AI-related Cryptocurrencies Efficiency

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Abstract

This study examines the market efficiency of AI-Crypto sectors by employing the Adjusted Market Inefficiency Magnitude (AMIM) calculated from daily log returns over a 6-month rolling window. Our primary objective is to identify distinct patterns of efficiency and inefficiency across various sectors such as Generative AI, AI Big Data, Cybersecurity, and Distributed Computing, in relation to the introduction of ChatGPT. The data reveals that while the Generative AI and AI Big Data sectors exhibit market efficiency, Cybersecurity, and Distributed Computing are characterized by marked inefficiency. A notable aspect of our findings is the significant improvement in market efficiency in most AI-Crypto sectors following the launch of ChatGPT, an exception being the Cybersecurity sector. This research contributes to the existing literature by providing a nuanced understanding of how technological advancements like ChatGPT influence market efficiency in emerging AI-Crypto markets. Our results suggest that market efficiency in these sectors is not static but evolves with technological innovations and sector-specific characteristics.

JEL Classification: C12, G14, G40

Keywords: Artificial intelligence, crypto assets, quantile-based efficiency, ChatGPT

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1. Introduction

ChatGPT's meteoric rise, driven by the expansive adoption of AI across conversational platforms, has markedly revolutionized digital interactions and the landscape of the financial industry. Saggu and Ante (2023) noted that since its introduction in November 2022, ChatGPT has made a notable impact on the cryptocurrency market, particularly those linked to AI, attracting a massive user base in a short period.

News from The Financial Times reveals AI-Crypto assets as one of the strongest and the most exciting crypto-investing theme for 2024. Not surprisingly, AI-Crypto assets will yield higher returns than other crypto assets (Chipolina, 2023).

We argue that as AI integrates further into the cryptocurrency world, efficiency in AI-Crypto assets is expected to rise significantly. Faster transaction speeds, improved security through anomaly detection, and enhanced predictive analysis are at the forefront of this shift. AI's ability to rapidly process and analyze vast amounts of data implies transactions can be completed more quickly and accurately, minimizing errors and reducing the time needed for confirmations. In essence, the marriage of AI and cryptocurrency is set to streamline operations, making the market more efficient, secure, and reliable for users and investors alike.

In line with Fama’s (1970) Efficient Market Hypothesis (EMH), asset prices are posited to fully encapsulate all available information, while Lo's (2004) Adaptive Market Hypothesis (AMH) posits a temporal evolution in market efficiency, suggesting a dynamic adaptation to external factors. Research on the efficiency of crypto indicates that market efficiency fluctuates over time (Almeida & Gonçalves, 2023) supporting the AMH. Studies examining the informational efficiency of Bitcoin and Ethereum (Alvarez-Ramirez & Rodriguez, 2021; Tiwari et al., 2018) suggest an emergent efficiency in the crypto markets (Urquhart, 2016). This is complemented by the findings of Brauneis & Mestel (2018) and Wei (2018), who note that cryptocurrencies become less predictable and more efficient as market liquidity increases. Tran and Leirvik (2020) further elaborate that cryptocurrency markets exhibit sensitivity to diverse events, influencing their efficiency, thereby underscoring the complexity of assessing their efficiency.

Aiming to explore the evolution of market efficiency in AI-Crypto sectors, this study uses Lo's (2004) Adaptive Market Hypothesis (AMH) and the Adjusted Market Inefficiency Magnitude (AMIM) from Tran and Leirvik (2019). We construct AI-Crypto indexes for sectors like Generative AI, AI Big Data, Cybersecurity, and Distributed Computing, using a market capitalization-weighted approach. Our research includes a quantile efficiency and quantile liquidity analysis, offering insights into market behavior before and after the ChatGPT 3 launch. This analysis sheds light on price predictability across bull and bear markets for various AI-Crypto sectors.

Different from previous literature on cryptocurrency's efficiency, our study contributes to the knowledge of AI-Crypto market efficiency by revealing temporal fluctuations in market efficiency within AI-Crypto sectors, highlighting dynamic efficiency changes over time motivated by the impact of technological advancements and market maturity. Sector-specific analysis reveals varying efficiencies: Cybersecurity and Distributed Computing show inefficiencies, while others like Generative AI demonstrate higher efficiency. Quantile efficiency analysis further dissects sector behaviors, with some showing higher efficiency like AI Big Data suggesting less predictability, as past trends less reliably indicate future directions. Notably, sectors like Generative AI demonstrate robust efficiency in bear and bull market conditions, indicating effective information assimilation during such periods. The robustness of our findings is reinforced by conducting a quantile liquidity analysis and by dividing the sample into pre- and post-ChatGPT 3 launch periods, confirming the consistency of our results and highlighting a shift towards higher efficiency and liquidity in all sectors.

2. Data and research methodology

2.1. Data

We use daily data up until December 31, 2023, to create several AI-Crypto index categories as proxies for Generative AI, AI Big Data, Distributed Computing, Cybersecurity, and for Top-Crypto sectors. Data was sourced and based on the coinmarketcap.com categories. The AI-Crypto indexes were constructed using a market capitalization-weighted methodology. We selected the top 10 most representative crypto assets of each AI-Crypto category, collected their historical data, and established a consistent date range for analysis. Each crypto assets' market capitalization was calculated by multiplying the current adjusting closing prices by the circulating supply, serving as the basis for its weight in the index. The index value was then obtained by aggregating these daily weighted prices, providing a comprehensive view of the AI-Crypto market's different sectors' performance. Table 1 shows the indexes composition.

(Table 1)

2.2. Adjusted Market Inefficiency Magnitude (AMIM)

The Adjusted Market Inefficiency Magnitude (AMIM) developed by Tran and Leirvik (2019) is a novel method for measuring market efficiency. The AMIM captures the time-varying properties of efficiency and presents a direct measurement of significance over time.

Under the Efficient Market Hypothesis prices should reflect all available information, rendering returns unpredictable (Fama, 1970). In an autoregressive AR(q) model if returns coefficients significantly deviate from zero the EMH is violated.

$$r_t = \alpha + \beta_1 r_{t-1} + \cdots + \beta_q r_{t-q} + \varepsilon_t \tag{1}$$

The AMIM calculations begin by normalizing autocorrelation coefficients from the Eq.(1), standardizing them to mitigate the effects of different standard errors and correlations. This normalization addresses the issue that raw coefficients could be misleading due to their correlation and standard errors. The Market Inefficiency Magnitude (MIM) in Eq.(2) is then calculated as the sum of absolute standardized coefficients of Eq.(1) scaled against the sum of these coefficients plus one. This value varies between 0 (efficiency) and nearly 1 (inefficiency).

$$MIM_t = \frac{\sum_{j=1}^{q} \left|\hat{\beta}_{j,t}^{standard}\right|}{1+\sum_{j=1}^{q} \left|\hat{\beta}_{j,t}^{standard}\right|} \tag{2}$$

MIM's reliance on the number of lags can lead to overestimation. To counter this, AMIM in Eq.(3) adjusts MIM by subtracting a range of confidence intervals (R_{CI}) from it and normalizing this value.

$$AMIM_t = \frac{MIM_t - R_{CI}}{1 - R_{CI}} \tag{3}$$

$AMIM_t \leq 0$ reveals efficiency, while $AMIM_t > 0$ represents the inefficiency of the crypto indexes. This model is robust against insignificant auto-correlation and provides a standardized comparison across different crypto indexes and time periods.

3. Results and discussion

3.1. Descriptive statistics

Table 2 and Figure 1 show evidence of non-randomness and autocorrelation (as indicated by the Box-Ljung statistic) suggesting potential market inefficiencies, where past performance could be indicative of future trends, contrary to the EMH. High kurtosis and skewness in returns suggest market inefficiencies, with extreme movements and asymmetric gains and losses challenging normal distribution expectations. Top-Crypto index presents negative skewness, suggesting that top crypto assets suffer more extreme losses than gains compared to AI-Crypto indexes.

(Table 2)

(Figure 1)

3.2. AI-Crypto market efficiency

Table 3 presents descriptive statistics for AMIM, calculated using daily log returns over a 6-month rolling window (Tran and Leirvik, 2019). Cybersecurity, Distributed_Computing, show inefficiency (AMIM> 0), while Generative_AI, AI_Big_Data and Top_Crypto exhibit efficiency (AMIM ≤ 0). This is statistically significant, as seen by the small size of the standard errors.

(Table 3)

Figure 2 depicts a 30-day Moving Average of AMIM trend for all indexes. There are evident fluctuations in market efficiency over time, and distinct patterns of efficiency and inefficiency that vary by IA related sector. These different efficiency levels suggest that certain sectors are more prone to inefficiency, possibly due to rapid technological changes and different levels of investor understanding. Notably, ChatGPT's emergence aligns with increased efficiency for almost all AI-Crypto indexes except Cybersecurity index. At first, most indexes demonstrated inefficiency, that in later stages improved to levels of efficiency. These findings support Lo's (2004) AMH indicating that market efficiency evolves and responds to market events.

(Figure 2)

3.3. Quantile-based efficiency

To better understand these dynamics, we analyze quantile efficiency. Figure 3 shows for Generative_AI index an inclination towards efficiency during extreme market conditions with a tendency towards high efficiency in bull markets. This suggests that this sector integrates information better during bull markets, potentially due to increased investor attention. The AI_Big_Data index maintains a consistent level of efficiency across market phases, with a slight decrease during bull markets, indicating robust incorporation of information into prices, even during extreme market conditions, likely due to the sector's tangible assets and data-driven technology.

In contrast, the Cybersecurity index demonstrates persistent inefficiency across both bear and bull markets, that might be attributed to the rapid evolution of cybersecurity threats, and substantial information asymmetry in the sector. Similarly, the Distributed_Computing index shows significant inefficiency, especially during extreme market conditions, suggesting speculative behavior in this emerging technology sector. This inefficiency may be attributed to the technical complexity and specialized nature of these sectors, leading to variable market reactions to new threats or innovations.

The Top_Crypto index maintains a high degree of market efficiency across all market conditions. This efficiency seems to heighten at bull and bear market conditions, reflecting the maturity, widespread understanding, and rapid assimilation of information among investors in this sector.

Our analysis supports that AI-Crypto markets efficiency is influenced by market maturity and sector complexity. The distinct efficiency and inefficiency patterns observed across lower, middle, and higher quantiles reflect markets differential reaction to new information, particularly under extreme conditions, supporting the EMH. This underscores the significance of understanding how each segment of returns responds to various market stimulus.

3.4. *Additional analysis*

To enhance the robustness of our analysis, we employ Amihud (2002) ratio for measuring market illiquidity and divide our sample into two distinct sub-periods: pre and post-ChatGPT 3 launch. Table 4, 5, and 6 show that in post-ChatGPT 3, technology sectors like Generative AI, AI Big Data, Cybersecurity, and others experienced positive mean returns, decreased volatility, higher liquidity, and remarkably enhanced market efficiency. Before ChatGPT 3, these sectors showed negative or smaller mean returns, higher risk, and less liquidity. The introduction of ChatGPT 3 marked a shift towards more stable, profitable, efficient, and liquid market conditions across all sectors analyzed.

(Table 4)

(Table 5)

(Table 6)

Table 7 reveals a positive correlation between inefficiency and illiquidity for sectors like Cybersecurity and Distributed Computing, and Top-Crypto, suggesting higher efficiency coupled with increased liquidity. A negative correlation is found in sectors like Generative AI and AI Big Data, suggesting that despite reduced liquidity, these sectors can operate efficiently. These results suggest that liquidity is a more significant influence on efficiency in sectors like Cybersecurity, Distributed Computing, and Top-Crypto than in the Generative AI and AI Big Data.

(Table 7)

Our quantile analysis in Figure 4 and 5 reinforces our findings. The results of efficiency prior to ChatGPT 3, closely mirrored our initial analysis, except for Generative_AI showing inefficiency across most quantiles, and Cybersecurity hovering near the efficiency threshold. Similarly, and evidencing the negative correlation between inefficiency and illiquidity (Table 7) before ChatGPT 3, AI_Big_Data present evidence of high illiquidity during bear and bull market conditions. Post-ChatGPT 3 launch, all indices, except Cybersecurity, consistently achieved levels of efficiency across all quantiles. Generative_AI and Cybersecurity exhibit high illiquidity especially in bear and bull markets, reflecting the negative correlation in Table 7.

(Figure 4)

(Figure 5)

These findings not only confirm our initial results but also underscore the significant positive influence of the ChatGPT 3 launch on the AI-Crypto sector. Additionally, redoing this analysis with simple returns yielded qualitatively similar outcomes, further validating the robustness of our conclusions.

4. Conclusions

In this paper we investigate market efficiency in AI-Crypto markets. Using Tran and Leirvik's (2019) AMIM with rolling window, we found distinct efficiency patterns influenced by sector maturity and complexity. Sectors like Cybersecurity and Distributed Computing show inefficiencies, while Generative AI demonstrate higher efficiency. Quantile efficiency analysis revealed higher efficiency sectors like AI Big Data suggesting less prices predictability, whereas Generative AI demonstrates robust efficiency in both bear and bull market conditions, suggesting less opportunity for above-average returns in such periods. We support that liquidity significantly influences efficiency in sectors like Cybersecurity, Distributed Computing, and Top-Crypto. This research presents evidence that the introduction of ChatGPT 3 improved overall market efficiency and liquidity across AI-Crypto sectors.

This evident variability underscores the importance of understanding market reactions to new developments and extreme conditions. Market anomalies and autocorrelation in financial time series suggest opportunities for above-average returns, which are more evident and confirmed in sectors such as Cybersecurity and Distributed Computer. The potential of AI-Crypto assets is promising but uncertain. Investors looking to surf the ChatGPT wave will require sophisticated strategies. Understanding efficiency variations and liquidity levels is key to optimize strategies, to detect valuation anomalies, and to anticipate trends, adjusting investors' portfolios. This knowledge improves risk control and the potential for gains in the unpredictable AI-Crypto market, enabling investors to strategically exploit these efficiency variations.

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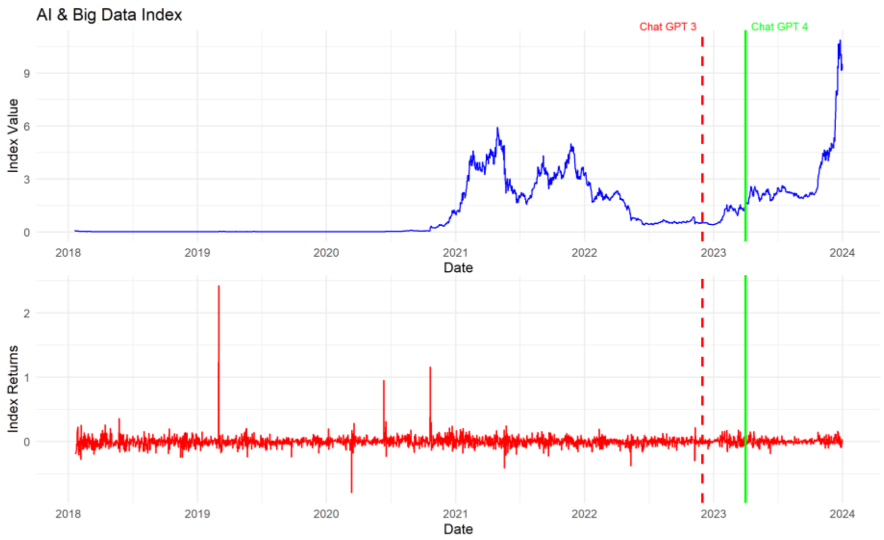
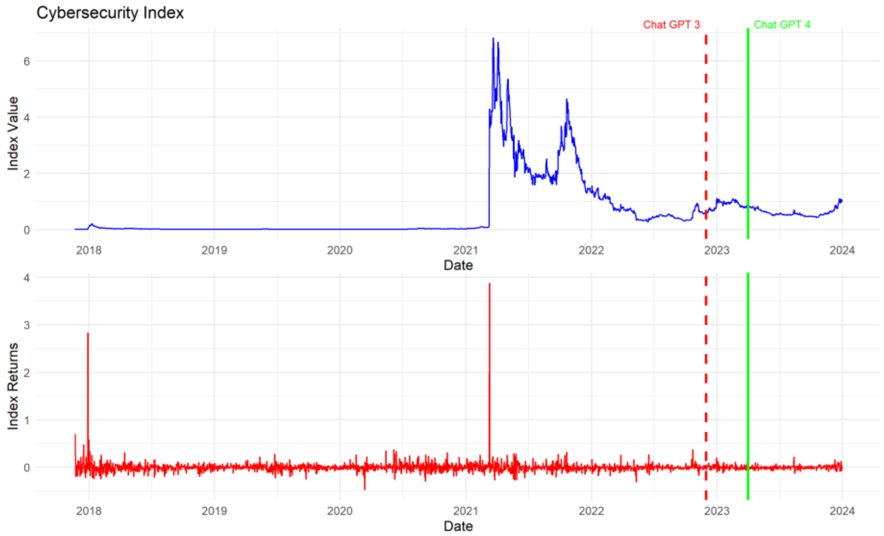
Table 1 – Indexes composition

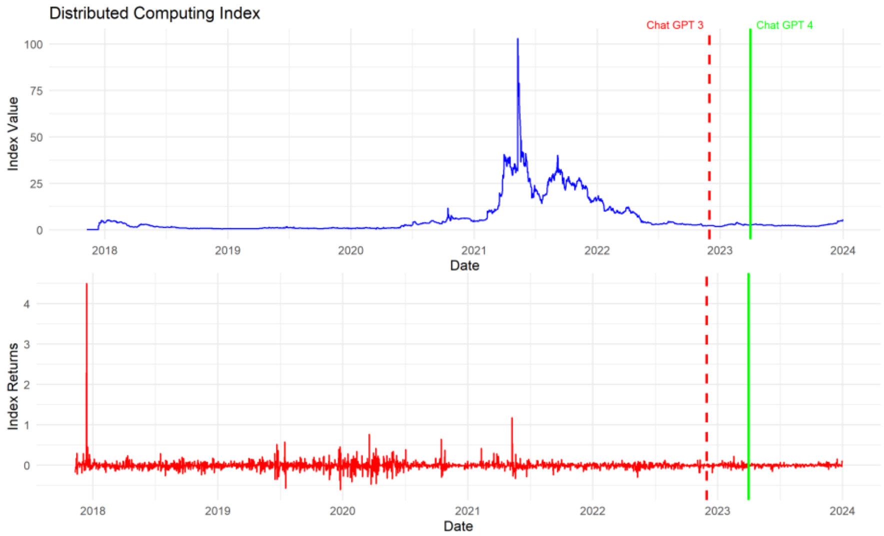
Generative_AI	Ai_big_data	Cybersecurity	Distributed_computing	Top_crypto
Numeraire	Injective	Shentu	Internet_Computer	Bitcoin
Artificial_Liquid_Intelligence	Graph	Forta	Filecoin	Ethereum
Delysium	Render	xMoney	Render	Tether
Image_Generation_AI	Oasis	Hacken	BitTorrent	BNB
AdEx	Akash	VIDT_DAO	Helium	Solana
ChainGPT	Fetch.ai	HAPI	Akash	XRP
Phantasma	SingularityNET	PolySwarm	Arweave	USDC
MurAll	Ocean	Lossless	Siacoin	Cardano
aiRight	inSure	CheckDot	Holo	Doge
Bittensor	dKargo	Quantstamp	Storj	TRON

Table 2 - Descriptive Statistics of AI-Crypto and Top-Crypto indexes

Variables	Obs.	Mean	Std. Deviation	Min.	Max.	Skewness	Kurtosis	ADF	Box-Ljung
Generative_AI	2243	0.00071%	0.07988%	-0.54532%	1.00128%	2.58824	31.4034	-12.6392***	20.8587***
Ai_big_data	2172	0.00101%	0.07713%	-0.79137%	1.16357%	1.93004	43.5806	-11.9947***	0.4169
Cybersecurity	2231	-0.00004%	0.07548%	-0.46781%	0.69803%	1.01950	11.8542	-12.0244***	12.0769***
Distributed_computing	2243	0.00065%	0.09059%	-0.60275%	1.18270%	1.45344	24.9958	-12.5826***	87.4105***
Top_crypto	3392	0.00134%	0.03727%	-0.46530%	0.22322%	-0.77668	14.4328	-14.0070***	1.2484


AI & Big Data Index
Chat GPT 3
Chat GPT 4
Index Value
Index Returns
Date
2018 2019 2020 2021 2022 2023 2024


Cybersecurity Index
Chat GPT 3
Chat GPT 4
Index Value
Index Returns
Date
2018 2019 2020 2021 2022 2023 2024


Distributed Computing Index
Chat GPT 3
Chat GPT 4
Index Value
Index Returns
Date
2018 2019 2020 2021 2022 2023 2024

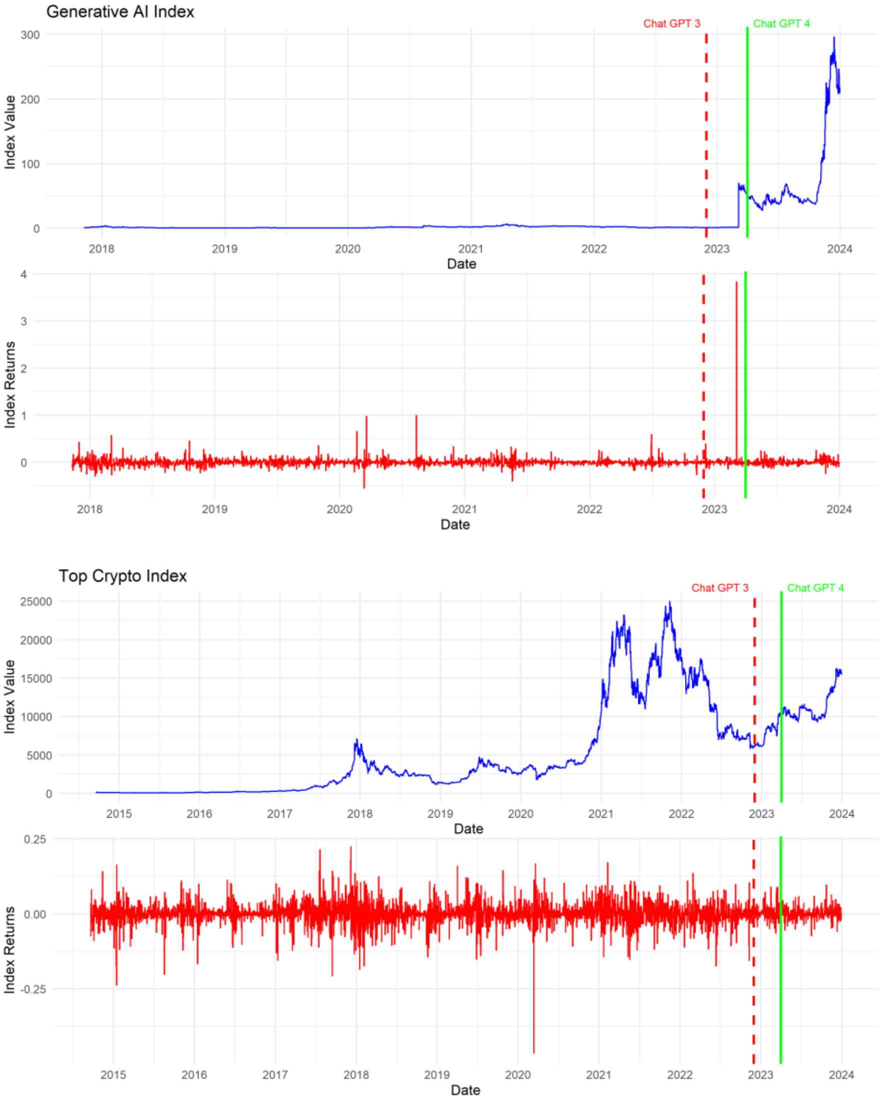


Figure 1 - Evolution of AI-Crypto and Top-Crypto indexes over time (prices (up) returns (down)).

Table 3 - Descriptive Statistics for AMIM

Variables	Obs.	$\overline{AMIM}$	Std. Deviation	Min.	Max.	Skewness	Kurtosis	Se
Generative_AI	2063	-0.00622	0.18280	-0.32588	0.40696	0.23962	2.63659	0.00404
Ai_big_data	1992	-0.03080	0.13375	-0.28203	0.31935	0.41288	2.35846	0.00300
Cybersecurity	2051	0.03552	0.16865	-0.26293	0.47410	0.38617	2.13665	0.00376
Distributed_computing	2063	0.14457	0.21302	-0.24501	0.58862	-0.11714	1.92699	0.00473
Top_crypto	3212	-0.11950	0.16051	-0.35835	0.29259	0.71858	2.47048	0.00283

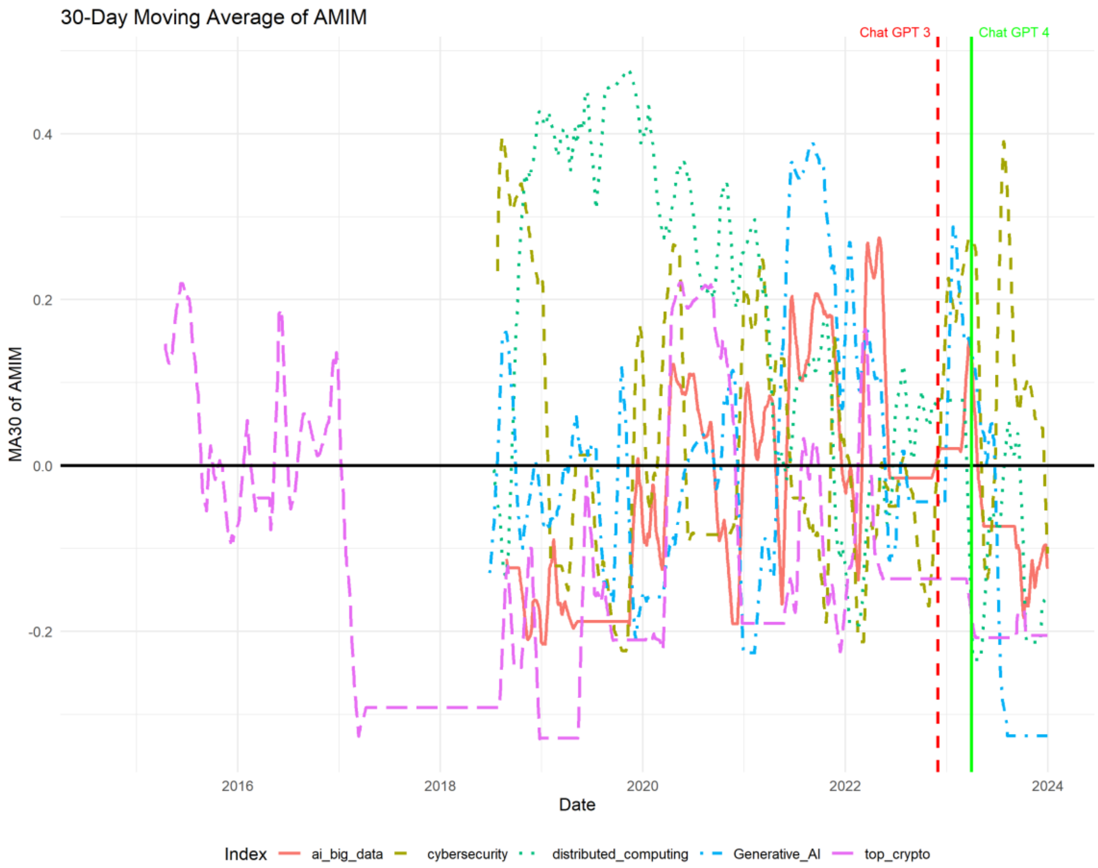
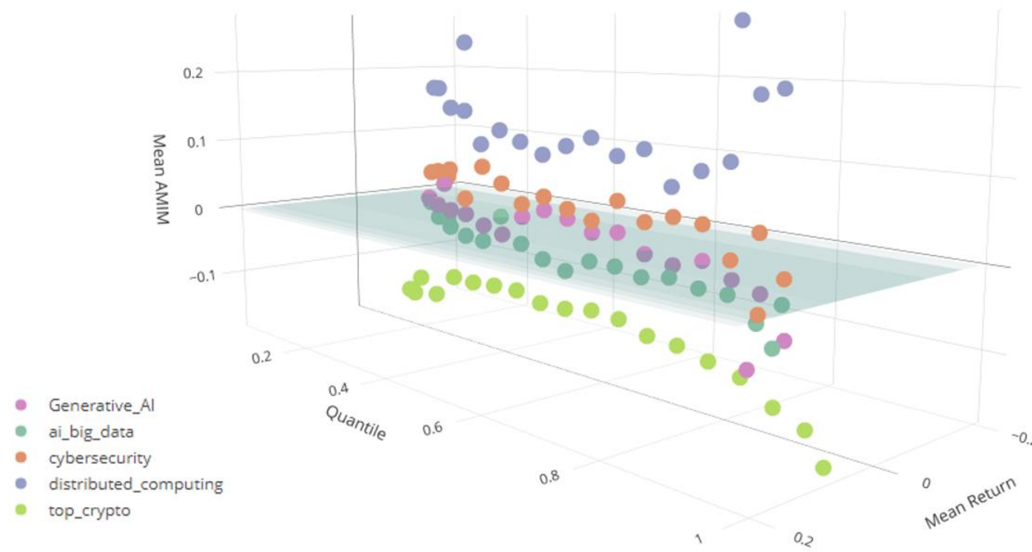


Figure 2 - Moving-Average 30 days (MA30) of AMIM for AI-Crypto and Top-crypto indexes.



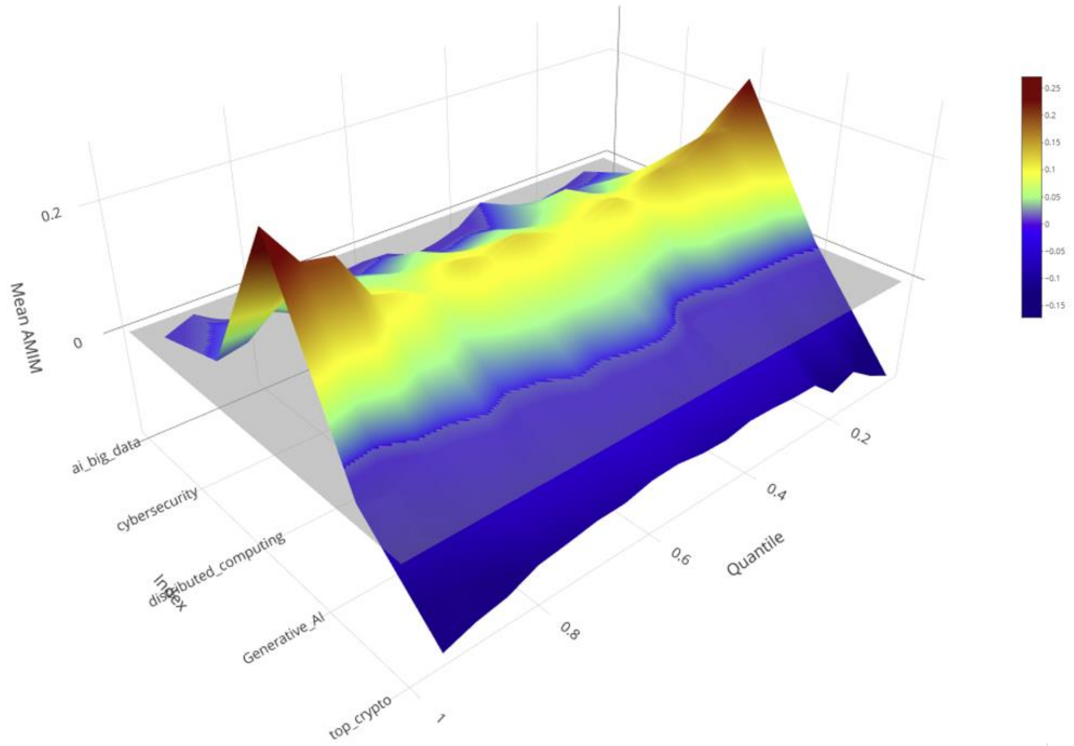


Figure 3 – 3D plots for AMIM-Quantile based efficiency for AI-Crypto and Top-crypto indexes.

Table 4 - Descriptive Statistics for ILLIQ

Variables	Mean	Median	Std. Deviation	Skewness	Kurtosis
Panel A – Full Sample					
Generative_AI	3.57093e-06	4.757e-08	2.3762e-05	16.5632	335.9430
Ai_big_data	9.42986e-05	6.1402e-09	0.0004019	7.7760	82.6013
Cybersecurity	4.35106e-05	6.0476e-07	0.00012521	8.1770	126.4544
Distributed_computing	1.11948e-07	4.9826e-10	1.4164e-06	22.2949	545.0590
Top_crypto	3.18958e-12	4.5931e-16	1.0162e-11	5.3904	47.0141
Panel B – Sample Before Chat GPT 3					
Generative_AI	4.3333e-06	9.7327e-08	2.6131e-05	15.0477	277.3904
Ai_big_data	0.00011539	5.4806e-07	0.00044185	7.0203	67.8428
Cybersecurity	5.2923e-05	3.4323e-06	0.00013629	7.5135	107.4956
Distributed_computing	1.3594e-07	1.0252e-09	1.5604e-06	20.2204	448.5405
Top_crypto	3.6124e-12	1.0772e-15	1.0744e-11	5.0514	41.8121
Panel C – Sample After Chat GPT 3					
Generative_AI	2.4345e-08	1.2099e-09	1.1753e-07	10.1960	122.2999
Ai_big_data	7.2566e-10	3.146e-10	1.6735e-09	6.9802	63.1279
Cybersecurity	2.7289e-08	1.7076e-08	3.2148e-08	4.1509	35.2159
Distributed_computing	4.0574e-10	2.2428e-10	5.0983e-10	3.4992	22.5660
Top_crypto	6.7637e-17	4.8632e-17	6.3027e-17	1.4281	4.9077

Table 5 - Descriptive Statistics of AI-Crypto and Top-Crypto indexes (Sub-samples)

Variables	Obs.	Mean	Std. Deviation	Min.	Max.	Skewness	Kurtosis	ADF	Box-Ljung
Panel A – Sample Before Chat GPT 3									
Generative_AI	1847	-0.00004%	0.08292%	-0.54532%	1.00128%	2.7157	32.3475	-12.2194***	20.5393***
Ai_big_data	1776	-0.00040%	0.08163%	-0.79137%	1.16357%	2.0048	42.4731	-10.9408***	0.4412
Cybersecurity	1835	-0.00034%	0.08095%	-0.46781%	0.69803%	0.9870	10.8133	-11.0290***	10.5153***
Distributed_computing	1847	0.00028%	0.09806%	-0.60275%	1.18270%	1.3997	22.1016	-11.5640***	74.8082***
Top_crypto	2996	0.00120%	0.03884%	-0.46530%	0.22322%	-0.7872	13.7717	-13.4355***	1.2542***
Panel B – Sample After Chat GPT 3									
Generative_AI	396	0.00421%	0.06397%	-0.23928%	0.39390%	1.0964	7.9345	-6.7353***	0.3352
Ai_big_data	396	0.00726%	0.05204%	-0.18799%	0.18136%	0.3168	4.5086	-6.5758***	0.0409
Cybersecurity	396	0.00131%	0.04179%	-0.12383%	0.22304%	0.8987	6.7015	-7.5407***	0.5105
Distributed_computing	396	0.00234%	0.04081%	-0.18291%	0.22959%	0.1531	7.3114	-6.8385***	3.5678*
Top_crypto	396	0.00229%	0.02212%	-0.07352%	0.09741%	0.6786	6.0639	-6.9500***	0.0313

Note: *, ** and *** denote statistical significance at 10%, 5 %, 1% levels, respectively.

Table 6 - Descriptive Statistics for AMIM (Sub-samples)

Variables	Obs.	$\overline{AMIM}$	Std. Deviation	Min.	Max.	Skewness	Kurtosis	Se
Panel A – Sample Before Chat GPT 3								
Generative_AI	1667	0.01687	0.16106	-0.26961	0.40696	0.69404	2.86503	0.00397
Ai_big_data	1596	-0.02603	0.14191	-0.22671	0.31935	0.35077	2.09433	0.00356
Cybersecurity	1655	0.01468	0.16403	-0.22671	0.47410	0.56931	2.31793	0.00408
Distributed_computing	1667	0.19745	0.19451	-0.24501	0.58862	-0.31035	2.04872	0.00482
Top_crypto	2816	-0.11014	0.16885	-0.35835	0.29259	0.55125	2.15353	0.00318
Panel B – Sample After Chat GPT 3								
Generative_AI	366	-0.08856	0.12994	-0.32763	0.26969	0.39335	2.84981	0.00679
Ai_big_data	366	-0.11072	0.12968	-0.34731	0.21255	0.29786	1.72635	0.00678
Cybersecurity	366	-0.01297	0.12406	-0.23647	0.33692	0.44396	2.79130	0.00648
Distributed_computing	366	-0.05746	0.11597	-0.36475	0.26236	0.16945	2.59919	0.00606
Top_crypto	366	-0.11179	0.17968	-0.38840	0.33350	0.75246	2.70861	0.00956

Table 7 - Correlation between inefficiency and illiquidity.

AMIM-ILLIQ	Generative_AI	Ai_big_data	Cybersecurity	Distributed_computing	Top_crypto
Full Sample	-0.04745**	-0.19768***	0.18891***	0.16585***	0.29855***
Sample Before Chat GPT 3	-0.08497***	-0.21789***	0.26904***	0.12184***	0.28883***
Sample After Chat GPT 3	-0.10824**	-0.02353	-0.17422***	-0.08465	-0.00369

Note: Pearson correlation coefficient for AMIM-ILLIQ. ** and *** denote statistical significance at 5 %, 1% levels, respectively.

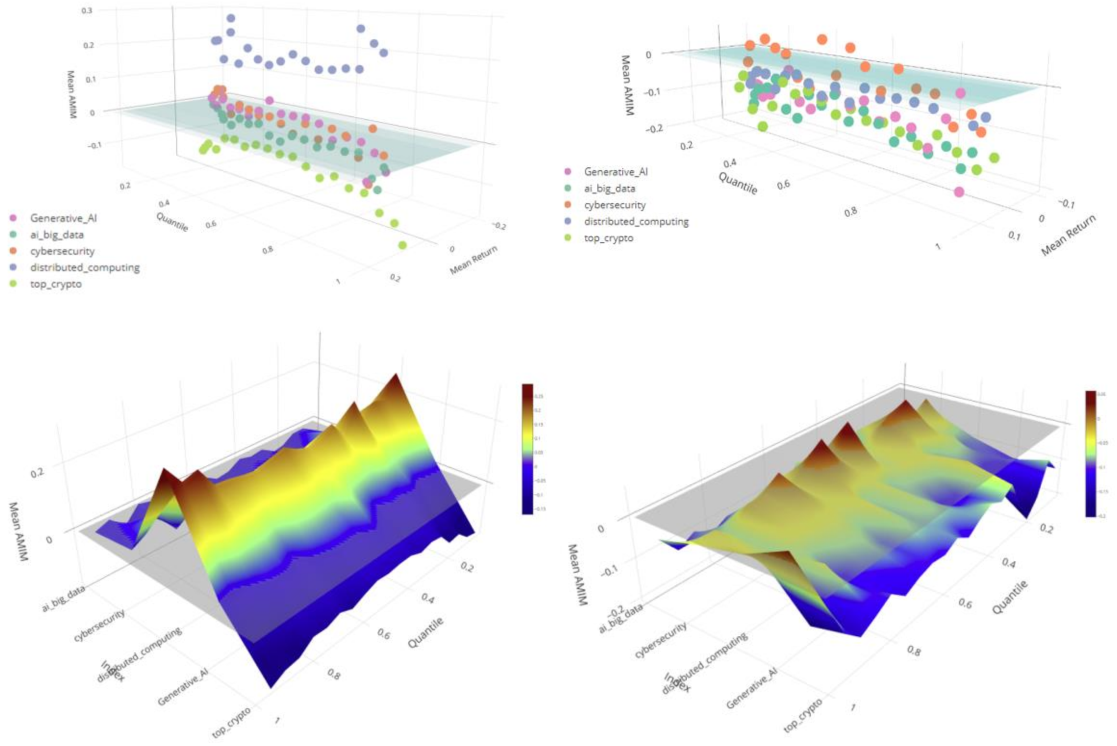


Figure 4 - 3D plots of AMIM-Quantile based efficiency for AI-Crypto and Top-crypto indexes Before Chat GPT 3 (left) After Chat GPT 3 (Right).

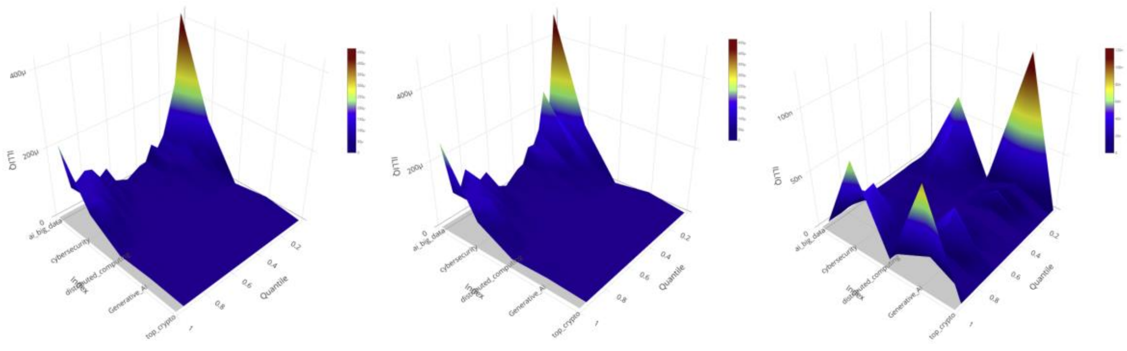


Figure 5 - 3D plots of ILLIQ-Quantile based illiquidity for AI-Crypto and Top-crypto indexes, full sample (right), Before Chat GPT 3 (middle), and After Chat GPT 3 (Right).