characteristics within the time series data. During the same period, the Hurst exponent of other cryptocurrencies decreased, approaching the 0.5 mark, suggesting a reduction in long-term memory effects. However, Tether exhibited a distinct pattern, with its index increasing from 0.4404 to 0.6275. Interestingly, the change in Ethereum's consensus mechanism had minimal impact on Tether, which stands out as the least decentralised cryptocurrency.

The analysis reveals that Ethereum's market efficiency has steadily improved with each update since its inception. Although there was a pronounced trend at the beginning, it gradually weakened over time, with the most significant reduction in long-term dependence occurring with the Ethereum 2.0 'The Merge' update. This implies a substantial improvement in the efficiency of the Ethereum market, aligning it more closely with the characteristics of an efficient market.

4.3 Ethereum Updates and Market Efficiency

The changes in the Hurst index provide insights into how each Ethereum update has impacted the market efficiency of virtual assets. Before the Byzantine update, both Ethereum and Ethereum Classic exhibited Hurst indexes exceeding 0.5, signifying a trend of market continuity. This implies that these markets might not have been fully efficient in incorporating available information. These inefficiencies could be attributed to the network divergence resulting from the community split. The newly forked Ethereum displayed an even higher Hurst index, indicating heightened confusion among participants during this transition. The split also introduced unforeseen vulnerabilities, underscoring its significant impact on participant behaviour and network security [79].

The Byzantium update in October 2017 aimed to improve smart contract functionality, enhance platform efficiency and introduce faster transaction speeds [80]. Following the Byzantine update, Ethereum's Hurst index dropped to 0.6753, signifying an enhancement in market efficiency.

The Constantinople update in February 2019 represented a significant stride in Ethereum's evolution as it moved towards transitioning from PoW to PoS. The primary focus was on optimising EVM operators' efficiency and mitigating the potential impact of the 'difficulty bomb'. After the Constantinople update, the Hurst index declined further from 0.6753 to 0.6042, bringing it closer to the 0.5 threshold. This shift indicated a weakening market trend and a transition towards a more balanced pattern in Ethereum's market dynamics. This result provides partial support for *Hypothesis 1*, which suggested that Ethereum's market efficiency would improve following major updates achieving its decentralisation objectives.

'The Merge' update in September 2022 marked a pivotal moment in Ethereum's evolution, as it aimed to transition the network into a more scalable and sustainable system. Following this update, Ethereum's Hurst index experienced the most substantial decrease during the study period, plummeting from 0.6042 to 0.5083. This reduction brought Ethereum's index closest to the 0.5 threshold among all virtual assets analysed. This significant decline in the Hurst index implies a notable improvement in market efficiency, consistent with *Hypothesis 1*.

4.4 Consensus Mechanism (PoW and PoS) and Other Cryptocurrency Markets

Beyond market efficiency, the transition from PoW to PoS through 'The Merge' update resulted in a significant reduction in Ethereum's energy consumption, ranging from 99.84% to 99.9996%. This shift has important implications from both social and business perspectives. From a social viewpoint, PoW-based cryptocurrencies like Bitcoin raised environmental and sustainability concerns due to their energy-intensive nature, while PoS-based cryptocurrencies are seen as more energy-efficient and eco-friendly. This could lead businesses and individuals concerned about environmental impact to favour PoS-based cryptocurrencies [9].

The choice between PoW and PoS consensus mechanisms has substantial implications for network governance and security. In PoS networks, security and validation are anchored in participants who hold stakes in the network. Validators have a vested interest in the network's success, as their holdings are at risk. This aligns network security with economic incentives. Conversely, PoW networks rely on miners who contribute computational power to secure the network. Security is directly linked to miners' capabilities and the computational resources they commit. The choice between PoW and PoS carries significant consequences for blockchain networks, impacting sustainability, governance and security. This decision should be carefully considered by cryptocurrency users, taking into account their objectives and values within the blockchain ecosystem [81].

Bitcoin and Ethereum Classic, both adhering to PoW, consistently demonstrate market inefficiency with Hurst indexes exceeding 0.5. Interestingly, in contrast to Ethereum, particularly after the Constantinople update, Bitcoin and Ethereum Classic's indexes exhibited striking similarity, highlighting comparable levels of persistence trend inefficiency. This lends support to *Hypothesis 2*, suggesting that the choice of consensus method significantly impacts market efficiency. Specifically, it suggests that PoS-type cryptocurrencies often foster more efficient markets compared to PoW-type counterparts.

Ripple, designed primarily for financial transactions with a high transaction volume and a substantial user base, displayed a consistent decline in its Hurst index over the study period. This indicates a shift towards market efficiency, potentially attributed to positive expectations regarding the outcome of the ongoing litigation with the U.S. Securities and Exchange Commission [82]. Despite variances in decentralisation compared to Ethereum, Ripple's market efficiency trends align with the broader trend observed. However, comprehensive investigation remains necessary to fully comprehend these trends, as they do not entirely align with prior research findings [53, 83].

In the case of Tether, the Hurst index displayed fluctuating patterns of inefficiency ranging between 0.4404 and 0.6275. It shifted from persistence to anti-persistence and back to persistence, indicating an inefficient market. This outcome aligns with previous research findings, suggesting that the Tether market may not be fully efficient [54, 84]. Furthermore, it can be inferred that the price trend of Tether, linked to the USD, can be highly volatile and unstable [85].

4.5 Ethereum and the Efficient Market Hypothesis

Vitalik Buterin's primary goal in conceiving Ethereum was to dismantle centralised systems through the transformative power of blockchain technology. The Ethereum White Paper introduced substantial improvements in computational efficiency, establishing an 'economic layer' for executing smart contracts while bolstering network security and the ecosystem as a whole [1].

Smart contracts broaden market access for investors, fostering a more transparent and inclusive financial environment. This transparency mitigates information disparities, empowering all stakeholders to make well-informed decisions [3, 86, 87].

EMH posits that financial markets are 'informationally efficient', meaning participants make decisions based on all available information, resulting in asset prices accurately reflecting their true value. Blockchain technology and smart contracts can be used to improve market efficiency by gathering more accurate and timely information [88, 89], and markets based on smart contracts have many similarities with the efficient market [90]. Smart contracts can potentially contribute to the democratisation of governance systems by enabling decentralised decision-making processes and coordination mechanisms [91]. We suggest that Ethereum's core functionality, namely smart contracts, democratises financial instruments. Although direct philosophical alignment between Ethereum and EMH is hard to find, it is possible to draw some parallels, i.e., both Ethereum and EMH are based on the idea of decentralisation and the democratisation of financial markets.

5. Conclusions

5.1 Summary and Implications

This study examined the impact of Ethereum's updates on cryptocurrency market efficiency. Ethereum's journey, from inception to 'The Merge', demonstrated significant improvement in market efficiency, aligning with *Hypothesis 1*. Bitcoin and Ethereum Classic, using PoW, consistently exhibited market inefficiency, supporting *Hypothesis 2*, especially after the Constantinople update. Ripple displayed a transition towards market efficiency, potentially influenced by ongoing dispute. Tether's market exhibited instability. These findings underscore the significance of technological advancements in shaping market efficiency in the cryptocurrency landscape. Conducting interdisciplinary research is essential for a comprehensive understanding of these dynamics.

Our research yields critical insights into the cryptocurrency landscape. Ethereum's consistent market improvements, especially through 'The Merge', highlight the pivotal role of technological advancements in enhancing market efficiency. This underscores the cryptocurrency market's adaptability in rapidly incorporating new information into asset prices. The choice of consensus mechanism is a substantial factor in cryptocurrency market dynamics. The divergence in market efficiency between PoW-based cryptocurrencies, like Bitcoin and Ethereum Classic, and PoS-based Ethereum underscores the significance of these mechanisms. PoS-based cryptocurrencies tend to exhibit superior market efficiency, offering valuable guidance for investors and policymakers. Lastly, cryptocurrency markets are multifaceted; Ripple's journey towards market efficiency, despite its unique decentralisation model, demonstrates that resolving securities disputes positively influenced its stability and efficiency. Conversely, Tether's volatile behaviour exposes the instability of stablecoins. These findings emphasise the necessity for comprehensive investigations into linked assets like the USD, contributing to a deeper understanding of market efficiency within the stablecoin sector.

5.2 Limitations and Future Research

While this study offers valuable insights, it's important to acknowledge its limitations and suggest future research directions.

This research has data and methodological constraints, primarily relying on historical daily price data and the Hurst index with R/S analysis, potentially limiting the depth of insight. Future studies should consider broader datasets, various cryptocurrencies and extended periods before and after 'The Merge'. The impact of data frequencies on market efficiency also demands exploration. Incorporating Detrended Fluctuation Analysis (DFA) could enhance robustness, especially with small sample sizes. Alternative methodologies like Network Analysis, System Dynamics and Transformer algorithms could provide a more comprehensive perspective.

The lack of cross-market comparisons is another limitation. Examining market efficiency variations across different cryptocurrency markets, including altcoins and stablecoins, can illuminate unique dynamics and trends, enhancing our understanding of cryptocurrency interactions.

Causality and external factors are not considered, posing a major limitation. Establishing causality between Ethereum's updates and market efficiency remains challenging. Future research could explore how regulatory changes, other major markets or global events like the COVID-19 pandemic affect consumer behaviour during crises [92–94]. Controls in the experimental design could help clarify the causal relationship.

In summary, this study provides valuable insights into cryptocurrency market dynamics, focusing on Ethereum's updates and their influence on market efficiency. As the market evolves, smart contract-based algorithms for pattern recognition and AI trading could further improve efficiency. Future studies should build upon these findings to develop a more nuanced understanding of this ever-evolving market.

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Author's Contribution:
JA conceptualised the study and contributed to methodology and investigation. JA also curated the data, conducted formal analysis, visualised the results and wrote the manuscript. EY and MK participated in methodology development, validation and review and editing of the manuscript. MK contributed equally to the final version of the manuscript and provided critical feedback throughout the process.

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