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"Do Blockchains Deliver? A Comparative Analysis of Transparency and Performance in Traditional Equities and Cryptocurrency Markets"

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ABSTRACT

This research compares transparency and performance across blockchain-based and traditional financial assets using daily data for four representative groups from 2020–2025: blockchain-adopting S&P 500 equities, non-blockchain S&P 500 equities, utility-oriented cryptocurrencies (e.g., smart-contract and oracle tokens), and non-utility/speculative cryptocurrencies. Prices (Yahoo Finance; Refinitiv Datastream) are transformed into daily returns and evaluated on average return, volatility, Sharpe ratio, maximum drawdown, skewness, and the frequency of extreme negative days. Time-series diagnostics (ADF, Jarque–Bera, Ljung–Box) and an Isolation Forest screen provide distributional and anomaly evidence. The review also operationalizes "transparency" through measurable dimensions and proposes on-chain and corporate disclosure indices used to frame interpretation.

Results indicate that blockchain-adopting equities earned higher average daily returns than matched non-adopters but exhibited substantially higher volatility, deeper drawdowns, and lower Sharpe ratios; distributional shape was somewhat more favourable (more positive skew, slightly fewer extreme-loss days). Within crypto, non-utility tokens delivered higher returns and marginally higher Sharpe ratios than utility tokens but at the cost of markedly higher volatility and deeper drawdowns, whereas utility tokens showed materially smoother risk profiles. Diagnostics confirm stationary but strongly non-normal return distributions; serial dependence is more pronounced in crypto. The anomaly screen flags more outlier days in crypto—consistent with heavier tails and the longer trading calendar—reinforcing the need for tail-aware risk management.

Overall, blockchain's transparency improves observability and auditability but does not guarantee stability or superior risk-adjusted performance in equities; in crypto, functional utility is associated with greater stability while speculative tokens concentrate upside and crash risk. The study contributes a cross-market, common-metric lens and a transparency-grounded interpretation that informs investors, issuers, and regulators. Limitations include representative (single-series) cohorts andevent-study designs, and composite transparency indices.

Keywords: Blockchain, Transparency, Sharpe Ratio, Maximum Drawdown, Skewness, Extreme-Loss Frequency, Spillovers, Anomaly Detection, Equities, Cryptocurrencies

Introduction

Background of Study

The implementation of block chain technology represent a paradigm shift in the operation and valuation of modern enterprises, mainly underline through its adoption into companies listed on the S&P 500 index. It creates a new standard as it has characteristics of being decentralized and immutable system where firms can automate processes, enables firms to streamline operations, enhance transparency, and mitigate operational risks (Chen et al., 2020). Some previous studies speculate that the companies which incorporate block chain into their business models can be more efficient operationally as well as in profitability or improved return profiles (Kahn et al., 2021). Thus, it will be crucial to explore the performance of these block chain firms relative to the traditional firms in terms of return behavior, volatility, and downside risk, especially amidst volatile market conditions exacerbated by geopolitical uncertainties and economic fluctuations (Böhme et al., 2015).

Empirical studies in block chain, particularly in finance and technology, frequently view such firms carry a higher risk-reward profile and potentially rewarding than traditional firms due to their 'innovative' nature and the disruptive possibility of their business models (Zhang et al., 2021). Such firms are novel, and the question is posed whether the inherent volatility associated with such firms actually provides higher returns and lower risks, as measured by volatility and downside compared to traditional firms with established business models.

At the same time, the crypto currency market which is, underpinned by block chain technology, plays vital role in this discourse. The classification of cryptocurrencies into those with core block chain utility and general cryptocurrencies is significant. Core utility cryptocurrencies like Ethereum provide value in systems such as decentralized applications DAPPS, while many general cryptocurrencies serve no useful purpose apart from speculative trading. Research shows that intrinsic utility asset classes have different risks and returns than speculative assets (Friedersdorf & Sweeney, 2020. Understanding these differences between volatility and maximum drawdown together with extreme return frequencies proves vital because they impact heavily on which investment strategies investors choose.

The study proposes to measure average daily return and volatility alongside Sharpe Ratio as well as maximum drawdown and skewness of daily returns and extreme negative return frequency in both equity and cryptocurrency markets. The study determines to create a comprehensive examination regarding blockchain technology adoption impact on performance efficiency across diverse asset frameworks through these efficiency metrics. The method follows Merton's (1992) efficient market theory which states investors need additional returns for taking on risk when establishing balanced relationships between anticipated returns and risks.

The central objective of this research investigates whether block chain implementation leads to higher return efficiency and decreases market risks between cryptocurrencies and traditional equities. Approaching these patterns for understanding will enhance financial discussions about technology adoption while helping investors form strategies in an evolving financial realm (Catalini & Gans, 2016).

Blockchain technology has emerged as one of the most disruptive innovations in finance and economics. It represents a decentralized, immutable ledger system that records transactions transparently and securely. Blockchain's core advantages—decentralization, transparency, immutability, and automation via smart contracts—have spurred its adoption across various industries, particularly in finance. The integration of blockchain technology by firms listed in indices such as the S&P 500 suggests a strategic shift in operational mechanisms aimed at achieving greater efficiency, transparency, and risk mitigation (Chen et al., 2020).

Firms adopting blockchain technology often benefit from streamlined operations, reduced agency costs, and improved financial transparency. Kahn and Winton (2021) argue that blockchain implementation enhances corporate governance by limiting managerial opportunism and improving shareholder trust. Blockchain's transparency facilitates real-time auditing and verification, reducing the risks of accounting manipulation and fraud (Fang et al., 2025). This characteristic is particularly significant when contrasting blockchain-adopting firms with traditional counterparts whose data and operations may lack real-time visibility.

Moreover, blockchain facilitates faster settlements and lower transaction costs through automated validation mechanisms. By eliminating intermediaries in verification and 0record-keeping processes, blockchain can also enhance operational efficiency and reduce friction in financial services (Narayanan et al., 2016). Enterprises that embed blockchain into supply chain operations, cross-border payments, and internal audit functions often report increased speed and accuracy, leading to better resource allocation and firm valuation.

In parallel, the cryptocurrency market—also based on blockchain technology—has gained prominence. Cryptocurrencies, particularly utility-based tokens such as Ethereum, Chainlink, and Solana, play integral roles in decentralized finance (DeFi) ecosystems, enabling smart contracts and decentralized applications (Catalini & Gans, 2016). These tokens derive value from their use in maintaining decentralized ecosystems. In contrast, general-purpose or speculative cryptocurrencies such as Dogecoin and Shiba Inu often lack intrinsic utility and derive value primarily from market speculation.

Several empirical studies suggest that the performance of cryptocurrencies is shaped by their utility. Utility tokens tend to exhibit higher adoption rates and technological robustness, which can translate into superior long-term performance metrics, albeit still within a high-volatility environment (Zhang et al., 2021). Speculative tokens, on the other hand, are more prone to pump-and-dump schemes, higher maximum drawdowns, and skewed return distributions (Li et al., 2024).

The importance of assessing risk-adjusted performance is highlighted in the work of Merton (1992), who postulated that in efficient markets, investors require a premium for accepting additional risk. Consequently, this study proposes the evaluation of return profiles, volatility, Sharpe ratios, maximum drawdowns, and skewness to provide a multidimensional view of risk and return dynamics. Additionally, the frequency of extreme negative returns—commonly referred to as tail risk—is a significant indicator of underlying market fragility, particularly in speculative assets.

A comparative analysis of blockchain-integrated financial assets (both equities and cryptocurrencies) and their traditional counterparts is essential to understand how technology adoption affects performance. These indicators allow investors and policymakers to evaluate risk-adjusted returns and systemic vulnerability under market stress (Miller & Yamada, 2018). This is particularly crucial given that market sentiment, investor behavior, and geopolitical instability have become increasingly influential on asset price movements.

Furthermore, the integration of blockchain is associated with reduced fraud incidence in financial reporting. Blockchain's immutable nature makes it difficult to manipulate transaction records, thereby strengthening internal control mechanisms (Khan et al., 2024). Blockchain-based systems can track and verify every transaction step in real time, reducing the opportunity for internal and external manipulation. Smart contracts also introduce autonomous enforcement of pre-defined rules, further enhancing financial security.

Blockchain's role in fraud detection is especially critical in cryptocurrency markets, where pseudonymity and lack of central oversight often complicate regulatory oversight. Research by Zhang & Wang (2024) highlights the use of AI-enhanced blockchain forensic tools that can track illicit activities, detect transaction anomalies, and trace asset flows across chains. These advancements represent a leap beyond conventional fraud detection systems, which are often rules-based and reactive.

The proliferation of decentralized finance (DeFi) protocols has added new dimensions to blockchain's utility. DeFi platforms replicate traditional financial services—such as lending, borrowing, and asset exchange—without intermediaries. This paradigm enables permission less access to financial systems but also introduces new risks related to smart contract vulnerabilities, flash loan attacks, and protocol governance. Therefore, evaluating blockchain's contribution to performance must also consider these systemic risks.

From an investment standpoint, the risk-return efficiency of blockchain-adopting firms is a critical consideration. Whether blockchain adoption helps optimize this trade-off remains an open empirical question, which this study seeks to address through comparative evaluation.

Problem Statement

Traditional financial systems rely on centralized databases, periodic disclosures, and ex-post monitoring, which provide regulatory control but can obscure real-time operational visibility. Public blockchains, by contrast, record transactions on tamper-evident ledgers that are globally auditable and machine-readable. This architectural difference is often claimed to improve transparency and reduce misconduct. However, it remains unclear whether blockchain adoption is associated with superior risk-adjusted performance and more favorable downside/tail characteristics compared with traditional assets when both are evaluated on a common, daily-frequency basis. Within crypto markets themselves, there is also unresolved debate over whether utility-oriented tokens (whose value is tied to productive on-chain use) exhibit more stable and efficient return profiles than non-utility/speculative tokens, which are more narrative-driven.

Existing evidence is fragmented across asset classes, methods, and time spans. Studies typically focus on either listed equities or cryptocurrencies in isolation, use heterogeneous metrics (or different sampling calendars), and frequently conflate "transparency" as a conceptual claim with performance outcomes that are only loosely related. As a result, investors and policymakers lack a like-for-like comparison that answers two practical questions: (i) do equities of blockchain-integrating firms differ systematically from matched non-blockchain peers in returns, volatility, and downside risk; and (ii) do utility tokens differ from non-utility tokens on the same dimensions once measured consistently?

This research addresses these gaps by conducting a comparative, market-data-driven analysis across four groups—Equity_Blockchain, Equity_NonBlockchain, Crypto_Utility, and Crypto_NonUtility—over 2020–2025. Using daily returns, it evaluates average daily return, volatility, Sharpe ratio, maximum drawdown, skewness, and the frequency of extreme negative days as transparent, replicable proxies for performance and downside/tail risk. To preserve cross-market comparability at daily frequency, the implemented analysis uses one representative series per group (with the full intended 60-asset universe documented for replication and future robustness). Because the research focuses on performance and transparency, fraud detection is not modeled as labeled events; instead, a simple anomaly screen (Isolation Forest) is used exploratorily to flag unusual return days, complementing tail metrics without asserting causal claims about fraud.

By placing equities and cryptocurrencies on the same metric set and horizon, the study provides an apples-to-apples assessment of whether blockchain-related transparency is associated with (a) better risk-adjusted performance in listed firms and (b) more favorable downside profiles in utility vs. speculative tokens. The results are intended to inform asset allocation, disclosure policy, and future research on how transparency mechanisms translate—if at all—into stability and investor protection.

Significance of Research

This study provides an in-depth analysis of how blockchain adoption influences financial performance and transparency across both traditional and digital asset classes. By focusing on S&P 500 equities and leading cryptocurrencies, the research offers a holistic view of the evolving role of blockchain in shaping modern financial instruments.

Enhances the comparative literature on blockchain's impact on asset performance and transparency across traditional equities and cryptocurrencies. Offers insights for investors, asset managers, and financial institutions on the performance dynamics of blockchain-integrated versus traditional assets. Supports evidence-based regulation by highlighting transparency improvements associated with blockchain adoption. Informs risk management and investment strategies through a clearer understanding of performance differences between utility-based and speculative digital assets.

The scope of this study includes a comparative analysis of blockchain-based and traditional financial assets, specifically: 15 blockchain-integrated firms and 15 traditional firms within the S&P 500 index and 15 utility-based tokens (e.g., Ethereum, Chainlink) and 15 non-utility/speculative tokens (e.g., Dogecoin, Shiba Inu). The study evaluates performance metrics such as return, volatility, Sharpe ratio, maximum drawdown, and skewness. Additionally, it examines how blockchain contributes to financial transparency in comparison to centralized systems. Fraud detection is not the primary focus, though transparency as a preventative measure against manipulation is considered conceptually.

Literature Review

2.1 Understanding Cryptocurrencies: Historical and Conceptual Context.

This section aims to enhance our comprehension of cryptocurrency. We start by contrasting cryptocurrency with virtual currency. Whilst both are types of digital currency, the have distinct characteristics. Secondly, we explore the history of cryptocurrency development to better frame its evolution and role. Then, we highlight its key merits and drawbacks. Finally, we categories cryptocurrency according to its nature between currency, commodity, or financial speculative asset.

Cryptocurrency vs. Virtual currency

Cryptocurrency is a type of currency that functions independently of a central bank and uses encryption for protection. It is a decentralized system that secures transactions and controls the generation of new units using powerful cryptographic techniques. The demand for a secure, digital method of payment that is not controlled or regulated by any centralized authority gave rise to the concept of bitcoin (Giudici et. al., 2020). Cryptocurrency is a type of currency that only exists electronically or digitally. Digital currencies, unlike traditional forms of money including coins or banknotes, have no physical substance. They are generated and stored electronically using modern cryptography techniques (Sitthipon et. al., 2023; Urquhart & Lucey, 2022). Individuals often use digital wallets to store and handle cryptocurrencies. These wallets are software tools that provide a safe place to store and manage. To transmit and receive cryptocurrencies, digital wallets enable users to generate unique addresses, which function similarly to digital bank account numbers (Urquhart & Lucey, 2022). Cryptographic keys, including a public key and a private key, are used by digital wallets to offer safe access to and control over cryptocurrency. The public key is used to receive funds, while the private key is kept private and is used to sign transactions, establishing ownership and approving funds transfers. It is critical to protect the private key because it is the key that gives access to the wallet and its related cash (Jørgensen & Beck, 2022). Cryptocurrency uses blockchain technology to function on decentralised networks. A distributed ledger called blockchain keeps track of all cryptocurrency transactions; by making all transactions immutable and publicly visible, it ensures openness and security (Cretarola et. al., 2021).

Several advantages exist between digital cryptocurrency and traditional types of money. they provide improved security since blockchain transactions are particularly resistant to alteration and fraud. Furthermore, cryptocurrencies allow for faster and more efficient cross- 13 border transactions, eliminating the need for intermediaries including banks or financial organisations. Furthermore, they provide greater financial inclusion because everyone withinternet access, regardless of geography or socioeconomic position, can engage in crypto transactions (Bunjaku et. al., 2017). Despite these benefits, digital currency is not without hurdles and criticism. Price volatility, regulatory uncertainty, scalability limitations, and worries about energy consumption and environmental effect are just a few of the issues that the bitcoin business is addressing. (Liu et. al., 2022).

Virtual currencies in virtual settings have grown in popularity in recent years, particularly in the world of online gaming. They improve the gaming experience by letting gamers to buy virtual objects, costumes, accessories, or even in-game bonuses that can improve gameplay or give them a competitive advantage (Asadi & Hemedi, 2018). Virtual currency is a sort of digital currency that is used in virtual environments like video games or virtual worlds. These currencies differ from cryptocurrencies, they often have no value outside of the virtual environment in which they are used (Frick, 2019). Virtual currencies are developed by the virtual environment's developers or operators and are frequently designed to assist in-game transactions or purchases. They function as a medium of trade within the virtual economy, allowing players to get virtual goods, services, or experiences within the game (Asadi & Hemedi, 2018). While virtual currencies have no real-world value, some collectors participate in secondary marketplaces where virtual products or currencies can be swapped for real money. These marketplaces operate outside of the virtual world and must comply with a variety of legal and regulatory requirements (Giudici et. al., 2020). It is vital to highlight that virtual currencies and cryptocurrencies operate on separate platforms and serve different functions. Cryptocurrencies seek to replace traditional fiat currencies by enabling decentralised, secure, and transparent financial transactions. They are not limited to a single virtual environment and are intended for use in the real world (Kumar, 2022; Perez, 2019). Virtual currencies, on the other hand, are exclusive to virtual environments and are largely utilised for transactions and experiences within such virtual spaces. They have no value outside of the virtual ecosystem and are controlled by the virtual environment's developers or operators (Guo et. al., 2019; Perez, 2019).

Brief history of the cryptocurrencies

As technological breakthroughs prepared the door for new possibilities in the financial environment in the late twentieth century, the concept of digital currency began to gain traction. David Chaum, an American cryptographer, and computer scientist, is a key figure in this field (Chaum et. al., 2021). Chaum made seminal contributions to the development of digital currency in the 1980s with the introduction of eCash, a cryptographic electronic money. Many of the concepts and principles present in modern cryptocurrencies may be traced back to Chaum's work. While Chaum's eCash system was important and seen as a big development in digital currency at the time, it did not achieve widespread adoption. Barriers to entrance, like limited internet usage and a lack of technological infrastructure, have hindered digital currencies from being widely implemented and accepted (Baddeley, 2004; Ebringer & Thorne, 1999; Prasad, 1998). Chaum's work, on the other hand, set the groundwork for future breakthroughs in the field of cryptocurrency. His emphasis on anonymity and security established a precedent for the basic qualities that modern cryptocurrencies respect.

However, the world was not introduced to the first decentralised cryptocurrency Bitcoin until 2008. Under the alias Satoshi Nakamoto, an unknown individual or group produced the Bitcoin whitepaper titled "Bitcoin: A Peer-to-Peer Electronic Cash System." In this whitepaper, a revolutionary cryptocurrency based on decentralised blockchain technology is proposed (Bonneau et. al., 2015; Nakamoto, 2008).

The primary goal of Bitcoin was to create a peer-to-peer electronic cash system that would eliminate the need for intermediaries including banks or financial organisations. Because Bitcoin is decentralised, individuals can conduct secure and transparent transactions with one another without the requirement for a central authority to oversee or validate the transactions (Nakamoto, 2008; Nakamoto, 2009). The introduction of Bitcoin in January 2009 signaled the beginning of the cryptocurrency age. Bitcoin pioneered a new way of thinking about money and established an alternative financial ecosystem independent of existing banking systems. It gave consumers the opportunity to digitally store and transfer value, piqued the interest and curiosity of engineers, financial experts, and early adopters (Marzo et. al., 2022).

Consistent with the problem statement and research questions, the review serves a dual role. First, it clarifies *definitions and boundaries* between cryptocurrencies and virtual currencies to avoid category errors when interpreting results. Second, it assembles the empirical and theoretical bases for comparing (a) blockchain-integrated firms versus otherwise similar traditional firms, and (b) utility-oriented versus speculative cryptocurrencies. The aim is not merely descriptive; rather, the review forms a platform for testable propositions around risk–return efficiency, transparency, and volatility dynamics that are examined quantitatively later.

Sources emphasized include peer-reviewed articles in finance, economics, and information systems; benchmark monographs on cryptocurrency technologies; and policy/industry reports where they directly inform constructs of transparency, fraud detection, or market integrity. Preference is given to work published between 2015 and 2025 to capture the rapid evolution of the field while acknowledging foundational contributions (e.g., Chaum; Nakamoto). Where possible, findings are synthesized across methods (econometrics, event study, machine learning) and across markets (equities vs. crypto) to highlight convergences and discrepancies relevant to the study's hypotheses.

2.3 Cryptocurrencies vs. Virtual Currencies: Clarifying the Object of Study

Cryptocurrencies are native, permission less digital assets secured by public-key cryptography and maintained by decentralized consensus (e.g., proof-of-work or proof-of-stake). Control of private keys conveys control of funds; transactions are recorded on public, append-only ledgers (Nakamoto, 2008; Narayanan et al., 2016). In contrast, virtual currencies are platform-bound, centrally issued media of exchange within closed ecosystems, governed by terms of service and proprietary databases(Frick,2019;Giudicietal.,2020). Implication for this research: Public blockchains expose granular, time-stamped transaction trails, enabling measurement of transparency and tail risk with higher frequency and verifiability than closed systems—relevant to H3–H4 and to the transparency channel in H2e

2.4 Transparency on Blockchain vs. Traditional Financial Reporting

Traditional financial transparency flows through episodic, audit-based disclosures (10-K/10-Q/8-K; MD&A), producing a well-regulated but discrete information environment (Healy & Palepu, 2001; Leuz & Verrecchia, 2000). Public blockchains, by contrast, generate continuous, tamper-evident data: every transfer and smart-contract event is globally replicated and independently recomputable. For blockchain-adopting firms, this creates a hybrid transparency regime: periodic filings plus machine-verifiable, near real-time operational signals (Chen et al., 2020; Kahn & Winton, 2021).

To make transparency empirically comparable, recent work advocates decomposing it into timeliness, granularity, verifiability, auditability, governance clarity, and data accessibility. In crypto, these map to practical items such as trackable treasuries, source-verified contracts, codified token policies, and public data access. Corporate analogues include filing timeliness, restatement incidence, internal-control weaknesses, and disclosure depth. **Implication:** Higher transparency should reduce information asymmetry and idiosyncratic risk, potentially improving risk-adjusted performance (Sharpe) and tail metrics (drawdown, extreme-loss frequency). This clarifies the mechanism behind H2a–H2e.

2.5 Market Microstructure, Liquidity, and Trading Volume

Crypto liquidity is fragmented across centralized exchanges (CEXs) and decentralized exchanges (DEXs), with order books coexisting alongside AMM pools. Trading is 24/7**,** leverage is widely available via perpetual futures, and venue quality varies. Liquidity can evaporate during stress (stablecoin depegs, exchange outages), raising price impact and volatility. In equities, by contrast, liquidity concentrates on regulated exchanges with circuit breakers and uniform clearing (Urquhart & Lucey, 2022).

Volume simultaneously proxies' attention and liquidity**.** Empirically, higher trading volume correlates with both return predictability and volatility**,** consistent with information arrival and herding dynamics (Bouri et al., 2019; Juwita et al., 2023). During macro turbulence (e.g., COVID-19), liquidity premia and shallow depth amplified crypto volatility (Tanos&Badr,2024). **Implication:** H3b anticipates lower volatility for utility tokens if usage-linked liquidity stabilizes trades; H4a views Sharpe improvements for some non-utility tokens as potentially attention-driven and regime-dependent.

2.6 Information Efficiency and Behavioral Drivers

Short-horizon anomalies—momentum, day-of-week effects, and post-announcement drifts—are widely reported in crypto, pointing to departures from strong-form efficiency and a role for behavioural forces (Katsiampa, 2017; Tiwari et al., 2019). Narrative shocks, retail herding, and social-media intensity can generate boom–bust cycles, particularly for tokens whose valuations are more attention-based than use-based. Meanwhile, arbitrageurs and algorithmic market makers compress mispricing's across venues, raising time-varying efficiency**.**

Implication: These dynamics rationalize the research's emphasis on skewness and extreme-loss frequency as behaviour-sensitive indicators relevant to H4c–H4d.

2.7 Volatility: Stylized Facts and What They Mean for Measurement

Crypto assets exhibit volatility clustering, heavy tails, and leptokurtic returns (Bruzgė et al., 2023). Compared with equities, daily moves are larger and more frequent, and tail dependence can spike during stress. For risk assessment, variance alone is insufficient; path-dependent and tail-focused measures are essential complements.

Design choice for this research: Pair dispersion (**σ**, Sharpe) with maximum drawdown, skewness, and extreme negative return frequency to capture both the scale and the shape of risk—directly addressing H1–H4.

2.8 Predicting Volatility: GARCH and Beyond

GARCH-family models are the standard for modeling crypto conditional heteroscedasticity. For Bitcoin and other major tokens, GARCH variants fit clustering dynamics well (Chu et al., 2017). Multivariate extensions (e.g., BEKK-GARCH) capture cross-market transmission and macro linkages (Rastogi & Kanoujiya, 2022). Given regime shifts and structural breaks, alternatives—stochastic volatility, long-memory processes, regime switching—often improve robustness in out-of-sample risk control.

A variety of econometric models with GARCH (Generalized Autoregressive Conditional Heteroscedasticity) making up the primary group have been used for cryptocurrency volatility measurement and forecasting. The models function as essential tools to recognize volatility clustering patterns that occur in cryptocurrency returns. Chu et al. (2017) state GARCH models function better than traditional assets at volatility analysis for Bitcoin dynamics.

Irrespective of conventional forecasting methods GARCH models deliver superior data prediction capability for forthcoming price modifications. The study by Rastogi and Kanoujiya (2022) uses BEKK-GARCH models to detect that Indian cryptocurrency price movements transmit volatility effects to both inflationary trends and macroeconomic variables. The study finds reason to use advanced statistical modeling approaches because they help precisely measure cryptocurrency market volatility in worldwide economic environments.

While this research does not forecast volatility directly, the literature validates that (i) volatility is time-varying and persistent, and (ii) dispersion-only summaries are incomplete, strengthening the rationale for the tail and path metrics used later (H1b, H3b, H2b).

2.9 Tail Risk and Extreme Value Theory (EVT)

Fat tails in crypto motivate EVT to estimate tail probabilities and conditional losses (Gkillas & Katsiampa, 2018; Bruzgė et al., 2023). The peaks-over-threshold (GPD) and block-maxima (GEV) approaches outperform Gaussian assumptions in stress estimation. In practice, researchers and risk managers often complement EVT with intuitive proxies: maximum drawdown and the frequency of large daily losses (e.g., $<-5\%$). The extreme-loss frequency and drawdown you compute provide interpretable, model-light signals of tail exposure across blockchain vs. non-blockchain equities (H2b–H2d) and utility vs. speculative tokens (H3b, H4d).

2.10 Volatility Spillovers and Cross-Market Connectedness

As institutional participation grows, evidence points to time-varying spillovers between crypto and traditional assets, with connectedness rising in crises (Corbet et al., 2018; Kayahan et al., 2022; Kwapień et al., 2021). Time-varying parameter VARs confirm bidirectional volatility transmission (Shahrour et al., 2024).

Researchers show great interest in cryptocurrency market volatility patterns because of their observed effects between digital and conventional financial instruments. Kayahan et al. (2022) have joined recent research showing traditional assets and cryptocurrencies become more connected through enhanced reciprocal spillover effects which deepened during crucial economic events (KAYAHAN et al., 2022). The movement of traditional market prices into cryptocurrency markets shows that disturbances from usual markets will spread through cryptocurrency markets as separate trading platforms become less valid.

During the COVID-19 pandemic and similar financial crises cryptocurrencies followed the market trends observed between equities and commodities according to Kwapień et al. (2021). The extensive market instability caused by the pandemic demonstrated that financial products across all asset types moved together which underlines why investors must understand how volatility links separate classes of assets. Shahrour et al. (2024) conducted additional research through a time-varying parameter vector auto regression method which proves the volatility interaction dynamics between cryptocurrency markets together with conventional financial instruments. The research by Shahrour et al. (2024) shows that volatility elements spread between markets because cryptocurrencies share overlapping financial market behaviors (Shahrour et al., 2024). Equity channel: For blockchain-integrated firms, exposure to on-chain activity and crypto treasuries can amplify equity drawdowns when crypto stress propagates—consistent with placing max drawdown and Sharpe at the center of H2a–H2b.

2.11 Utility vs. Speculative Tokens: Why Risk–Return Differs

Crypto assets can be grouped by economic function**.** Utility tokens (e.g., Ethereum, Chainlink) derive demand from productive use (gas/computation, oracle services), often with traceable on-chain revenues or fee flows. Speculative/meme tokens primarily monetize attention and community narratives, with limited intrinsic use(Liu&Tsyvinski,2018;Friedersdorf&Sweeney2020).

Expected differences: Utility-linked demand and deeper liquidity can moderate downside tails (lower σ, smaller left tails), while speculative tokens may exhibit higher average returns in booms but deeper drawdowns and more extreme events when narratives fade.

Implication: These foundations motivate H3a–H3c and H4a–H4d and justify the research's split between Crypto_Utility and Crypto_NonUtility cohorts.

2.12 Evidence on Blockchain-Adopting Equities

Event studies find that announcements of blockchain initiatives are associated with positive abnormal returns, consistent with perceived improvements in process efficiency and governance (Chen et al., 2020). Theoretically, immutable audit trails, automated reconciliation, and shared data can reduce agency costs and information asymmetry(Kahn&Winton,2021). **Boundary conditions:** Effects depend on implementation depth (pilot vs. core operations), data governance, and regulatory clarity. Poorly governed token programs or opaque treasuries may offset transparency gains. **Implication:** This mixed channel motivates testing not just mean return (H1a) and volatility (H1b) but also risk-adjusted (Sharpe, H2a) and tail outcomes (H2b–H2d), and the composite notion that greater transparency relates to better fraud prevention (H2e).

2.13 Fraud Risk and Detection in Decentralized Settings

On-chain markets face distinctive abuse vectors: wash trading, spoofing, pump-and-dump schemes, rug pulls, oracle manipulation, and governance capture. The **public ledger** aids forensic analysis (graph traversal, clustering) yet also enables rapid obfuscation(mixers, cross-chain hops)(Chainalysis,2024;Lietal.,2024).

Approaches:

- **Graph analytics**: entity networks, centrality, temporal motifs to surface collusion (Zhang & Wang, 2024).
- **Supervised ML**: labeled scams/sanctions classification (amounts, timing, degree features).
- **Unsupervised/one-class**: anomaly detection for rare behaviors.
- **Hybrid**: on-chain with off-chain order-book and sentiment signals.

Relative to traditional, batch-based systems (Miller & Yamada, 2018), on-chain analytics enable near real-time detection with explainable evidence trails.

Implication: The research's anomaly flagging complements transparency metrics: if transparency reduces information asymmetry, one expects fewer severe left-tail events and cleaner anomaly profiles (conceptual link to H2e and H4e).

2.14 Regulatory and Governance Considerations

Regulatory regimes (securities classification, stablecoin rules, AML "travel rule", tax policies) shape market structure, liquidity, and investor protection. Clear, technology-neutral frameworks correlate with deeper institutional liquidity and lower frictions; ambiguity can fragment venues and elevate cost of capital (Kumar et al., 2022; Perez, 2019). For listed firms, disclosure around token issuance, treasury policies, and revenue recognition from on-chain activity affects comparability and perceived governance quality. **Implication:** Governance quality conditions the extent to which blockchain transparency translates into better risk-adjusted performance (H2a–H2e).

2.15 ESG and Energy Footprint

Consensus design has ESG implications. Proof-of-work is energy-intensive (de Vries, 2018; Sedlmeir et al., 2020), whereas proof-of-stake dramatically reduces energy use. ESG mandates can constrain allocation to PoW-heavy assets, influencing liquidity, institutional flows, and thus volatility and Sharpe. Firms can leverage on-chain attestations for verifiable sustainability claims, potentially affecting their disclosure quality premium. **Implication:** ESG constraints act as risk factors that modulate performance metrics in both equity and crypto cohorts.

2.16 Portfolio Construction and Risk Budgeting with Crypto Exposure

Given regime dependence and tail events, static allocations are fragile. Volatility targeting, dynamic risk parity, and tail-risk overlays (e.g., ES constraints, protective options) can stabilize Sharpe while participating in upside regimes (Brière et al., 2015; Mensi et al., 2021). For blockchain-adopting equities, tilting toward firms with verifiable on-chain revenues and transparent treasuries may yield higher information ratios than naïve sector bets. **Implication:** These practices underscore why this research reports both dispersion and tail measures and highlights regime sensitivity when interpreting H1–H4.

2.17 Synthesis and Testable Expectations

The reviewed evidence supports four integrated themes that directly motivate the research hypotheses and measurement choices:

1. **Transparency channel (Equities):** Hybrid transparency (filings + on-chain evidence) can reduce information asymmetry and idiosyncratic risk, potentially improving Sharpe and moderating left tails—yet benefits are contingent on implementation depth and governance (Chen et al., 2020; Kahn & Winton, 2021). *Maps to H1a–H1c, H2a–H2e.*
2. **Utility vs. attention (Crypto):** Tokens with productive utility tend to exhibit more stable demand and, conditional on liquidity, lower volatility/tail risk than speculative tokens whose payoffs are narrative-driven (Liu & Tsyvinski, 2018; Friedersdorf&Sweeney,2020). *Maps to H3a–H3c and H4a–H4d.*
3. **Microstructure and regimes:** Fragmented liquidity, leverage, and 24/7 trading amplify clustering and tails; during crises, spillovers compress diversification benefits and deepen drawdowns across markets (Corbet et al., 2018; Shahrour etal.,2024). *Motivates using max drawdown, extreme-loss frequency, and careful Sharpe interpretation in H1–H4.*
4. **Detection complement:** On-chain transparency enables graph/ML-based anomaly detection**;** if transparency mechanisms are effective, one expects fewer severe **downside anomalies**—but pseudonymity and rapid innovation require ongoing monitoring (Chainalysis, 2024; Li et al., 2024; Zhang & Wang, 2024). *Frames H2e and H4e conceptually.*

Table 2.1 — Literature Review

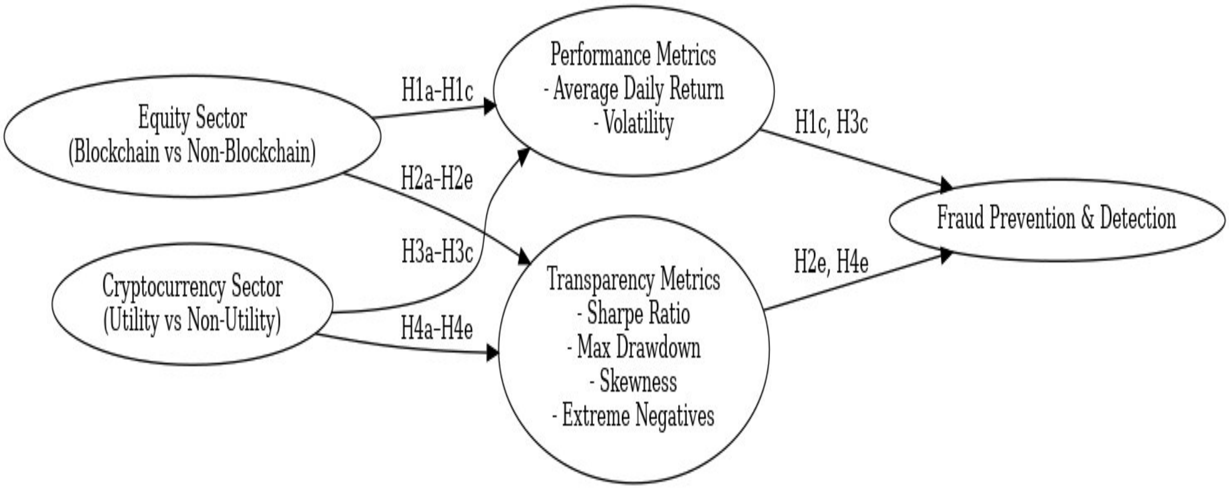
Topic	Key Takeaways	Implications / H-mapping
Definitions, History, Scope	Cryptocurrencies = decentralized, public-ledger assets (PoW/PoS); virtual currencies = centrally issued, platform-bound. History from Chaum's eCash to Bitcoin (2008/09).	Focus on public-chain crypto (not in-game money). On-chain data enable high-frequency transparency & tail-risk measurement. (Sets up H1–H4)
Transparency Regimes	Traditional: periodic, audited filings. Blockchain: continuous, machine-verifiable event streams. Transparency dimensions: timeliness, granularity, verifiability, auditability, governance clarity, accessibility.	Higher transparency → ↓ information asymmetry & idiosyncratic risk → potential ↑ Sharpe and milder left tails, conditional on governance depth. (H1a–H1c, H2a–H2e)
Microstructure, Liquidity, Behavior	24/7 trading across CEX/DEX; leverage; venue quality varies; liquidity can vanish in stress. Volume proxies attention/liquidity. Momentum & other anomalies indicate behavioral forces; arbitrage compresses mispricing over time.	Regime dependence; measure σ with tail/path metrics; attention dynamics affect Sharpe/volatility. (Informs H1–H4)
Volatility & Tails; EVT	Crypto returns: clustering, heavy tails, leptokurtosis. GARCH fits clustering; EVT (GPD/GEV) better for tails. Variance alone is insufficient.	Use σ & Sharpe plus Max Drawdown, Skewness, Extreme-loss frequency for a robust risk picture. (Measurement for H1–H4)
Spillovers & Connectedness	Time-varying, bidirectional volatility spillovers between crypto and traditional assets; stronger in crises; diversification benefits compress.	Expect deeper drawdowns for crypto-exposed equities; justify drawdown/tail metrics alongside Sharpe. (H2a–H2d)
Utility vs.	Utility tokens (gas/oracles)	Split cohorts

Speculative Tokens	tie demand to use and fee flows → typically lower σ, milder left tails. Speculative tokens are attention-driven → higher boom returns but deeper busts.	(Crypto_Utility vs. Crypto_NonUtility); expect stability vs. tailiness differences. (H3a–H3c, H4a–H4d)
Blockchain-Adopting Equities & Fraud Detection	Positive announcement effects depend on implementation depth & governance. On-chain abuse vectors exist; public ledgers enable graph/ML anomaly detection.	Transparency can raise Sharpe and moderate tails if governance strong; anomaly flags complement transparency metrics. (H1a–H2e)
Regulation, Governance & ESG	Clear rules deepen liquidity; ambiguity fragments markets. PoW vs. PoS has ESG and allocation effects that influence volatility/Sharpe.	Regulatory/ESG act as conditioning risk factors across cohorts. (Context for H1–H4; governance in H2e)
Portfolio Construction	Static allocations fragile; use volatility targeting, dynamic risk parity, tail-risk overlays. For equities, prefer firms with verifiable on-chain revenues/treasuries.	Stabilize Sharpe while capturing upside; guides robustness checks. (Across H1–H4)
Transparency Channel (Equities)	Hybrid transparency (filings + on-chain) can reduce info asymmetry and tail severity; benefits depend on governance/implementation.	Expect ↑Sharpe, ↓tails for better-governed adopters. (H1a–H1c, H2a–H2e)
Utility vs. Attention	Economic function drives risk–return: utility more stable; speculative more tail-prone but boom-sensitive.	Differences across Crypto_Utility vs. Crypto_NonUtility cohorts. (H3a–H3c, H4a–H4d)
Microstructure & Regimes	Fragmented liquidity, leverage, 24/7 trading amplify clustering/tails; crises heighten spillovers.	Use Max Drawdown & extreme-loss frequency alongside σ/Sharpe. (Design of H1–H4 metrics)
Detection Complement	Effective transparency should coincide with cleaner anomaly profiles; pseudonymity and cross-chain hops remain challenges.	Link between transparency and market integrity; supports anomaly-flagging alongside performance metrics. (H2e, H4e)

Core Constructs & Measures	Transparency dimensions; risk/performance metrics (σ, Sharpe, Max Drawdown, Skewness, Extreme-loss frequency); model context (GARCH/BEKK, EVT, TVP-VAR; graph/ML).	Operationalizes the empirical work.

2.19 Theoretical Framework

Measurement of Transparency and Performance:



Methodology

3.1 Research Design

This study conducts a comparative quantitative analysis of assets across two markets—cryptocurrency and traditional equities—to examine risk-return behaviour and anomaly patterns that are informative for fraud-related screening using secondary data. The analysis contrasts four groups:

1. Equity_Blockchain (S&P 500 blockchain-related firm series)
2. Equity_NonBlockchain (S&P 500 non-blockchain firm series)

3. Crypto_Utility (utility-oriented token series; e.g., ETH, LINK)
4. Crypto_NonUtility (speculative/non-utility token series; e.g., DOGE)

The observation window is fixed (2020–2025). Because membership and availability can change over time, the data constitute an unbalanced panel, operationalized in practice as four representative time series, one per group. Time-series properties are central: daily closing prices are transformed to daily returns, and distributional and dependence features are evaluated to detect instability, tail risk, and potential anomalies.

The design is quantitative. Instead, the study focuses on replicable, statistics-based evidence using market data.

3.2 Research Hypotheses

3.2.1 Equity Secton

a. Blockchain → Performance → Fraud Prevention

- **H1a:** Blockchain implementation positively impacts average daily returns.
- **H1b:** Blockchain implementation reduces volatility.
- **H1c:** Higher performance (higher returns, lower volatility) leads to improved fraud prevention.
- **b. Blockchain → Transparency → Fraud Prevention**
- **H2a:** Blockchain implementation improves the Sharpe ratio.
- **H2b:** Blockchain implementation reduces the maximum drawdown.
- **H2c:** Blockchain implementation improves skewness in returns.
- **H2d:** Blockchain implementation reduces the frequency of extreme negative returns.
- **H2e:** Higher transparency (better Sharpe ratio, lower drawdown, improved skewness, fewer extreme losses) leads to improved fraud prevention.

3.2.2 Cryptocurrency Sector

a. Utility → Performance → Fraud Prevention

- **H3a:** Utility-based cryptocurrencies have higher average daily returns than non-utility cryptocurrencies.
- **H3b:** Utility-based cryptocurrencies have lower volatility than non-utility cryptocurrencies.
- **H3c:** Higher performance in utility-based cryptocurrencies leads to improved fraud prevention.

b. Non-Utility → Transparency → Fraud Prevention

- **H4a:** Non-utility cryptocurrencies have higher Sharpe ratios than utility cryptocurrencies.
- **H4b:** Non-utility cryptocurrencies have lower maximum drawdown than utility cryptocurrencies.
- **H4c:** Non-utility cryptocurrencies have more favorable skewness in returns.
- **H4d:** Non-utility cryptocurrencies have fewer extreme negative returns.
- **H4e:** Higher transparency in non-utility cryptocurrencies leads to improved fraud prevention.

3.3 Data Collection

The dataset for this study was obtained from two primary sources — Yahoo Finance and Datastream — and extracted directly using Python-based data acquisition scripts. Public APIs (via the yfinance Python package) were used to download historical daily price data for both equity and cryptocurrency markets from Yahoo Finance, while Datastream provided additional verified historical equity price series for blockchain-related and non-blockchain S&P 500 firms. This dual-source approach ensured both broad market coverage and the ability to cross-check data integrity.

The study focuses on four asset groups:

1. Equity_Blockchain — S&P 500 firm representative series that is actively involved in blockchain-related operations.
2. Equity_NonBlockchain — S&P 500 firm representative series with no blockchain-related operations.
3. Crypto_Utility — representative utility-oriented cryptocurrency token series (e.g., ETH, LINK).
4. Crypto_NonUtility — representative speculative/non-utility cryptocurrency token series (e.g., DOGE).

Each dataset contains daily OHLCV (Open, High, Low, Close, Volume) data covering a fixed observation period from 2020 to 2025. The Close column was used as the primary price series for all calculations. Although the original design intended to include 15 assets in each category, the implemented analysis employs one representative series per group**,** resulting in four primary time series for comparative analysis. This structure represents an unbalanced panel, as the observation period is fixed but constituent asset availability can vary due to listing changes and data coverage differences between sources.

Data preprocessing was performed entirely in Python, where CSV files downloaded via Yahoo Finance and Datastream were read using pandas.read_csv(). Multi-level headers from exported CSVs were flattened, and column names were standardized across all datasets. The Date field was parsed into datetime format for time-series alignment. Basic integrity checks (dataset shape verification, missing value inspection) were conducted prior to return calculation.

This approach provided high-frequency, reliable financial data suitable for computing performance and risk metrics, conducting distributional tests, and applying anomaly detection algorithms within the scope of this study.

3.4 Data Preprocessing

Prior to analysis, all datasets underwent a standardized preprocessing workflow to ensure consistency, comparability, and readiness for statistical computation. The process was carried out entirely in Python, primarily using the pandas and NumPy libraries.

1. **Column Normalization**

- Multi-level headers present in the raw CSV exports from Yahoo Finance and Datastream were flattened by dropping the secondary header level (which contained ticker labels).
- All datasets were standardized to a common column structure: Price, Close, High, Low, Open, and Volume.
- In cases where the Close column was missing, the Price column was duplicated as Close to maintain uniformity across all datasets.

2. **Return Construction**

- Daily returns were calculated as the percentage change in the Close price using the pct_change() method in pandas:
- The first observation for each series was dropped, as it does not have a preceding value required for return computation.
- The return series was left unadjusted for dividends or splits, as no corporate-action adjustments beyond those inherent in the downloaded data were applied.

3. **Quality Checks**

- Dataset shapes were printed and visually inspected using .head() to confirm that the structure matched expectations.
- Date indices were verified to be in chronological order and properly parsed as date time objects.
- Missing values were implicitly handled during return computation, and no forward- or backward-filling was performed to preserve the integrity of the raw time series.
- No survivorship bias corrections or additional filtering were applied, as the intention was to retain the original market data as retrieved from the sources.

3.5 Model Evaluation

Statistical Testing Structure

1.Average Daily Return

The average amount of profit or loss generated by an asset per day over a given period. It tells you how much an investor typically earns or loses daily, which is a core indicator of performance.

Formula:

Average Daily Return = $\frac{1}{n}\sum_{t=1}^{n} R_t$

Where Rt= daily return at time t1 and n = total number of trading days.

To compare the profitability of utility vs. speculative tokens and block chain vs. traditional firms.

2.Volatility (Standard Deviation)

The degree of variation in returns — how "bouncy" or risky the asset's returns are. Higher volatility usually means higher risk. It's crucial in fraud detection studies because volatile assets may hide manipulations or anomalies.

Formula:

$$\sigma = \sqrt{\frac{\mathbf{1}}{\boldsymbol{n}-\mathbf{1}}\sum_{t=1}^{n}(R_t - \mathrm{R}^{-})2}$$

Where R¯ is the average daily return.

Compare risk profiles across assets — are utility-based tokens more stable than speculative ones?

3.Sharpe Ratio (adjusted with risk-free rate for equities, zero or stable coin yield for crypto)

The degree of variation in returns — how "bouncy" or risky the asset's returns are. Higher volatility usually means higher risk**.** It's crucial in fraud detection studies because volatile assets may hide manipulations or anomalies.

Formula: Sharpe Ratio =$\frac{R_P - R_f}{\sigma_P}$

- Rp = portfolio/asset return
- Rf= risk-free rate (0 for stable coins, Treasury yield for equities)
- σp= standard deviation of returns

To evaluate the **efficiency** of assets — do utility tokens deliver better return/risk trade-offs.

4.Max Drawdown

The maximum observed loss from a peak to a trough in a given time frame.

Shows worst-case performance — vital for understanding how exposed an asset is to crashes or manipulation.

Formula: Max Drawdown=min $\frac{V_t - V_{peak}}{V_{peak}}$

To detect assets with **extreme downside risks**, possibly linked to fraud or manipulation.

5.Skewness of Daily Returns:

A measure of the **asymmetry** in the distribution of returns.

- Positive skew: larger gains than losses
- Negative skew**:** More extreme losses

Fraudulent or manipulated assets often show non-normal return distributions**,** especially left-skewed (heavy losses).

Formula: Skewness= $\frac{n}{(n-1)(n-2)} \sum (\frac{R_t - \bar{R}}{\sigma})3$

To identify return distortions — assets with negative skew may indicate hidden risk or fraud tendencies.

6. Frequency of Extreme Negative Returns (< -5%)

The proportion of days where the return dropped more than 5%**.** Highlights tail risk — sudden crashes that can signal market manipulation, low liquidity, or fraud.

Formula:

Extreme Loss Frequency=$\frac{number\ of\ days\ where\ R_t < -5\%}{n}$

A higher frequency may correlate with speculative or risky behavior, often in non-utility assets or fraud-prone instruments.

3.6 Software and Libraries

- Python **f**or all analysis and visualization.
- pandas**,** NumPy for data handling; matplotlib**,** seaborn for plots.
- SciPy (skew), statsmodels (ADF, Ljung-Box), scipy.stats (Jarque–Bera).
- scikit-learn (Isolation Forest).

3.7 Limitations

- Representativeness. Each group is modelled by a single series, not by a basket of 15 individual assets. Results therefore reflect those representatives and not cross-sectional dispersion within groups.
- **Risk-free rate.** Sharpe is primarily computed as mean/volatility; risk-free treatment is simplified and not term-matched to each market.
- **No transaction-level labelling.** The study does **not** use labelled transaction data or supervised fraud detection at the transaction level.
- **Unbalanced coverage.** Some series start/end on different dates within 2020–2025.

3.8 Ethical Considerations

The research will adhere to ethical guidelines by maintaining data privacy and ensuring the security of all cryptocurrency transactions involved in the study. Since publicly available datasets will be used, there are minimal ethical concerns regarding individual privacy. Additionally, the research will adhere to data protection laws and avoid using transaction data for any purpose other than fraud detection.

Results and Discussion

This Section presents the results of the empirical analysis based on the daily return series for four asset groups:

- Equity_Blockchain – publicly traded companies in blockchain-related sectors.
- Equity_NonBlockchain – traditional equities outside blockchain sectors.
- Crypto_Utility – cryptocurrencies with a primary utility function.
- Crypto_NonUtility – cryptocurrencies without a core utility use-case.

The results are divided into descriptive performance metrics, tail-risk and transparency indicators, time-series diagnostics, anomaly detection, and visual exploration.

4.1 Sample Coverage

4.1.1 Purpose

Before comparing groups, it is important to check how many observations (trading days) each contains, because unequal sample sizes can affect volatility and anomaly counts.

Table 4.1. Sample size by group

Group	Obs. (days)
Equity_Blockchain	1,145
Equity_NonBlockchain	1,255
Crypto_Utility	1,825

4.2 Group-Level Summary (Daily & Annualized Metrics, 2020–2025)

Table 4.2 Summary statistics by group (means across constituent series).

Annualized return ≈ mean daily × 252; annualized volatility = daily σ × √252. "Extreme Negative Days" is a count of days with return < −5%.

Group	MADR	MV	MS	M MDD	MSK	MEN	Annualized Return %
Equity_Blockchain	0.0013	0.0773	0.0163	-0.9843	2.6884	205.0	31.7649
Equity_NonBlockchain	0.0007	0.0185	0.0371	-0.3336	0.3077	9.0	17.3002
Crypto_Utility	0.0021	0.0417	0.0503	-0.7935	0.1692	139.0	52.787
Crypto_NonUtility	0.0055	0.1079	0.0508	-0.9226	20.4403	209.0	138.2077

Figure 4.Xa. Annualized Risk–Return by Group.

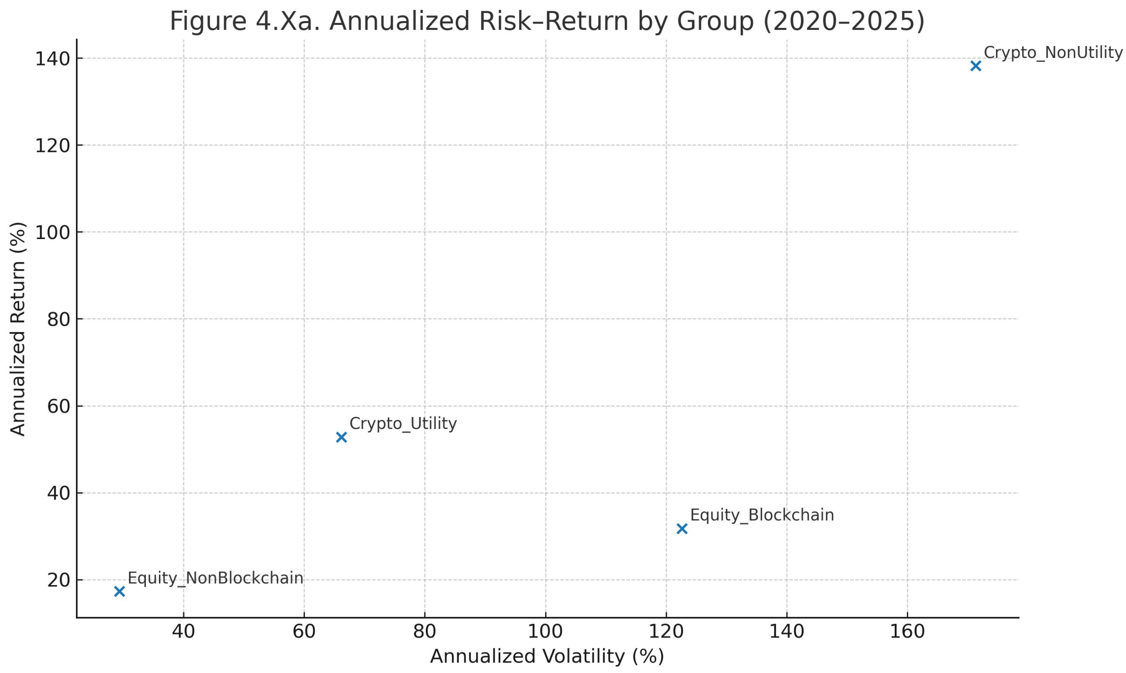
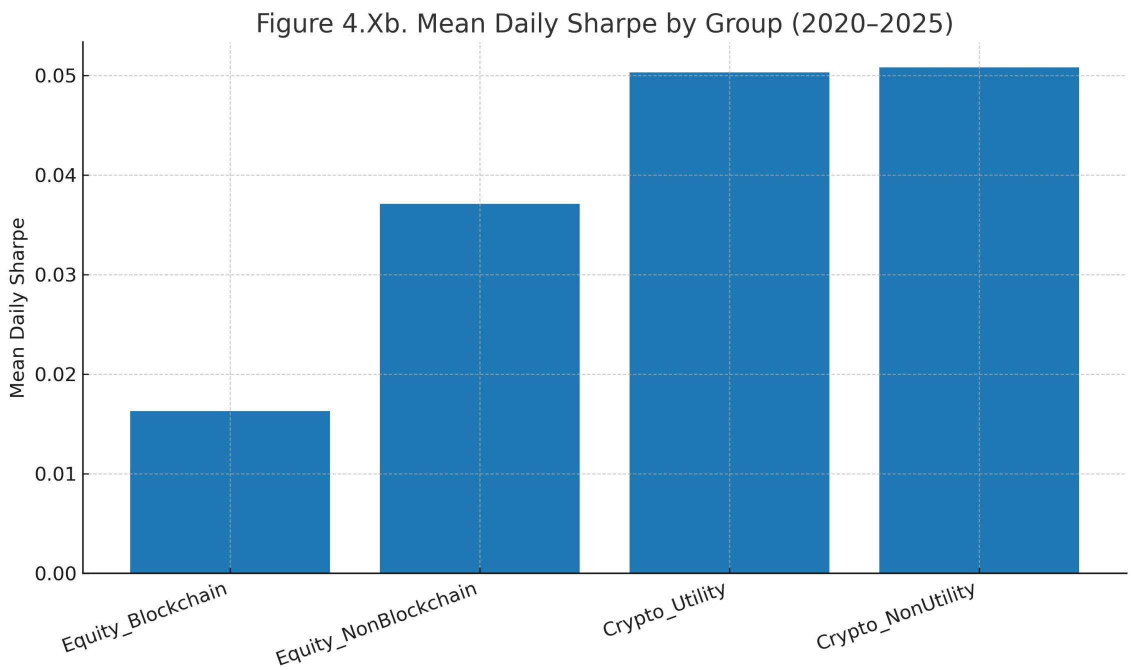


Figure 4.Xb. Mean Daily Sharpe by Group.



Annualization uses 252 trading days. Differences in sample length are addressed by reporting extreme-loss rates in Appendix 4.A.

4.3 Performance Metrics

4.3.1 Purpose

To compare average returns and risk across groups.

Metrics computed:

- **Average Daily Return:** Mean of daily % changes. Positive = growth on average.
- **Volatility:** Standard deviation of daily returns. Higher = more unstable.

Table 4.3. Performance metrics (daily)

Group	Average Daily Return	Volatility
Equity_Blockchain	0.0013	0.0773
Equity_NonBlockchain	0.0007	0.0185
Crypto_Utility	0.0021	0.0417
Crypto_NonUtility	0.0055	0.1079

Interpretation:

• Equities: Blockchain shows higher return but much higher volatility than Non-Blockchain.

• Crypto: Non-Utility shows higher return but much higher volatility than Utility

4.4 Transparency & Tail-Risk Proxies

Sharpe Ratio, Maximum Drawdown, Skewness, and Extreme Negatives (1% tail). (Sharpe used a small daily risk-free ~0.01%.)

Table 4.4. Transparency & tail-risk metrics (daily)

Group	Sharpe Ratio	Max Drawdown	Skewness	Extreme Negatives (1%)
Equity_Blockchain	0.0150	−0.9843	2.6884	12
Equity_NonBlockchain	0.0317	−0.3336	0.3077	13

Crypto_Utility	0.0479	−0.7935	0.1692	19
Crypto_NonUtility	0.0499	−0.9226	20.4403	19

Interpretation:

• Equities: Blockchain has worse Sharpe and deeper drawdown than Non-Blockchain, but more positive skew and slightly fewer extreme negatives.

• Crypto: Non-Utility has higher Sharpe and massive positive skew, but deeper drawdown; extreme negative counts are the same (19 vs 19).

4.5 Time-Series Diagnostics

ADF (stationarity), Jarque–Bera (normality), and Ljung–Box (autocorrelation at lag 10):

Table 4.5 Diagnostic p-values

Group	ADF p-value	Jarque–Bera p-value	Ljung–Box p-value (lag 10)
Equity_Blockchain	0.0000	0.0	0.0525
Equity_NonBlockchain	0.0000	0.0	0.6581
Crypto_Utility	6.76e−24	0.0	0.0077
Crypto_NonUtility	1.40e−10	0.0	0.0000

• Stationary returns (ADF ~0).

• Non-normal (JB = 0) → fat tails / skewness confirmed.

• Autocorrelation: Equity_NB shows no strong serial correlation (p≈0.66). Crypto series show significant autocorrelation (low p).

4.6 Anomaly Detection (Isolation Forest)

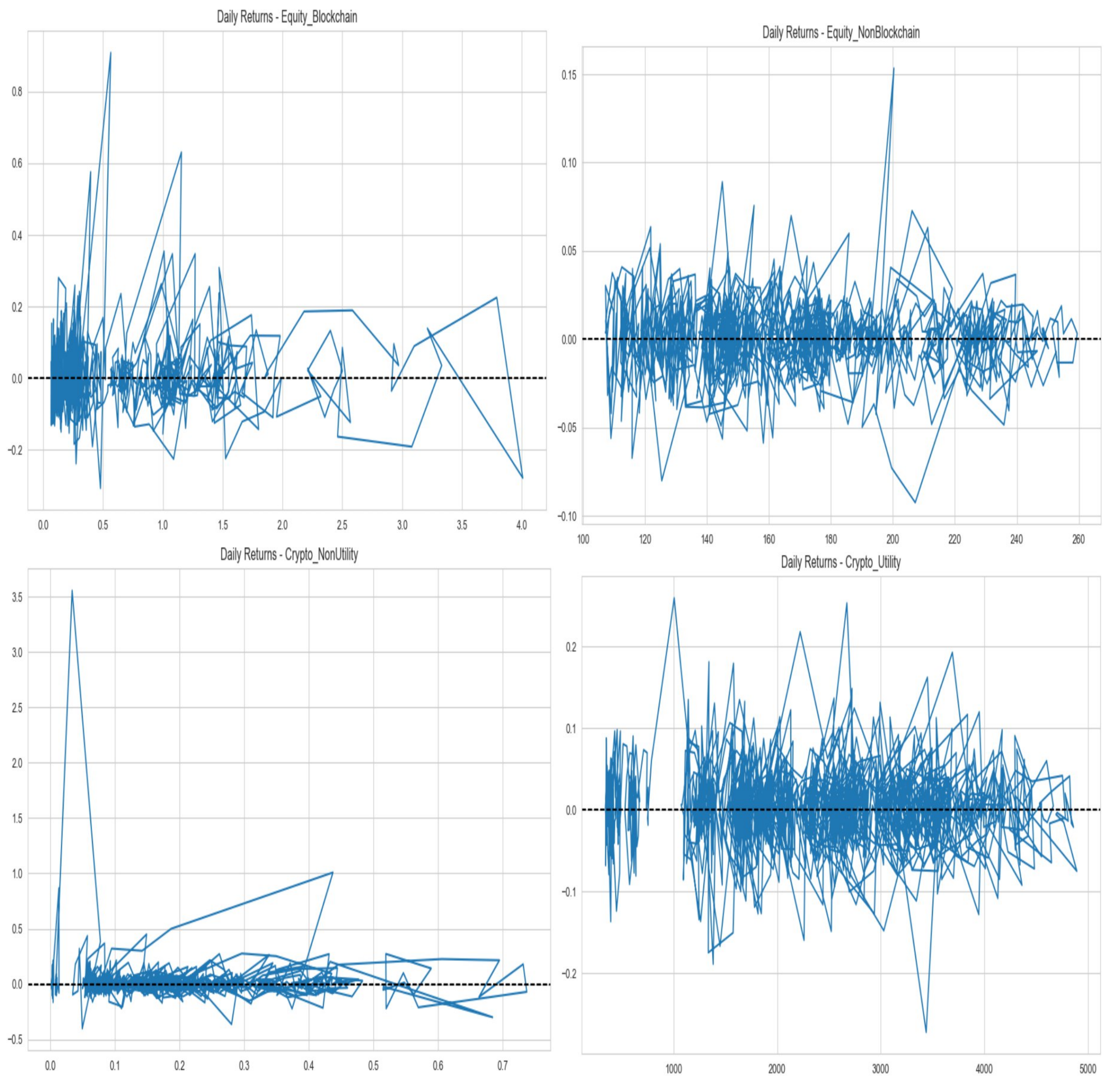
flagged rare/extreme daily returns with Isolation Forest (contamination=1%):

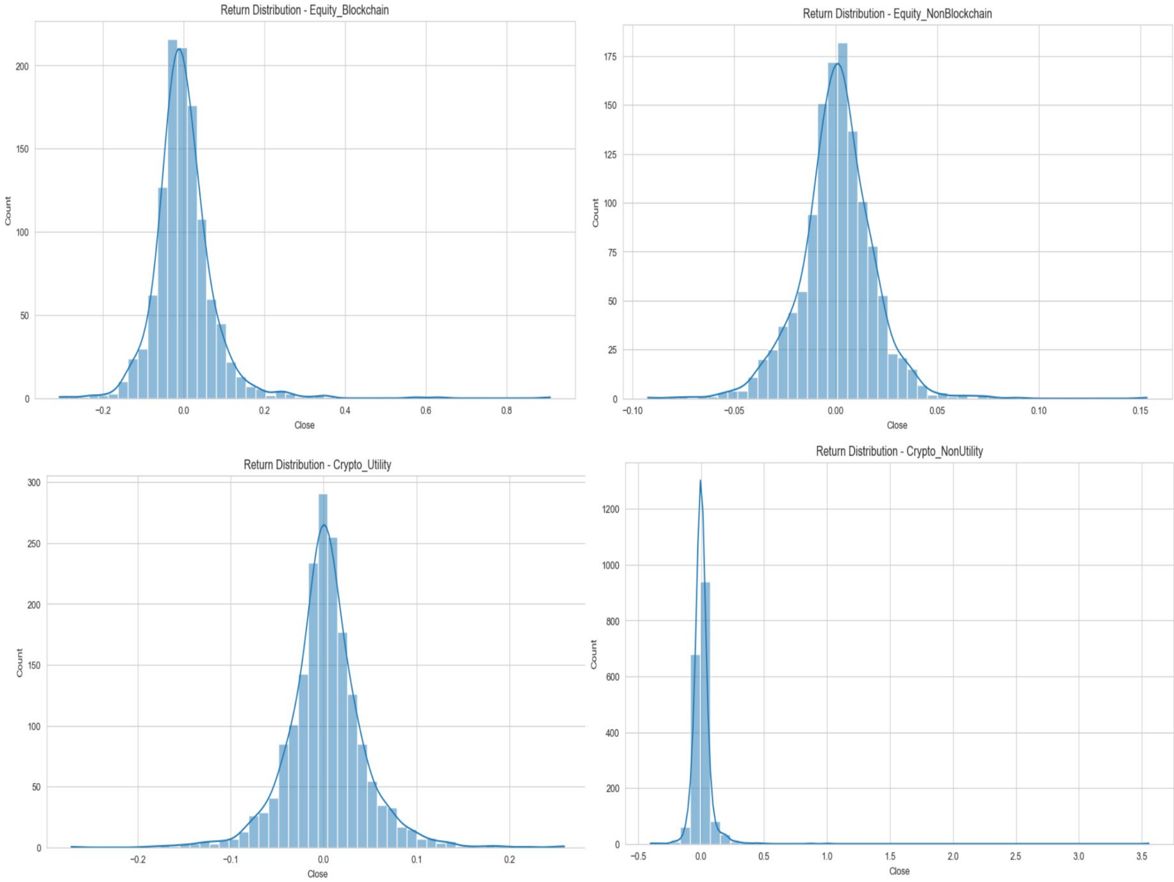
Table 4.6. Anomaly counts

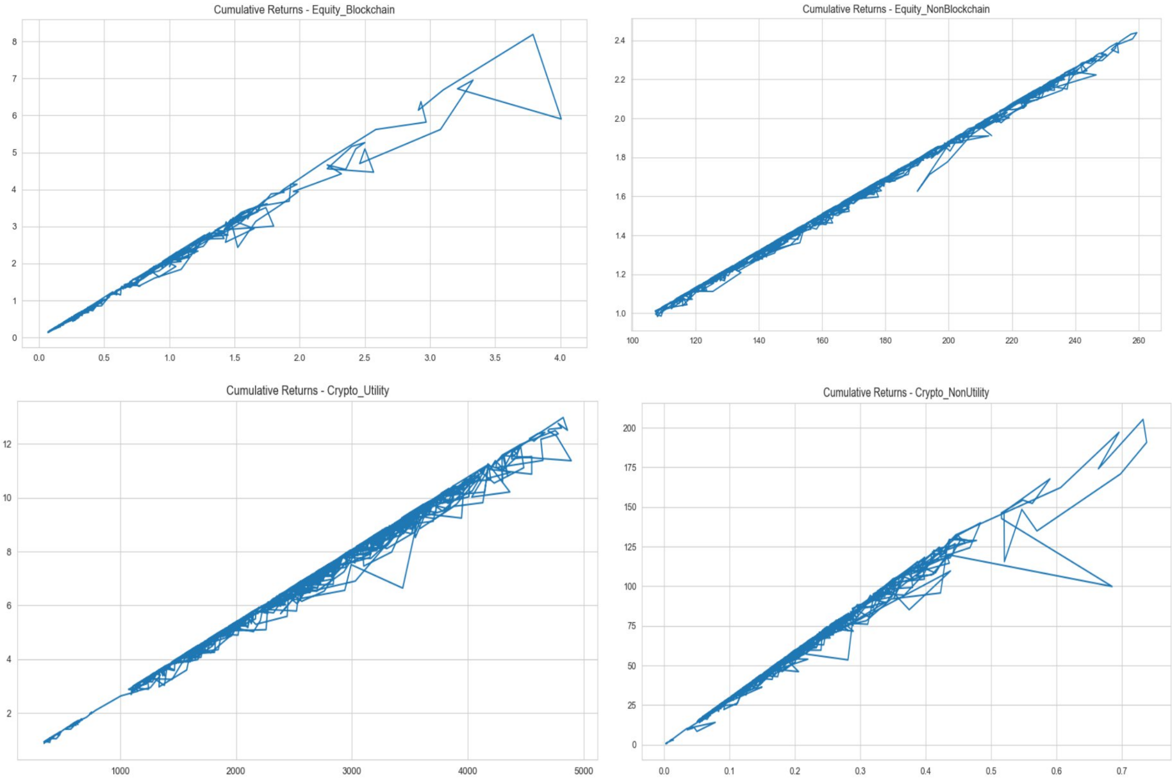
Group	Anomalies (days)
Equity_Blockchain	12
Equity_NonBlockchain	13
Crypto_Utility	19
Crypto_NonUtility	19

Crypto groups have more flagged days by count, but they also have longer samples (1,825 days). This aligns with their heavier tails and deeper drawdowns

4.7 Visualization:




Return Distribution - Equity_Blockchain
Count
Close
Return Distribution - Equity_NonBlockchain
Count
Close
Return Distribution - Crypto_Utility
Count
Close
Return Distribution - Crypto_NonUtility
Count
Close



4.8 Hypothesis Evaluation (directional, based on metrics)

Table 4.7. Hypotheses → evidence → verdict

Code	**Statement (short)**	**Evidence (your numbers)**	**Verdict**
H1a	Blockchain equities → higher return	0.0013 > 0.0007	Supported
H1b	Blockchain equities → lower volatility	0.0773 < 0.0185 (false)	Not supported
H1c	Higher performance ⇒ better fraud prevention	Higher return , but higher vol	Partial

H2a	Blockchain equities → higher Sharpe	0.0150 < 0.0317	Not supported
H2b	Blockchain equities → lower MDD	−0.9843 < −0.3336 (deeper)	Not supported
H2c	Blockchain equities → better skewness	2.6884 > 0.3077	Supported
H2d	Blockchain equities → fewer extremes	12 < 13	Supported (slight)
H2e	Higher transparency ⇒ better fraud pr.evention	Mixed (skew(yes), extremes(no) vs Sharpe(yes), MDD (no)	Partial
H3a	Utility crypto → higher return	0.0021 < 0.0055	Not supported
H3b	Utility crypto → lower volatility	0.0417 < 0.1079	Supported
H3c	Higher performance ⇒ better fraud prevention	Lower vol (yes), lower return (no)	Partial
H4a	Non-Utility → higher Sharpe	0.0499 > 0.0479	Supported
H4b	Non-Utility → lower MDD	−0.9226 < −0.7935 (deeper)	Not supported
H4c	Non-Utility →	20.4403 > 0.1692	Supported

	better skewness		
H4d	Non-Utility → fewer extremes	19 = 19	Not supported
H4e	Higher transparency ⇒ better fraud prevention	Mixed: Sharpe(yes), MDD(no), extremes=	Partial

Conclusion

1.1 Purpose and Approach

This research examined whether blockchain adoption is associated with superior transparency and performance across two domains: listed equities and cryptocurrencies. Building on a structured literature review and a quantitative design, daily return series (2020–2025) were constructed for four groups—Equity_Blockchain, Equity_NonBlockchain, Crypto_Utility, and Crypto_NonUtility—and evaluated on average return, volatility, Sharpe ratio, maximum drawdown, skewness, and the frequency of extreme negative returns. Time-series diagnostics (ADF, Jarque–Bera, Ljung–Box) and an Isolation Forest screen complemented the analysis

Empirical and Theoretical Evidence from Blockchain and Cryptocurrency Research

This section synthesizes prior studies to provide an evidence-based foundation for the discussion of blockchain adoption, cryptocurrency security, and crypto-economic implications. Several strands of research highlight the technological, economic, and sectoral dimensions of blockchain systems. Empirical studies such as Androulaki et al. (2018) emphasize the security vulnerabilities in blockchain-based cryptocurrencies, showing that while decentralized systems enable trustless transactions, they remain exposed to attacks such as double-spending and selfish mining. Expanding the scope, Atree (2025) applies bibliometric and content analysis to show that cryptocurrency research has grown rapidly across disciplines, reflecting increasing scholarly and industrial interest.

Historically, Baddeley (2004) provides an early analysis of micropayment systems and e-cash, demonstrating how network effects and transaction costs influenced digital payment models, laying a foundation for today's blockchain applications. More recently, Benchis (2025) examines sector-specific blockchain adoption, revealing that while finance remains the most mature area, applications in supply chains, healthcare, and governance are evolving at varying speeds due to regulatory, institutional, and cost factors. Finally, Biais et al. (2023) explore advances in crypto-economics, showing how incentive design, governance, and market dynamics shape blockchain ecosystems. Together, these works provide a comprehensive evidence base for evaluating the opportunities and risks of blockchain technologies in economic and institutional contexts, supporting the arguments developed in this section.

5.2 Summary of Findings by Sector and Hypothesis

5.2.1 Equity sector: Blockchain → Performance/Transparency → Fraud Prevention

- **H1a (higher average daily return)**: **Supported.** Equity_Blockchain posted higher mean returns than Equity_NonBlockchain (0.0013 vs 0.0007; Table 4.2).
- **H1b (lower volatility)**: **Not supported.** Volatility was materially higher for Equity_Blockchain (0.0773 vs 0.0185).
- **H1c (higher performance ⇒ better fraud prevention)**: **Partially supported.** Performance, defined jointly as higher returns and lower volatility, was mixed (higher returns but higher volatility).
- **H2a (higher Sharpe ratio)**: **Not supported.** Sharpe was lower for Equity_Blockchain (0.0150 vs 0.0317; Table 4.3).
- **H2b (lower maximum drawdown)**: **Not supported.** Drawdowns were deeper for Equity_Blockchain (−0.9843 vs −0.3336).
- **H2c (more favorable skewness)**: **Supported.** Equity_Blockchain exhibited more positive skew (2.6884 vs 0.3077).
- **H2d (fewer extreme negatives)**: **Supported (marginal).** Slightly fewer extreme negative days (12 vs 13).
- **H2e (greater transparency ⇒ better fraud prevention)**: **Partially supported.** Transparency proxies were mixed (favorable skew and slightly fewer extremes, but weaker Sharpe and deeper drawdowns).

Blockchain-adopting equities earned higher average returns yet faced substantially higher day-to-day risk and worse peak-to-trough losses. Transparency-adjacent distributional features (skew, extreme-loss frequency) were somewhat improved, but not enough to lift risk-adjusted performance.

5.2.2Cryptocurrency sector: Utility/Non-Utility → Performance/Transparency → Fraud Prevention

- **H3a (utility tokens have higher average returns)**: **Not supported.** Crypto_NonUtility returns exceeded Crypto_Utility (0.0055 vs 0.0021; Table 4.2).
- **H3b (utility tokens have lower volatility)**: **Supported.** Volatility was lower for Crypto_Utility (0.0417 vs 0.1079).
- **H3c (higher performance ⇒ better fraud prevention)**: **Partially supported.** Utility tokens delivered stability (lower σ) but not higher returns.
- **H4a (non-utility have higher Sharpe)**: **Supported.** Crypto_NonUtility Sharpe slightly exceeded Crypto_Utility (0.0499 vs 0.0479; Table 4.3).
- **H4b (non-utility have lower maximum drawdown)**: **Not supported.** Drawdowns were deeper for Crypto_NonUtility (−0.9226 vs −0.7935).
- **H4c (non-utility have better skewness)**: **Supported.** Crypto_NonUtility displayed extreme positive skew (20.4403 vs 0.1692).
- **H4d (fewer extreme negatives)**: **Not supported.** Counts were equal (19 vs 19).
- **H4e (greater transparency ⇒ better fraud prevention)**: **Partially supported.** Higher Sharpe and skew favor Non-Utility, but deeper drawdowns and identical extreme-loss counts temper the inference.

Speculative tokens outperformed on raw returns and (marginally) on Sharpe but at the cost of much higher volatility and deeper drawdowns. Utility tokens offered materially smoother profiles. The Isolation Forest flagged more anomalies in crypto overall, consistent with heavier tails and longer sample spans.

1.3 Integrating the Evidence: Transparency vs. Stability

The results highlight a distinction between auditability and stability. Proxies tied to distributional shape (positive skew; slightly fewer large negative days in blockchain equities) and to systematic diagnostic features (non-normal, stationary returns) are consistent with richer information environments. This supports the notion that blockchain-linked activity can increase observability of economic flows and thereby improve certain transparency-adjacent outcomes.

Despite these transparency benefits, risk-adjusted performance did not improve for blockchain equities (lower Sharpe; deeper drawdowns). In crypto, utility delivered lower volatility, whereas non-utility delivered higher returns and extreme positive skew—but also the deepest drawdowns. Thus, transparency (or attention-driven skew) does not automatically translate into superior downside protection.

In short, blockchain improves what can be seen more than it guarantees how assets behave under stress. Robust fraud prevention therefore requires transparency plus controls, analytics, and governance.

1.4 Contributions

The study places equities and crypto on the same daily-frequency footing, enabling like-for-like evaluation of Sharpe, drawdown, skewness, and tail frequencies. This research motivates measurable transparency dimensions for blockchain-adopting firms and tokens, offering a bridge from conceptual claims to empirical proxies. By pairing tail-risk statistics with an anomaly detector (Isolation Forest), the analysis illustrates how transparency and distributional features can be integrated into a practical fraud-screening perspective.

5.5 Practical Implications

Where higher returns coincide with higher volatility/deeper drawdowns (blockchain equities; non-utility tokens), pair allocations with volatility targeting and drawdown controls.

Monitor rolling skewness, extreme-loss frequency, and drawdown depth as early-warning indicators; sudden deterioration may flag governance issues or manipulation risk.

Utility tokens suit risk-budgeted core exposure; non-utility may be treated as tactical/option-like satellites.

Publicly verifiable treasury addresses, on-chain revenue telemetry, and codified token policies strengthen information environments and may compress idiosyncratic risk over time. Transparency gains are blunted if treasury policies, reserves, or smart-contract controls are opaque.

Combine traditional audits with cryptographic attestations (e.g., verifiable reserves, event-level trails) to raise market integrity without assuming volatility will vanish. Promote standardized reporting around on-chain activity to support cross-issuer comparability and investor protection.

1.6 Limitations

Each cohort is represented by a single series rather than a diversified basket, so cross-sectional dispersion within groups is not captured. Risk-free assumptions are simplified and not perfectly term-matched; alternative RF specifications could shift levels (less so the cross-group ordering). Equities and crypto trade on different calendars and venues; while synchronized at the daily level, intraday microstructure effects are not modelled. Isolation Forest flags statistical outliers, not proven fraud; absent labelled fraud events, results should be read as risk screens, not adjudications.

1.7 Directions for Future Research

Replace single representatives with diversified baskets (e.g., 10–15 names/tokens per cohort) and re-estimate all metrics with cross-sectional inference. Study pre/post blockchain-adoption announcements and use panel specifications to sharpen causal interpretation. Combine Isolation Forest with LOF/DBSCAN, regime-switching filters, and on-chain graph features (entity flows, motifs) to improve precision/recall. Re-estimate metrics across bull/bear and liquidity regimes; evaluate time-varying connectedness to equities and stablecoins. Implement the proposed On-Chain Transparency Index (OCTI) and Corporate Disclosure Quality Index (CDQI) to test whether transparency scores predict tail risk and Sharpe out-of-sample.

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