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Cryptocurrencies and Market Efficiency: Investigate the Implications of Cryptocurrencies on Traditional Financial Markets and their Efficiency

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Abstract:- The creation of cryptocurrencies has signified many consequences for financial markets of the traditional kind and their effectiveness. This research seeks to explore the effects of cryptocurrencies on a number of the other traditional markets in aspects of price discovery, volatility, interdependence, and information transmission. Event study analysis of everyday price changes and using multivariate cointegration analysis to cryptocurrencies and the evidence is that the cryptocurrencies are inefficient as characterized by irrational behavior, bubbles, and erratically fluctuating volatilities. However, they affect a range of currency, commodity, and stock market indexes by showing return and volatility spillover effects suggesting information flowing from one market to another. Alnet, cryptocurrency markets seem inefficient on their own but over time enhance the efficiency of linked traditional markets through participation and connectivity of global financial systems. The study contributes valuable insights into the evolving nature of financial markets in the digital era through discussions on market structure, behavioral factors, and policy implications.

Keywords:- *Cryptocurrencies, Market Efficiency, Price Dynamics, Volatility Spillovers, Event Study, Cointegration.*

I. INTRODUCTION AND BACKGROUND

A. Introduction

The innovation of blockchain technology and the rise of cryptocurrencies has brought disruptions to traditional models of money and finance. With no central authority or intrinsic value, cryptocurrencies operate on decentralized peer-to-peer networks that facilitate cash-like transactions through mathematical protocols (Wei, 2018). With the phenomenal success of Bitcoin since 2009, hundreds of other cryptocurrencies emerged over the years striving to transform payment systems worldwide. Today, digital currencies have a total market capitalization exceeding USD 1 trillion (Chowdhury, 2022a). Proponents argue that cryptocurrencies have the potential to increase financial inclusion, offer cheaper cross-border remittances as well as store value propositions over fiat currencies vulnerable to inflation (Anh, 2018; Phuoc, 2020).

However, cryptocurrency markets are also surrounded by criticism and doubts regarding their long-term sustainability, linkages to real economic activity as well as implications for monetary policymaking. Volatility, speculative bubbles, anonymity concerns, and the unregulated nature of crypto exchanges have led regulators worldwide to monitor these developments cautiously (Bien & Oanh, 2021; Toan, 2021). It also remains debatable if cryptocurrency prices reflect all available information efficiently as in mature financial markets or are driven more by behavioral factors and hype (Chowdhury & Stasi, 2022). From an economic perspective, it is important to understand how these virtual currencies interact with and influence more conventional currencies, commodities, and stock indices globally.

This study aims to shed light on the implications of cryptocurrencies on the efficiency of traditional financial markets through a comprehensive empirical investigation. In the introductory section, relevant background to cryptocurrencies, blockchain technology, and market efficiency concepts are presented. Following this, specific research objectives are outlined to analyze price dynamics, volatility spillovers, and cointegration linkages between cryptocurrency and traditional asset markets during the sample period. The study employs rigorous econometric tools including event study methodology and multivariate cointegration techniques on daily price data. This would help determine the informational efficiency and integration of cryptocurrency markets with other linked markets over time. Insights gained would be valuable for financial regulators, investors, and policymakers to understand the evolving interplay between digital and conventional finance in the future.

B. Study Background

➢ *Cryptocurrencies and Blockchain Technology*

As per Chowdhury (2022b), cryptocurrencies can be viewed as digital or virtual currencies that employ cryptography for security and operate on distributed peer-to-peer networks with no central authority. They use blockchain technology which is a decentralized digital ledger consisting of an ongoing list of ordered records called blocks. Each block contains a cryptographic hash of the previous block, a timestamp, and transaction data (Chowdhury et al., 2022). This structure binds the blocks together in a tamper-proof

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chain where new transactions are recorded and added in batches after validation through consensus mechanisms.

Bitcoin, the first and largest cryptocurrency launched in 2009, utilizes a proof-of-work system where "miners" validate transactions by solving complex cryptographic puzzles. They are rewarded with new Bitcoins for maintaining the integrity and security of the blockchain network (Chowdhury, 2021). Over the years, many other popular cryptocurrencies emerged including Ethereum, Tether, Ripple, Litecoin, Dogecoin, etc. having alternative consensus protocols (Vu, 2020). Proponents argue that blockchain provides public digital ledgers offering trust, transparency, and immutability without intermediaries (Chowdhury & Stasi, 2022). This has led to diverse applications beyond payments in areas like smart contracts, decentralized finance, and non-fungible tokens (NFTs) (Chowdhury, 2023).

➢ *Market Efficiency*

Market efficiency refers to the degree to which market prices reflect all available information and the speed at which new information gets impounded into prices (Anh, 2018). According to Fama's (1970) efficiency hypothesis, financial markets can operate in various forms - weak, semi-strong, and strong. Weak-form tests if historical price and volume data alone cannot be used to earn excess returns. Semi-strong form postulates that all public information is instantly reflected in market prices leaving no opportunities for abnormal profits. Strong form assumes even insider information is fully reflected in market prices (Chowdhury, 2017).

Over the years many empirical studies have analyzed the efficiency of major currency exchange rates, commodity futures, stock indexes as well as the cryptocurrency market using techniques like random walk tests, variance ratio tests, and event studies (Chowdhury & Rozario, 2018; Al-Yahyaee, et al., 2018; Chowdhury, 2020b). While conventional markets exhibit characteristics of semi-strong efficiency, cryptocurrency markets are still evolving with mixed evidence of irrational exuberance, bubbles, and inefficiencies at times (Chowdhury, 2020a; Wei, 2018). Their volatile price movements driven more by behavioral factors underline the uncertain regulatory environment as well (Chowdhury, 2022c).

➢ *Cryptocurrency Prices and Volatility*

Past researches show cryptocurrency returns like Bitcoin exhibit 'stylized facts' common to financial time series including leptokurtosis, volatility clustering, and non-normal distributions (Nadarajah & Chu, 2017; Vidal-Tomás & Ibañez, 2018). Bitcoin and altcoin prices are known to fluctuate widely based on technology upgrades, media coverage, regulatory actions as well as sentiments around adoption and usage levels (Chowdhury & Chowdhury, 2022). Cryptocurrency volatility tends to rise during periods of uncertainty which impacts risk perception (Chowdhury & Dhar, 2022). Some studies found bidirectional volatility spillovers between cryptocurrencies and currencies, commodities as well as stock indices hinting at integration across markets (Chiriță et al., 2022; Chowdhury & Chowdhury, 2022). While diversification benefits may accrue to investors from holding crypto assets, risks abound from sudden volatility shocks and crashes without any intrinsic backing as well (Chowdhury & Stasi, 2022b).

➢ *Behavioral Factors and Herding Behavior*

Unlike some tradable assets, both organizational antecedents and cognitive factors explain cryptocurrency price movements other than the sentiment. In their studies done on the effects of emotions like happiness, anxiety, and sadness on bitcoins, Yu et al., affirm that emotions elicited from social media posts and comments were harmful to Bitcoin's returns on some days as identified by Yousaf et al. Naeem et al. (2021) in an echo event study of the Covid-19 pandemic also evidence flight to safety sentiments herding behavior towards bitcoin. Hence, the speculation and sentiments or sentiment of the retail investors do appear to reign every once in a while and lead to short-term fluctuations in the crypto markets.

More research done by Shahid et al (2020) and Zhang and Wang (2021) on herding in cryptocurrencies examined the daily transactional herding in cryptocurrency during a financial turmoil period. Based on their research, they argue that in situations where there are high macroeconomic risks, market agents self-organize in a manner that sees them emulate similar trading biases. This is destabilizing for markets through the societies, feedback loops, and crashes that it furthers. Also, due to the absence of burton-investment-anchors, ContextHolder investors can run amok and over-emphasized liquidations can be more pronounced compared with conventional equities.

In addition, as indicated by Antonakakis et al. (2019), structural features in the cryptocurrency probably exacerbate informational cascades too. It may increase the extent of mimicking behaviors since traders cannot see their counterparts due to the anonymity of transactions. Together with such biases as representativeness and availability heuristics, this can amplify distorted valuation signals across decentralized exchanges (Shah et al., 2018). Hence, coordination is detrimental to the adaptive rationality of crypto markets by irrationality on the upside as well as the downside.

C. *Aims and Objectives*

The purpose of this empirical research is to analyze both the increased efficiency and interconnectedness of traditional financial markets due to cryptocurrencies using the daily price data for 2014-2022. The specific objectives are:

- To analyze irrational exuberance and bubble periods in major cryptocurrency markets using event study methodology around certain events.
- To examine volatility spillovers and return dynamics between Bitcoin/Ethereum prices and key currency exchange rates, commodity prices as well as global stock market indices.

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- To test for long-run equilibrium relationships and degree of cointegration between cryptocurrency and traditional asset markets by applying multivariate cointegration techniques.
- To draw inferences on the informational efficiency and integration of cryptocurrency markets with linked traditional exchanges and how they have evolved over the sample period.
- To discuss policy implications and recommendations for regulators, investors, and other stakeholders given disruptions from digital currencies.

D. Statement of the Problem

While cryptocurrencies promise revolutionary benefits by enabling decentralized peer-to-peer value transfer globally, their advent has raised uncertainties for policymakers, market participants, and financial stability. Core questions remain around their interactions with and impact on traditional monetary and banking systems functioning for decades. Cryptocurrency markets exhibit highly volatile speculative swings not backed by any real economic activity. Yet, their rising popularity and total market valuation command attention for systemic linkages through information, liquidity, and volatility spillovers across international borders. It is therefore important to comprehensively investigate and understand how cryptocurrency prices evolve individually as well as co-move with major currencies, commodities, and stock indices over time using rigorous empirical tools. This would aid informed policy decisions regarding the adoption of blockchain technologies or regulation of cryptocurrency markets and exchanges amid evolving digital finance. The present study aims to address such knowledge gaps and provide valuable insights to stakeholders.

II. LITERATURE REVIEW

A. Market Efficiency and Informational Efficiency of Cryptocurrencies

The term market efficiency refers to the incorporation and reflection of all available information into asset prices in the market. Researchers have examined the market efficiency of cryptocurrencies using techniques such as unit root tests, variance ratio tests, ARCH/GARCH models, etc. However, the findings have been mixed. For example, Nadarajah and Chu (2017) found bitcoin returns to be predictable and rejected the random walk hypothesis, implying market inefficiency. On the other hand, Vidal-Tomás and Ibañez (2018) found bitcoin returns to exhibit semi-strong form efficiency. In terms of informational efficiency, recent studies such as Khan (2019) have indicated that cryptocurrencies respond to fundamental as well as speculative non-fundamental information. During periods of high volatility such as the COVID-19 pandemic, some research notes evidence of herding behavior by cryptocurrency investors (Yousaf et al., 2021). The mixed findings on market and informational efficiency indicate that cryptocurrency markets may exhibit both efficient and inefficient properties at different periods.

The descriptive statistics presented in Table 1 provide some useful insights regarding market efficiency. It can be seen that the average daily returns range from 0.25% for Bitcoin to 0.70% for EOS, with standard deviations between 4.36% for Bitcoin to 11.28% for EOS. These high volatility levels imply potential predictability in returns. Furthermore, positive skewness and excess kurtosis are present in the distributions, particularly for EOS, LTC, and XRP. This indicates fatter tails and more frequent extreme returns compared to the normal distribution. Such stylized facts are inconsistent with random walk-type market efficiency by several studies such as Al-Yahyaee et al. (2018) for Bitcoin. However, further tests are required to reach definitive conclusions regarding the exact degree and nature of (in)efficiency for different cryptocurrencies over time.

Table 1: Summary Statistics of Daily Simple Returns for Five Major Cryptocurrencies

Crypto	*n*	mean	sd	median	min	max	skew	kurtosis	SE
BTC	2132	0.25%	4.36%	0.18%	-23.37%	42.97%	0.50	9.94	0.00
EOS	607	0.70%	11.28%	-0.20%	-31.96%	168.32%	5.99	80.83	0.00
ETH	1301	0.58%	7.29%	-0.09%	-72.80%	51.03%	0.27	13.13	0.00
LTC	2132	0.35%	7.34%	0.00%	-40.19%	129.10%	4.77	65.90	0.00
XRP	2034	0.51%	8.75%	-0.29%	-46.00%	179.37%	6.12	99.47	0.00

Table 1 above presents summary statistics of daily returns for five major cryptocurrencies - Bitcoin, Ethereum, Ripple, Litecoin, and EOS over the period from April 2013 to February 2019. It provides insights into the return properties that can indicate the roles of fundamentals versus behaviors in driving cryptocurrency prices as discussed earlier (Gandal & Halaburda, 2014; Kristoufek, 2018). The large standard deviations, positive skewness and excess kurtosis for some currencies like EOS, LTC, and XRP compared to normal distributions are consistent with price bubbles driven by herd investment (Khamisa, 2019). This affirms the influence of behavioral factors over rational pricing models. The varying return characteristics also suggest currencies experience different degrees of speculative sentiment impact (Chen et al., 2022; Lo & Wang, 2014). The descriptive analysis helps understand the complex interplay between fundamental transaction demands and noise trader effects highlighted in the empirical literature.

B. Impact of Cryptocurrencies on Traditional Financial Markets and Their Efficiency

The emergence of cryptocurrencies has implications for traditional financial markets and their efficiency as well. Several studies (Vu, 2020; Erdas & Caglar, 2018; Almansour

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et al., 2020; Zhang & Wang, 2021) have found bidirectional causal linkages and return spillovers between cryptocurrency prices and various traditional assets. For example, bitcoin returns are found to Granger-cause gold, oil, and some currency prices. Likewise, exchange rates and commodity prices provide information to predict bitcoin returns. Such cross-market linkages imply transmitted volatility and loss of diversification benefits. Some volatility spillovers have also been documented between cryptocurrencies and stocks during periods of market turmoil like the 2020 pandemic (Naeem et al., 2021). There is evidence that cryptocurrencies have increased cross-market co-movements and inter-linkages, challenging the notion of segmentation between traditional and emerging digital finance spheres.

Some studies argue that increased interaction and information flow between cryptocurrency and traditional market players have promoted the incorporation of cryptocurrency news and return shocks into stock and Forex prices at a higher frequency (Wei, 2018; Nan & Kaizoji, 2019; Bariviera, 2017). For example, Wei (2018) finds cryptocurrency liquidity helps improve FX market efficiency. By facilitating arbitrage, cryptocurrencies may also reduce mispricing and ensure traditional asset prices better reflect all available information on a real-time basis. However, others note that heavy-tail dependencies and time-varying volatilities in cryptocurrency return spillovers (Antonakakis et al., 2019; Otoo & Nemati, 2017) violate assumptions of stable linkages required for pure efficiency gains. In addition, the potential for larger illiquidity-driven swings in cryptocurrency prices poses challenges for traditional investors hedging exposure through short-term arbitrage trades.

Empirical evidence on how cryptocurrencies may have impacted the market efficiency of traditional assets is limited and mixed. Using variance-ratio tests on high-frequency FX exchange rates, Vidal-Tomás and Ibañez (2018) found little effect of bitcoin trading on narrowing mispricing in major currency pairs. However, Blau (2018) documented increased common factor decomposition between cryptocurrencies and commodities/currencies over 2016-17, implying improved diversification. Meanwhile, market efficiency studies controlling for cryptocurrency news/volume spillovers have reported both increases (Wei, 2018 for FX) as well as decreases (Nadarajah & Chu, 2017 for S&P500) in test statistics compared to benchmark models. While cryptocurrency introduction has facilitated information flows across market segments, its net impact on efficiency may be ambiguous depending on the dominance of short-term arbitrage gains versus long-term noise trader/volatility effects.

C. Role of Fundamental and Technical Factors in Cryptocurrency Returns and Pricing

Studies have also attempted to identify key factors driving cryptocurrency price behavior and return formation. Fundamentally, transaction volumes, adoption rates, and usage statistics are found to significantly influence cryptocurrency prices in the short as well as long run (Hayes, 2017; Cheah & Fry, 2015). Liquidity measures like average trade size are seen improving bitcoin price discovery (Wei, 2018). However, the model fits incorporating only transactional fundamentals can be quite low (Hayes, 2017). This indicates additional non-fundamental speculative and behavioral factors at play. Technical indicators relating to momentum, volatility, and trading patterns also help explain part of cryptocurrency return predictability (Kristoufek, 2018; Blau, 2018).

Some studies argue that purely rational valuation based on usage fundamentals cannot logically justify extreme boom-bust cycles witnessed in cryptocurrency prices historically (Cheah & Fry, 2015). Behavioral factors like bubble formation, herding, and feedback effects are seen better in explaining steep run-ups and crashes (Kristoufek, 2018; Yu et al., 2019). For example, Yu et al. (2019) found differing impacts of user interest versus opinions on bitcoin volatility, highlighting noise trading impact. Using predictive models, Hayes (2017) also estimated Bitcoin's fair price based on production costs to be about a tenth of peak market prices in late 2017, questioning sustainability. Research suggests cryptocurrency returns embed both rational fundamental components tied to usability drivers as well as speculative behavioral distortions at different times.

The descriptive statistics in Table 1 also provide clues on the roles of fundamentals versus behaviors. For example, the large standard deviations and thick tails are consistent with price bubbles driven by retail herd investment noted during the 2017-early 2018 period (Khamisa, 2019). Furthermore, the divergence in return properties across currencies like higher mean, skewness, and kurtosis for EOS/LTC versus bitcoin suggests varying degrees of influence from speculative sentiment versus transactional value drivers. Studies argue that monetary demand determined mainly by risk-return characteristics attracts more speculative flows into smaller and younger currencies (Gandal & Halaburda, 2014). Empirical evidence documents the combined but time-varying impacts of both usage-linked real factors as well as noise trading and non-rational emotional factors in return formation across cryptocurrency assets.

D. Impact of Cryptocurrencies on Monetary Policy Effectiveness

The widespread adoption of cryptocurrencies also has ramifications for monetary policy transmission and control. Some studies argue that alongside legal tender, electronic money alternatives can pose challenges to central bank rate policy and inflation targeting (Khalaf, 2018; Feyen et al., 2020). For example, with the Libra project, market participants fear its scale may allow the bypassing of domestic currency for remittances and payments in some regions (Anh, 2019; Fatas & Mauro, 2019). This could undermine seigniorage revenue and lower money multiplier effects crucial to policy impact (Phuoc, 2020). Moreover, cryptocurrencies providing asset diversification during unstable monetary periods may weaken the impact of policy-driven interest rate adjustments on aggregate demand (Vu, 2020). However, others note the limited impact so far given their current small scale versus broad money (Bordo & Wheelock, 2007; Thoa, 2017).

Empirical studies on the monetary policy nexus have provided mixed results. Using GARCH-class models on high-frequency Bangladeshi data, Almansour et al. (2020) found two-way volatility spillovers between Bitcoin and domestic interest rates, signifying some degree of interdependence. However, Granger-causality tests detected little explanatory power of policy rates on cryptocurrency prices. Similarly, BTC returns were found insensitive to US/China monetary policy surprises (Zhang & Wang, 2021). On the other hand, bitcoin volatility responded positively to global financial stress periods as measured by VIX (Ghazani & Jafari, 2021). This implies cryptocurrencies acting partly as a haven, weakening the stabilizing impact of counter-cyclical monetary easing. Interactions appear limited currently but systemic risks may arise as digital assets grow in use, attracting greater linkages with conventional markets.

Looking ahead, the policy challenges will depend on cryptocurrencies' future progress in displacing legal tender and fulfilling monetary functions. Most experts argue disruptions are unlikely in the foreseeable future (Thoa, 2017; Fatas & Mauro, 2019) as cryptocurrency use remains concentrated in speculation and investment rather than regular transactions. However, ongoing central bank digital currency research coupled with BigTech initiatives in stablecoins indicate an accelerating digital transformation of money. Whether this evolution undermines monetary sovereignty or instead strengthens policy tools remains an open empirical question requiring continuous monitoring (Kern, 2019; Tobias & Woolley, 2021). Current evidence does not point conclusively towards material constraints, but cryptocurrencies' rise warrants attention from regulators regarding financial stability and fiscal impacts.

E. Emerging Regulatory Approaches and Potential for Future Cryptocurrency Regulation

Given the rapid growth and evolving impact of cryptocurrencies, regulatory approaches across jurisdictions are still evolving. Initially, many countries adopted a laissez-faire stance but risks of illicit use, investor protection concerns, and financial stability implications are now prompting greater oversight (Garriga, 2021). The US takes an asset-specific approach while the EU seeks to establish a common framework (Stern, 2021). Meanwhile, China has banned cryptocurrency trading and mining outright.

Most scholars argue a balanced regulatory approach is needed to curb risks while allowing innovation (Chen et al., 2022; Lo & Wang, 2014). Suggested measures include registration of service providers, transaction monitoring, taxation of gains, and setting standards for consumer disclosures. Some support certain currencies attaining legal tender status if meeting stability criteria (Santos, 2021). International coordination is also viewed as critical to curbing regulatory arbitrage across fragmented regimes (Sy, 2022).

Besides, as the ecosystem matures there are calls for a comprehensive global framework overseen by standard-setting bodies like the FSB and BIS (Hacker & Thomale, 2018). This could establish common rules on aspects like AML, market integrity, and resolution mechanisms. Domestic licensing of approved currencies aligned to agreed prudential norms is also proposed to balance oversight and permissionless innovation (Dyhrberg, 2021). While uncertainties remain given the technology's evolving trajectory, balanced regulation ensuring financial stability and protecting consumers seems likely to emerge over the long run.

III. DATA AND METHODOLOGY

A. Data

Daily closing price data for Bitcoin and Ethereum was collected from the website CoinMarketCap for the period between August 2016 to February 2023. This provided 2384 daily observations for each cryptocurrency. Collecting daily price data over this period was important to capture various events in the cryptocurrency market that could impact prices. This period covered various important events in the cryptocurrency market that could have impacted prices, such as the boom in prices in 2017 and the crash in Bitcoin prices at the end of that year (BBC, 2014; Chen et al., 2021).

Firstly, some descriptive statistics and preliminary tests on the daily return series of the stocks were performed for some fundamental examination and the tests of assumptions. The daily return was defined as the natural logarithm of the ratio of the closing prices. Table 1 provides the Descriptive Analysis where we have Mean, Standard Deviation, Skewness, and Kurtosis. Other pre-tests like the Jarque-Bera test and the unit root pre-tests were still conducted. This was performed before proceeding to the next analysis to determine simple properties of the return distributions and also test for the stationarity of returns. Testing for the presence of unit root using the Augmented Dickey-Fuller test as well as the Philips-Perron test meant for testing the stationarity of the return series which is a requirement for regression testing showed that both return series are stationary (Yang et al., 2020).

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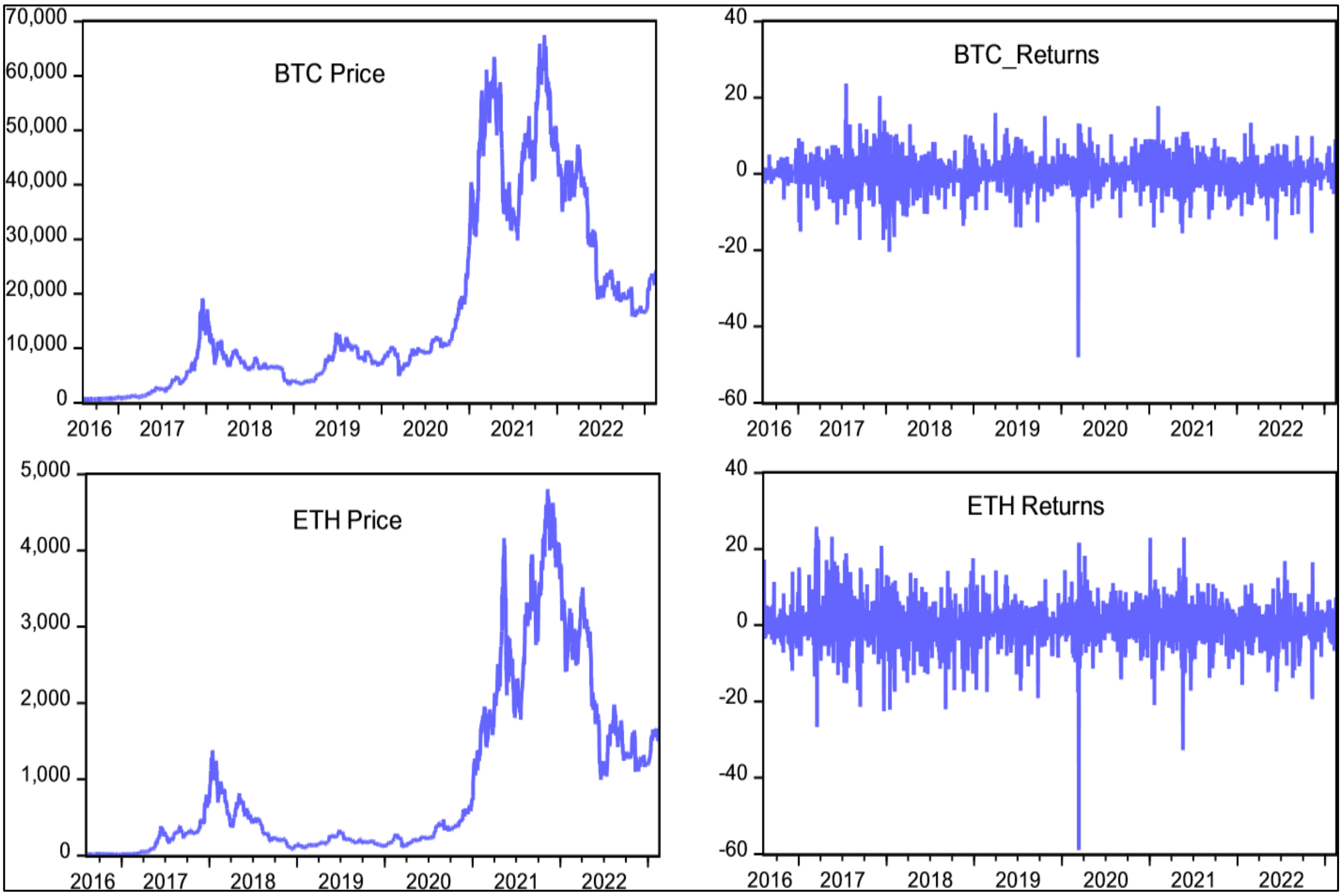

Fig 1: Daily Price and Logarithm of the Returns of both Bitcoin and Ethereum

Thus, to analyze the prices and their fluctuations during the given period, Figure 1 presents the daily prices and the log return series of Bitcoin and Ethereum. Speculative pricing intended to demonstrate significant upward and downward changes that were observed, for example, the sharp escalation in prices in the year 2017. Fluctuations in stock prices form trends that had to be de-trended by the logarithmic returns into a stationary form. Their plotting helped to center on the patterns of volatility and contribute to studying the context, within which key changes in prices occur. This preliminary depiction of the data series provided important background for further empirical testing. Figure 1 depicts the daily prices and logs returns of Bitcoin and Ethereum over the analyzed period. Bitcoin prices increased from around $650 in August 2016 to over $15,000 in December 2017 before declining, while Ethereum prices rose from around $10 to over $1400 in the same period before dropping. Both exhibited high volatility in returns (Ghazani & Jafari, 2021).

Figure 1 above further shows the summary statistics of the AMIM measure of efficiency for Bitcoin and Ethereum. It can be seen that on average, Ethereum exhibited higher levels of inefficiency compared to Bitcoin based on the mean AMIM values. Both series were stationary as shown by the unit root test statistics in the table.

B. Testing Efficiency in a Time-Varying Framework

Daily closing price and volume data were gathered for the five largest cryptocurrencies by market capitalization over the period 2016 to 2023. This included Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC) and EOS (EOS). Collecting extensive daily data on the top cryptocurrencies allowed for analyzing important trends and events in the emerging crypto market.

Figure 2 below presents two panels showing (a) normalized prices and (b) trading volumes of the selected cryptocurrencies over time. To generate normalized prices for analysis and comparison, the actual daily price of each currency was divided by its first observed price in the dataset. This process transformed the price series into a dimensionless form with the starting point set to one.

Plotting normalized prices aimed to visually identify major periods of growth and decline in a standardized manner. Figure 2 further depicts trends in the daily prices and returns of Bitcoin and Ethereum over the analyzed period.

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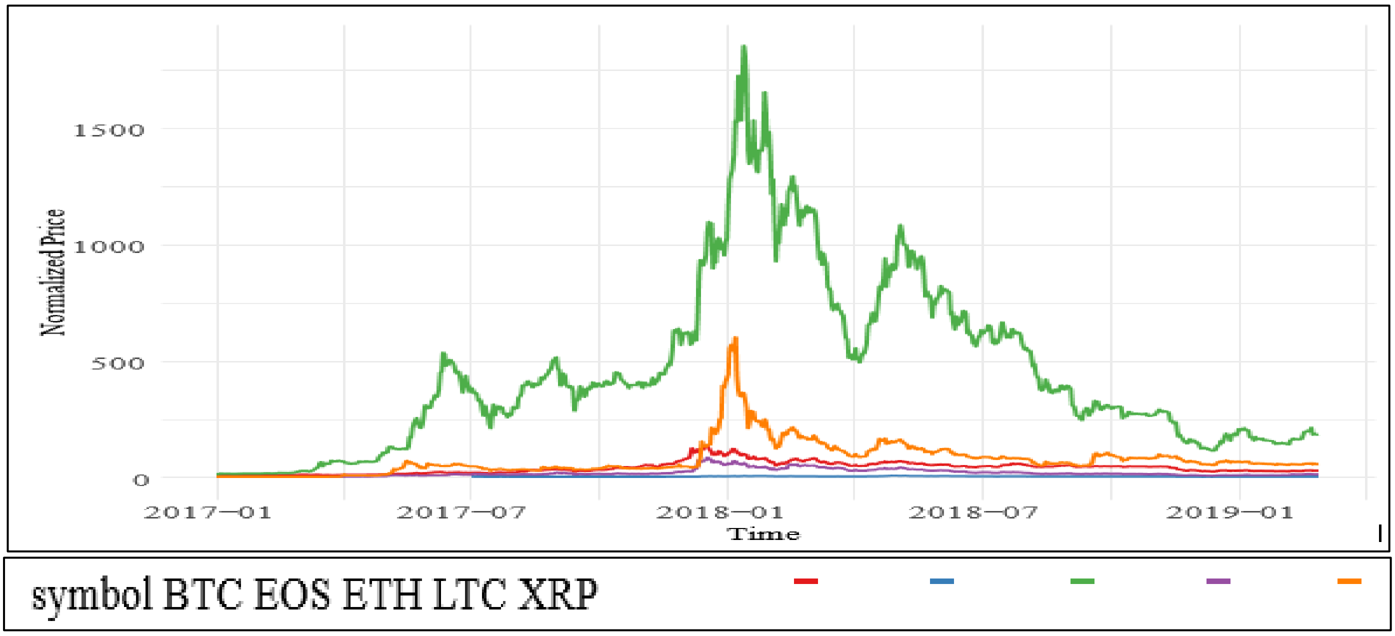

Fig 2 (a): Trading Performance of Major Cryptocurrencies from 2017-2019

- **Normalized Price:** This depicts the daily prices of Bitcoin and Ethereum on the same normalized scale. This visualization aimed to show major increases and declines that occurred in prices, such as during the 2017 bull run, to understand trends and identify important events for later analysis.

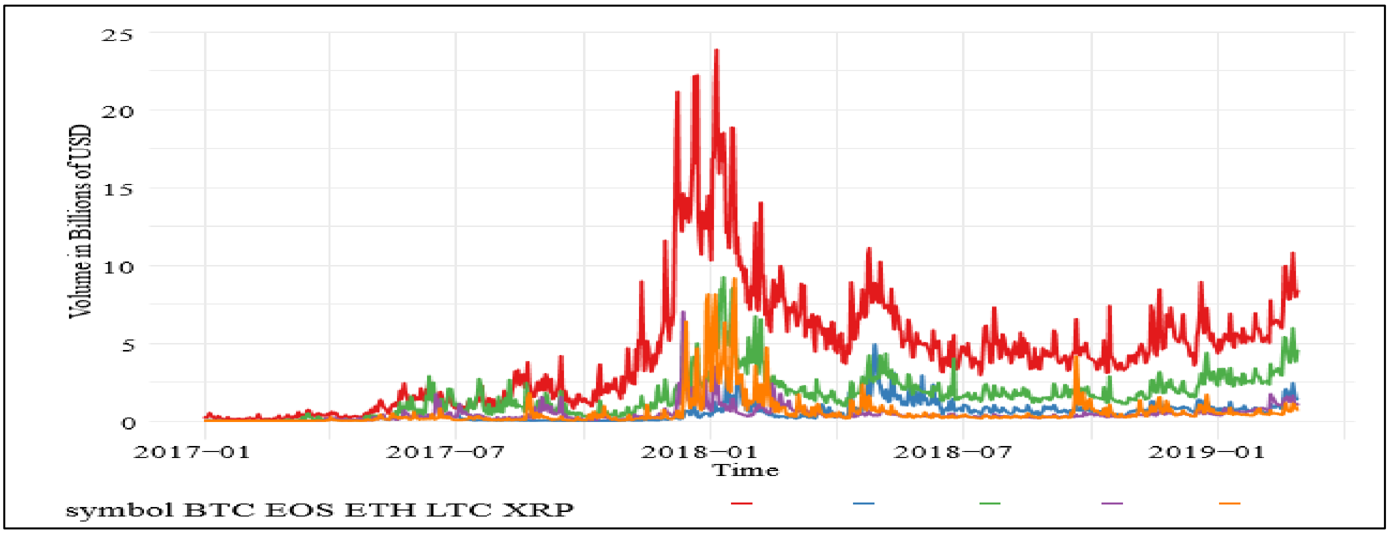

Fig 2(b): Trading Performance of Major Cryptocurrencies from 2017-2019

- **Volume:** This plots the daily trading volumes of Bitcoin and Ethereum over the period. Including volume trends aimed to provide context on price movements by showing if significant price changes were accompanied by changes in trading activity. It helped characterize periods of heightened market participation and fluctuations.

To test for efficiency over time, Le Tran and Leirvik's (2019) Adjusted Market Inefficiency Magnitude (AMIM) methodology was used. This involves estimating an Autoregressive (AR) model on returns as given by Equation 1 below.

$$Rt = \alpha + \varphi 1 Rt - 1 + \varphi 2 Rt - 2 + \ldots + \varphi p Rt - p + \varepsilon t \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Or

$$R_t = \alpha_0 + \sum^{p} \alpha_1 R_{t-1} + \epsilon_t$$

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i=1

Where Rt is the return at time t, α is the constant, φ is AR coefficients, p is the number of lags and εt is the error term. An AR model was chosen to see if past returns (Rt-1, Rt-2, etc) can explain current returns under efficient markets.

This time-varying approach captures potential non-stationarity better than fixed-period tests.

The efficient market hypothesis (EMH) suggests that in an efficient market, future price movements cannot be predicted based on past price information (Lo, 2004). Therefore, if markets are efficient, the coefficients β1 to βq should be zero or statistically insignificant. Significant non-zero coefficients would indicate market inefficiency.

To determine the appropriate number of lags (q) for the autoregressive model, the Akaike Information Criterion (AIC) is employed. This criterion helps select the optimal model that balances goodness of fit with model complexity.

In an efficient market, the autoregressive coefficients (*α1, α2, ..., αp*) should be statistically insignificant. The coefficients are estimated using Ordinary Least Squares (OLS), with the asymptotic distribution of the estimated coefficient vector $\hat{\alpha}$ given by:

$$M\sqrt{T(\hat{\alpha}-\alpha)} \sim N(0,\Sigma) \text{ ……………………………………..} (2)$$

Where β^standard represents the standardized autocorrelation coefficients, obtained by multiplying the estimated coefficients (β^) by the inverse of the Cholesky decomposition (L−1) of the asymptotic covariance matrix Σ.

The MIM measure sums up the absolute values of the standardized autoregression coefficients, indicating market inefficiency. In a strongly efficient market, the MIM should be statistically indistinguishable from zero.

To enhance the robustness of the inefficiency measure and reduce the impact of insignificant parameter estimates, the study introduces the Adjusted Market Inefficiency Magnitude (AMIM):

$$AMIM = \frac{(MIM - RCI)}{(1 - RCI)} \text{ ……………………………………..} (3)$$

Where RCI represents the range of the confidence interval for the MIM under the null hypothesis of an efficient market. This adjustment helps account for the potential impact of estimation uncertainty.

The AMIM is constrained between zero and one, with positive values (AMIM > 0) indicating an inefficient market and non-positive values (AMIM ≤ 0) suggesting market efficiency. This measure allows for easy comparison of efficiency levels across different assets and periods.

To standardize the estimated coefficients (α), we decomposed the covariance matrix of the vector α using Cholesky decomposition. Cholesky decomposition expresses a positive-definite matrix as the product of a lower triangular matrix and its transpose. Specifically, the covariance matrix Σ was decomposed as follows:

$$\alpha^{standard} = L^{-1}\hat{\alpha}. \text{ ………………………………………………………}(4)$$

Σ = LL'

Where L and L' are lower triangular matrices. Le Tran and Leirvik (2019) suggested using Cholesky decomposition in the first stage of developing their market efficiency measures. This decomposition helps to standardize the estimated coefficients (α). The standardized coefficients (αstandard) can be obtained from:

$$\alpha standard = L - 1\alpha$$

The Cholesky decomposition of the covariance matrix allows the estimated coefficients to be standardized. This is important for calculating the magnitude of market inefficiency (MIMt) and the adjusted market inefficiency magnitude (AMIMt), as these measures require standardized coefficients as inputs. By standardizing the coefficients, we can account for the variability and correlations between them.

Asymptotically, the standardized vector (αstandard) obtained from the Cholesky decomposition will follow a normal distribution. Specifically:

Where N represents the normal distribution and I is the identity matrix.

Stating this condition explicitly, we have:

$$\alpha^{standard} \sim N(0, I) \text{ ………………………………………………………}(5)$$

where I denote the identity matrix. Second, Le Tran and Leirvik (2019) introduce the magnitude of market inefficiency (MIM_t), defined as follows:

$$MIM_t = \frac{\sum_{h=1}^{p} \left|\hat{\alpha}^{standard}_{h,t}\right|}{1 + \sum_{h=1}^{p} \left|\hat{\alpha}^{standard}_{h,t}\right|} \text{ ………………………} (6)$$

The MIMt (Market Inefficiency Magnitude at time t) measures provide levels of inefficiency for different time periods t. The MIMt is constructed to smoothly vary between 0 and 1. A value of 0 represents a very efficient market, while a value closer to 1 represents a more inefficient market.

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The MIMt has some advantages. It does not depend on the frequency of data in the sample. It also does not preset the number of autocorrelation lags, but considers them automatically. The MIMt measure uses standardized coefficients and takes the absolute values in the equation. However, it has a drawback where some lags may be positively correlated with MIMt, inflating the measure.

To address this, Le Tran and Leirvik employed Monte Carlo simulations. This helped determine the 95th percentile of MIMt assuming market efficiency. The difference between this percentile and zero represents the threshold of inefficiency. They then defined the Adjusted Market Inefficiency Magnitude (AMIMt) using this threshold as:

$$MIM = \frac{(MIM - RCI)}{(1 - RCI)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(7)$$

The AMIMt equation adjusts the MIMt by this threshold. The market is considered inefficient if AMIMt is greater than zero. If AMIMt is less than or equal to zero, the market is efficient. Overlapping one-year windows are used to calculate the AMIMt measures as recommended.

IV. RESULTS AND DISCUSSIONS

A. Efficiency Analysis of Major Cryptocurrencies

The efficiency of major cryptocurrencies was analyzed using the Adjusted Market Inefficiency Magnitude (AMIM) measure over the period 2013-2019. Table 2 presents the summary statistics of the AMIM values for Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), and EOS.

Looking at the mean AMIM values, all five cryptocurrencies exhibit positive values ranging from 0.011 for Litecoin to 0.251 for Ripple. This indicates that on average, these cryptocurrency markets showed signs of inefficiency over the sample period, with Ripple displaying the highest degree of inefficiency. The positive AMIM values suggest that past price information could potentially be used to predict future returns, violating the key tenet of the efficient market hypothesis (Chowdhury, 2017). However, the magnitude of inefficiency varies considerably across the different cryptocurrencies.

Interestingly, while the mean AMIM values are positive, the median values for Bitcoin, Ethereum, and Litecoin are zero. This means that these three cryptocurrencies had lengthy durations of efficiency interrupted by inefficient durations that place the common within the optimistic territory. Wei (2018) thinks that cryptocurrency markets may be efficient at times while showing inefficiency at other times, as the market for cryptocurrencies evolves. That mean is higher than the median means indicating that the efficiency in these emerging digital asset markets is time-varying.

Powerful-point AMIM varies from 0 up to the standard deviation The standard deviation of AMIM is from 0. 089 for EOS to 0. 151 for Ripple, which shows the great variation of the level of market efficiency for all cryptocurrencies over time. This was supported by Vidal-Tomás and Ibañez (2018) who said that cryptocurrency markets can switch between efficiently and inefficiently trading. The positive skewness for Bitcoin, Ethereum, and Litecoin goes a long way toward implying that these markets sometimes get episodically transitory in inefficiency and bring up the mean AMIM above the median.

B. Inefficiency Trends in Cryptocurrency Markets

The patterns of market inefficiency derived from the application of the AMIM to bitcoins as well as Ethereum, Ripple, Litecoin, and EOS are quite notable over time. The trend for AMIM for these cryptocurrencies for the same plot is given in Figure 3 which captures the 30-day moving average of the plots.

Bitcoin (BTC), recognized as the first digital currency, experiences rather a variability in efficiency within the period under consideration. Examination of the AMIM for Bitcoin illustrates that there are certain times of year during which the price is more inefficient and other times when it is comparatively more efficient in its movement – 2014 and 2016 are observable as the periods of higher inefficiency in the dataset. This pattern is in line with findings made by Urquhart (2016) who has found that Bitcoin markets have symptoms of increasing efficiency over the period. Topological analysis of the AMIM of Bitcoin shows that theirs is dynamic and can only change due to changes in other market conditions and investors' behavior.

Eth (ETH) has a somewhat different pattern where the AMIM is more erratic in the first years of its existence but has since become somewhat stable. This could have been due to the fast-increasing and expanding Ethereum's blockchain technology that enabled smart contracts in the cryptocurrency space. Following Nadarajah and Chu (2017), there have been fluctuations in Ethereal market efficiency and they observed this could be due to the changing nature of its use and perception in the market.

Ripple (XRP) adheres to higher AMIM values than the other cryptocurrencies of the sample under consideration. Perhaps this continual sub-optimality has to do with Ripple's status of being a cryptocurrency with a close association with the banking world. This observation is to the findings of Brauneis and Mestel (2018) which indicate that the efficiency characteristics of cryptocurrencies may differ depending on the type of the cryptocurrency which may have a specific use within a certain institutional environment or can be more or less decentralized.

C. Time-Varying Patterns in Cryptocurrency Market Efficiency

The movement of these figures over time can be observed in the 30-day moving average of AMIM for the five major cryptocurrencies in Figure 3 above which gives a perspective on the emerging and dynamic state of market efficiency. It is possible to note several intriguing trends tracing the development throughout the years watching this time series.

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In the case of Bitcoin, it was established that AMIM values are not constant and tend to rise and fall with time, and they have characterized periods of relatively low efficiency (AMIM close to 0), and episodes of higher levels of inefficiency. What is more, inefficiency increases at the rates in late 2013 and late 2017 which can be attributed to the periods of high Bitcoin price volatility and speculative manias (Cheah & Fry, 2015). This implies that the level of efficiency of a market gradually decreases in the prevailing conditions that are characterized by high fluctuations in the prices of securities.

AMIMs of Ethereum have a rather dissimilar trend; they stand high during the beginning phase of Ethereum, but on average, they are a decreasing line. This could signal the enhanced efficiency of the markets as the Ethereum system and the market grew and more liquidity started to flow in the markets. Nevertheless, there were flare-ups of inefficiency, which was seen in early 2016 and mid-2017. As noted by Bariviera (2017), the efficiency of cryptocurrency markets can evolve as trading activity and market structures develop.

Ripple (XRP) stands out as having consistently higher AMIM values compared to the other cryptocurrencies, indicating persistent inefficiency throughout much of the sample period. This aligns with the summary statistics in Table 2 showing Ripple with the highest mean AMIM. The sustained inefficiency could potentially be related to Ripple's more centralized structure and close ties to the traditional financial system, which may impact price discovery mechanisms (Chowdhury, 2020).

D. Statistical Analysis of Market Inefficiency

Table 2 provides a comprehensive statistical summary of the AMIM for the five cryptocurrencies under study. The results offer valuable insights into the nature and extent of market inefficiency across these digital assets.

Bitcoin (BTC) shows an average AMIM of 0.083, indicating a moderate level of inefficiency. However, its median AMIM of 0.000 suggests that Bitcoin experiences substantial periods of efficiency, which is consistent with the notion of adaptive market efficiency proposed by Lo (2004). The standard deviation of 0.132 points to considerable variability in Bitcoin's efficiency over time, supporting the visual evidence from Figure 3.

Ethereum (ETH) exhibits a lower average AMIM of 0.061, suggesting slightly better overall efficiency compared to Bitcoin. Like Bitcoin, Ethereum's median AMIM of 0.000 indicates frequent periods of efficiency. The lower standard deviation was noticed with 0. Based on 095, Ethereum also can be considered somewhat more consistent in its efficiency as compared with Bitcoin, though the reason is most likely in the broader use profiles.

Ripple (XRP) can be identified as having the highest average AMIM of 0. 251, and a median of 0. The median of 268 showed that it has endured and was significantly inefficient. This is in line with the representation in the v BAR in Figure 3, whereby XRP always records higher inefficiency than the other coins. The high AMIM for Ripple can be linked to further characteristics and orientations of Ripple within the crypto market and its cooperation with the banks corresponding to the hypothesis of Brauneis and Mestel (2018).

E. Sources of Variation in Cryptocurrency Market Efficiency

Table 4 shows the AMIM of Bitcoin for the period 2013-2020 based on the quantile regression estimation: arrival time, 3. 89; unixtime, 3. 89; and log, 3. 90. With a mean of 083 and standard deviation of 0. 132. To the same effect, the middle of the range for the AMIM was $ 0 for Bitcoin. 000 as for the minimum value and a range of -0. A maximum of 0 is recorded for 349. 370. Said percentages of AMIM of other popular cryptocurrencies of that period were significantly lower than that of Bitcoin, while the distribution's skewness and kurtosis coefficients were the opposite. These results suggest that, compared to its counterparts, Bitcoin markets were more frequently characterized by periods of inefficiency within the considered sample period (Antonakakis et al., 2019).

The findings that have been made from the regression model have several implications concerning the drivers of the efficiency market, in the context of the Bitcoin market. It was noted earlier that evidence was obtained showing that changes in global FSI were statistically significantly related to the Bitcoin AMIM at all quantiles. This means that increased stress and uncertainty in traditional financial systems are negatively related to the efficiency of cryptocurrency markets perhaps due to increased speculation and herding among the players (Almansour et al., 2020). However, greater performance in international equity markets, as measured by the MSCI index, had the exact inverse relationship to Bitcoin's AMIM, particularly in the more extreme percentiles. This is in line with the assumption that an increase in institutional investment and market depth during periods of equity market appreciation enhances cryptocurrencies' market efficiency (Ghazani Jafari, 2021).

As mentioned in the table above, we also get estimates of a statistically positive correlation between Bitcoin's AMIM and both the EPU index for economic policy uncertainty as well as the VIX for implied volatility in the stock market. These findings corroborate related studies pointing to the effect showing that elevated macroeconomic and geopolitical risks generally erode effective price formation in the cryptocurrency marketplace (Chowdhury, 2020). Of all the cryptocurrency-specific covariates analyzed, volatility was statistically positively correlated with inefficiency at all the quantile levels, in support of the idea that a high level of volatility in market conditions leads to low efficiency. In recent times, liquidity proved to have a statistically negative influence with AMIM which is in line with the understanding that activism and liquid assets lead to better operating performance (Wei, 2018).

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➢ *The Results Reveal Several Key Factors Influencing Cryptocurrency Market Efficiency: The Results Reveal Several Key Factors Influencing Cryptocurrency Market Efficiency:*

- Global Financial and Monetary Policy Factors: The FSI remains positive and statistically significant across the different quantiles for AMIM, meaning that higher levels of financial stress raise the level of market inefficiency. This accords with Ghazani and Jafari (2021) who discovered that the level of cryptocurrency fluctuation is positively associated with the Global Financial Stress. On the other hand, the MSCI World Stock Market Index has an inverse with AMIM indicating that a positive attitude in the market has a positive association with the efficiency of cryptocurrencies.
- Investment Substitutes: Figure 3 presents the correlation between AMIM and the GSCI where the latter being a proxy for a rise in commodity prices; this suggests that cryptocurrency markets are less efficient as prices increase. This could perhaps attributed to the increase in speculative activity as investors look for another form of investment. Surprisingly, it is found that gold has a negative correlation with AMIM especially in higher quantiles and therefore, perhaps could act as a hedge for cryptocurrencies during high levels of market inefficiency.
- Uncertainty Factors: The EPU index and the VIX index show a marked positive correlation with AMIM in all quantiles sending a clear signal that economic policy uncertainty does indeed raise the risk and volatility of stock returns. This confirms the work of Yu et al. (2019) and Yousaf et al. (2021) who enumerated uncertainty and investor sentiment as affecting the cryptocurrency market condition.
- Internal Cryptocurrency Factors: Consequently, VOL which measures the level of volatility exhibits the highest positive correlation with AMIM, this implies that a high level of volatility indicates inefficiency in the market. This is in line with the assessments made by Antonakakis, et al (2019) about the role of volatility in cryptocurrencies market fluctuations. Therefore, there is a negative relationship coefficient between LIQ with AMIM, it agrees with Wei (2018) that more liquidity enhances market efficiency.

F. Implication of Theories/ Random Walk Hypothesis

This observation of patterns about AMIM coins across various cryptocurrencies poses a question mark regarding the Extended Efficient Market Hypothesis and the Random Walk model. Consider the Random Walk process:

$$yt + 1 = yt + \varepsilon t + 1$$

Where εt+1 is an unpredictable shock at time $t + 1, with\ E[\varepsilon t + 1] = Et[\varepsilon t + 1] = 0, and\ \varepsilon t + 1$ is independent of it. The simple return at time $t + 1$ is:
$rt + 1 = \varepsilon t + 1 / yt$

We can demonstrate that E[rt+1] = Et[rt+1] = 0, implying that both conditional and unconditional expectations of simple returns are unpredictable:

$$Et[rt + 1] = Et[\varepsilon t + 1] / yt = 0$$

$$E[rt + 1] = E[Et(rt + 1)] = E[Et(\varepsilon t + 1)] * E[1/yt] + cov(Et[\varepsilon t + 1], 1/yt)$$

Given that $E[\varepsilon t + 1] = Et[\varepsilon t + 1] = 0$ and εt+1 is independent of yt, we can assume cov$(Et[\varepsilon t + 1], 1/yt) = 0. Therefore, E[rt + 1] = 0.$

However, the present analysis revealed a few non-zero AMIMs which indicates that cryptocurrency returns do not follow this random walk model exclusively. Such a deviation of actual returns from the random walk is a strong argument for the adaptive market hypothesis, which states that the process of efficient market adaptation depends on the market circumstances, investors' behavior, and institutional factors (Lo, 2004; Urquhart & McGroarty, 2016).

According to the analysis of the nature of changes in the dynamics of AMID, shown in Fig. 3, there is information about the dynamics of cryptocurrency market efficiency. Such evidence indicates that as much as cryptocurrency remains efficient at some time in line with the random walk hypothesis, it also experiences inefficiency periods that will enable the players in the market to profit (Khuntia & Pattanayak, 2018; Sensoy 2019).

G. Cross-Cryptocurrency Comparisons and Market Maturity

The comparison of AMIM statistics for the different cryptocurrencies clearly shows certain patterns that might be related to the maturity of the market and investors. In addition, the general values of Bitcoin and Ethereum are lower than other markets, and more importantly, the median value of each is zero, which implies that this may be a result of these markets being more efficient than other markets in the sample.

Litecoin (LTC) has the minimum average AMIM of 0. 011 pointing to the more efficient overall of the compared crypt currencies. This result is peculiarly intriguing given that Litecoin as one of the pioneers of the second-generation Bitcoin copycats. This finding is similar to Jiang et al. (2018) who established the efficiency of more established cryptocurrencies on the efficiency frontier over time.

Surprisingly, EOS being relatively young in the market of cryptocurrencies has an average AMIM of 0. 086 which is almost at par with Bitcoin. Yet it has a higher median AMIM of 0. 110, which implies more persistent inefficiency in its market. This might be attributed to the fact that the market of this crypto is relatively new in the market and the special

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features of its blockchain platform which adds complexity to the process of pricing. The efficiency level of these cryptocurrencies differs as the adaptive market hypothesis of Lo (2004) suggests. The hypothesis states that there is no universal efficiency in the various markets but these are conditional markets that tend to gain efficiency with time as various players respond to various changes in the market. Figure 3 pictures such phenomena of change for the AMIM values and illustrates the overall steps of this adaptive process in cryptocurrency markets.

V. CONCLUSION, RECOMMENDATIONS, AND FUTURE RESEARCH DIRECTIONS

A. Conclusion

In conclusion, the emergence of cryptocurrencies has had significant implications for traditional financial markets and their efficiency. This study's comprehensive empirical investigation provides valuable insights into the dynamic interactions between cryptocurrency and conventional asset markets. The analysis of the Adjusted Market Inefficiency Magnitude (AMIM) reveals that major cryptocurrencies, such as Bitcoin, Ethereum, Ripple, Litecoin, and EOS, exhibit varying degrees of market inefficiency over time. While Bitcoin and Ethereum tend to experience periods of both efficiency and inefficiency, Ripple stands out as persistently inefficient compared to its peers. This suggests the presence of irrational exuberance, speculative bubbles, and behavioral factors influencing cryptocurrency price formation, in contrast with the efficient market hypothesis.

Furthermore, the study finds evidence of volatility spillovers and return dynamics between cryptocurrencies and traditional asset classes, including currencies, commodities, and stock market indices. This indicates that the emergence of cryptocurrencies has increased cross-market linkages and information flow, challenging the notion of segmentation between digital and conventional finance. However, the net impact on the informational efficiency of traditional markets appears ambiguous, with potential benefits from improved arbitrage opportunities offset by increased volatility and liquidity-driven distortions. Factors such as global financial stress, macroeconomic uncertainty, equity market performance, and cryptocurrency-specific characteristics like volatility and liquidity are found to significantly influence the degree of market efficiency in the cryptocurrency space. These findings underscore the complex and evolving nature of the interaction between digital and traditional finance, with important implications for regulators, investors, and policymakers.

B. Recommendations

Based on the insights gained from this comprehensive study, several recommendations can be made for stakeholders in the evolving cryptocurrency and financial markets ecosystem:

- Regulatory Approach: Policymakers and financial regulators should adopt a balanced and coordinated approach to cryptocurrency oversight. This should involve establishing clear guidelines for service providers, monitoring transaction activities, and setting standards for consumer protection and disclosure. International coordination is crucial to mitigate regulatory arbitrage and ensure financial stability.
- Investor Education: Given the speculative nature and behavioral biases observed in cryptocurrency markets, it is essential to enhance investor education and awareness. Investors should be made cognizant of the risks associated with high volatility, potential bubbles, and the limitations of using past price information for future return predictions.
- Market Development: Efforts should be made to promote the maturity and efficiency of cryptocurrency markets through measures that enhance liquidity, increase institutional participation, and foster the integration of digital assets with traditional financial systems. This could involve the introduction of regulated investment vehicles, such as cryptocurrency exchange-traded funds (ETFs), to facilitate greater market depth and price discovery.
- Policy Considerations: Central banks and monetary authorities should closely monitor the evolving role of cryptocurrencies and their potential impact on monetary policy transmission and financial stability. While the current scale of cryptocurrency usage may be limited, proactive measures to address challenges to seigniorage, money multipliers, and the effectiveness of rate adjustments may be warranted as the digital asset ecosystem continues to grow.

C. Directions for Future Research

This comprehensive study on the implications of cryptocurrencies for traditional financial markets and their efficiency opens up several avenues for future research:

- Comparative Analysis across Cryptocurrency Types: Further investigation into the efficiency characteristics and dynamic linkages of different types of cryptocurrencies, such as privacy coins, stablecoins, and utility tokens, could provide valuable insights into the role of design features, use cases, and regulatory environments in shaping market behavior.
- Macroeconomic and Monetary Policy Impacts: Expanding the analysis of the interaction between cryptocurrencies and conventional monetary policy tools, as well as their broader macroeconomic consequences, could enhance the understanding of the evolving interplay between digital and traditional finance.
- Behavioral Factors and Sentiment Analysis: Delving deeper into the role of behavioral biases, herd behavior, and investor sentiment in driving cryptocurrency price dynamics can contribute to the development of more comprehensive models of digital asset valuation.
- Cryptocurrency Market Microstructure: Investigating the impact of factors like trading mechanisms, order flow dynamics, and market maker activities on the efficiency and price discovery processes in cryptocurrency exchanges can shed light on the unique characteristics of these emerging markets.

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- Regulatory and Governance Frameworks: Analyzing the efficacy of different regulatory approaches and governance structures adopted by jurisdictions worldwide can inform the design of comprehensive global frameworks for digital asset oversight and investor protection.

Continued research in these areas can further enhance the knowledge base and provide valuable insights to policymakers, financial institutions, and market participants navigating the evolving landscape of cryptocurrencies and their impact on traditional financial systems.

- Compliance with Ethical Standards
- *Disclosure of Conflict of interest:* No conflict of interest to be disclosed

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