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Special Thanks: Yanan Zhao, Tuan Anh Le and Manh Ha Nguyen for their excellent support of the JFDA production team.

Inaugural Editorial

The Launch of the Journal of FinTech and Digital Assets (JFDA)

The launch of the Journal of FinTech and Digital Assets (JFDA) marks the establishment of a rigorous intellectual home for the architects of the new economy. Our mission is to serve as the primary confluence for three historically disparate worlds: decentralized technology, traditional financial regulation, and high-fidelity quantitative modelling.

JFDA is not merely a repository of observations; it is a laboratory for theory and a compass for practice. We are committed to publishing scholarship that transcends the "hype cycles" of the market to provide deep, enduring insights into the mechanisms of value, the architecture of trust, and the evolution of global monetary systems. By fostering a multidisciplinary dialogue, we aim to ensure that the digital assets of tomorrow are built upon the robust academic foundations of today.

A Foundation of Intellectual Stewardship

The birth of a new journal is a monumental undertaking that relies entirely on the collective "intellectual stewardship" of a dedicated community.

• To our Advisory and Editorial Boards: We owe a debt of gratitude to the distinguished scholars and practitioners who recognized the necessity of this platform. Your vision and willingness to lend your reputation to this inaugural issue have been our greatest assets.

• To our Peer Reviewers: You are the guardians of our integrity. Thank you for your "unseen labour"—the meticulous vetting and constructive critiques that have elevated these manuscripts from drafts to definitive works of scholarship.

• To our Founding Supporters: Your belief in the importance of independent research provided the momentum required to turn a concept into a publication. We extend our sincere gratitude to our colleagues at Lincoln University, particularly Yanan (Digital Services Analyst), for their unwavering support. We also recognize the vital contributions of our researchers and partners at Auckland University of Technology, Università degli Studi di Milano-Bicocca, Foreign Trade University (Dr. Manh Ha Nguyen and Associate Professor Van Ha Nguyen), and Kyoto University.

• To our Authors: Our deepest thanks go to the contributors of this inaugural issue. Submitting research to a new journal requires not only academic excellence but a shared sense of vision. By entrusting us with your intellectual labour, you have provided the energy that transforms our ambitions into reality. Your dedication to pushing the boundaries of FinTech theory forms the bedrock of this journal.

An Invitation

The scholarship presented in this first issue is not intended to be the final word on these subjects, but rather the opening notes of a global conversation. As we look toward future volumes, our doors are wide open to the next wave of researchers, innovators, and policy architects.

We invite you to submit your work to JFDA. We specifically seek contributions that challenge the status quo - papers that provide the "disciplined disruption" necessary to move the needle. Whether your expertise lies in the micro-level engineering of Decentralized Finance (DeFi) protocols, the macro-economic implications of Tokenized Real-World Assets (RWAs), or the ethical frameworks of Algorithmic Governance, there is a place for your voice here.

Our commitment to our contributors is simple: a rigorous yet agile peer-review process, global visibility, and a platform that values intellectual courage as much as technical precision.

The digital asset revolution is an unfolding story, and its most impactful chapters have yet to be written. We invite you to pick up the pen and join us in defining the future of finance.

Be part of shaping the future of FinTech and Digital Assets.

With warmest thanks,
Cuong Nguyen
On behalf of the JFDA Editorial Team

THE JOURNAL OF FINTECH & DIGITAL ASSETS

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| Case Studies

Stablecoins in Japan: Regulatory Architecture, Monetary Strategy, and the Construction of Hybrid Digital Money Infrastructure.

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Abstract
Stablecoins have evolved from niche instruments supporting crypto-asset trading into structurally significant components of global payment infrastructure and digital monetary strategy. Japan was among the first major economies to establish a comprehensive legal framework governing fiat-backed stablecoins, embedding issuance within prudential supervision and restricting participation to regulated financial institutions. This early regulatory clarity positioned Japan as a pioneer in stablecoin governance.

However, global developments-particularly the rapid expansion of U.S. dollar-denominated stablecoins, which collectively hold over USD 150–180 billion in U.S. Treasury-related assets-have reframed stablecoins as instruments of currency competition and sovereign financial influence. At the same time, multilateral institutions such as the Bank for International Settlements (BIS) and the Financial Stability Board (FSB) have emphasised the need for governance safeguards, reserve transparency, and cross-border coordination to mitigate systemic risk.

This article situates Japan's stablecoin framework within comparative international policy debates and argues that Japan is moving toward a hybrid digital money architecture. In this emerging model, regulated stablecoins coexist with tokenised deposits and prospective central bank digital currency (CBDC) initiatives. While Japan's prudential model enhances systemic resilience, maintaining strategic relevance will require interoperability, scalability, and deeper integration into cross-border digital financial networks, particularly in the Asian region.

Keywords: Cryptocurrency, Digital money, Japan, Regulation, Stablecoins.
JEL Classification: A10, G00, F40.

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1. Introduction

Stablecoins as Systemic Financial Infrastructure: The first generation of stablecoins emerged as transactional tools within crypto-asset exchanges. Their primary objective was functional: to reduce settlement friction without exposure to volatile cryptocurrencies. However, over time, three structural transformations occurred:

a. Stablecoins became embedded in decentralised finance (DeFi) ecosystems.

b. They increasingly served as cross-border remittance mechanisms.
c. Their reserve assets became linked to sovereign bond markets.

This transformation altered their regulatory and macroeconomic significance. Stablecoins now function as:

- Programmable liquidity instruments
- Parallel payment infrastructures
- Synthetic digital representations of sovereign currency

International organisations have correspondingly recalibrated their analytical frameworks. The BIS has questioned whether privately issued stablecoins can replicate the singleness of money - a foundational characteristic of modern monetary systems. The FSB has emphasised governance, reserve transparency, and redemption risk mitigation. The ECB has raised concerns regarding currency substitution effects and monetary transmission.

Japan's regulatory approach predates this convergence but aligns with its underlying principles. The question is whether alignment is sufficient in a world where scale, interoperability, and strategic adoption matter as much as prudential design.

Digital Money Hierarchy and Monetary Sovereignty: Modern monetary systems operate through a hierarchy.

- Central bank money (ultimate settlement asset)
- Commercial bank deposits
- Narrow money instruments
- Shadow banking liabilities

Stablecoins introduce a novel layer. They are:

- Privately issued
- Backed by sovereign currency
- Operable on distributed ledger infrastructure
- Programmable through smart contracts

Unlike bank deposits, stablecoins may circulate globally without direct reliance on domestic banking rails. This characteristic introduces potential shifts in monetary hierarchy.

Monetary sovereignty involves control over currency issuance, payment systems, and transmission mechanisms. If foreign-currency stablecoins become dominant in cross-border digital commerce, domestic currency influence may erode — even without traditional capital account shifts.

In the Japanese context, this shift in monetary hierarchy is further shaped by the country's bank-centric financial system and regulatory emphasis on institutional trust. Unlike jurisdictions where non-bank fintech entities drive stablecoin adoption, Japan's framework embeds digital money innovation within existing financial intermediaries. This institutional configuration may limit rapid scaling but enhances credibility and regulatory consistency. Therefore, the strategic question for Japan is not merely regulatory adequacy but currency presence in programmable financial ecosystems.

2. Japan's Regulatory Architecture: Structure and Intent

Japan classifies fiat-backed stablecoins as electronic payment instruments. This legal classification reflects three strategic intents:

- Integration into prudential supervision
- Avoidance of crypto-asset volatility spillover
- Preservation of banking intermediation

Issuance restrictions to licensed banks and trust entities ensure institutional accountability. Reserve backing requirements mitigate credit risk. Segregation of assets protects consumers.

However, the conservative design also limits rapid market scaling relative to jurisdictions permitting fintech-led issuance. The trade-off is clear: credibility versus speed.

In addition, Japan's Payment Services Act introduces a tiered framework for fund transfer service providers, which indirectly influences stablecoin design and issuance models. Emerging initiatives, including yen-linked digital payment tokens such as JPYC, illustrate how private-sector experimentation is taking place within regulatory boundaries. At the same time, digital-native banks such as GMO Aozora Net Bank, Minna Bank, and UI Bank indicate potential future integration points between stablecoins and retail digital banking services.

3. Financial Stability Implications of Stablecoin Growth

Stablecoins introduce new financial stability channels:

a. Liquidity Risk

Large-scale redemption events could trigger rapid asset liquidation if reserves include longer-duration securities.

b. Sovereign Bond Market Linkages

If reserves are invested in sovereign debt, stablecoin growth may affect yield dynamics and liquidity conditions.

c. Interconnectedness with Tokenised Finance

Stablecoins increasingly serve as collateral in decentralised lending protocols and tokenised securities markets.

d. Operational and Cyber Risk

Programmability introduces smart contract vulnerabilities. Japan's prudential model addresses redemption and reserve risk but must adapt to interconnectedness and operational complexity as scale increases.

Comparative Regulatory Strategies: Divergent Paths in Digital Currency Governance

Stablecoin regulation has evolved along three identifiable models: prudential integration, innovation-led licensing, and strategic federalisation.

1. United States: Strategic Federalisation

The United States initially allowed rapid private-sector growth of dollar-denominated stablecoins before regulatory consolidation. Stablecoins such as USDC and USDT scaled globally, embedding themselves in digital asset markets and cross-border liquidity networks.

Recent legislation of the GENIUS Act signals a shift toward federal-level oversight frameworks. Importantly, U.S. discourse increasingly recognises that regulated stablecoins may reinforce demand for U.S. Treasury securities, creating a feedback loop between digital liquidity growth and sovereign bond markets.

This reflects a strategic reframing: stablecoins are not merely fintech innovations but potential instruments of dollar reinforcement.

2. European Union: Stability and Monetary Autonomy

The EU's Markets in Crypto-Assets (MiCA) regulation introduces licensing requirements, reserve backing rules, and supervisory oversight for stablecoin issuers. However, the European debate extends beyond prudential design.

The ECB has repeatedly highlighted risks of currency substitution, emphasising that large-scale stablecoin adoption could influence monetary transmission and financial stability. The digital euro initiative can be understood partly as a response to private digital currency expansion. Europe's model thus combines prudential oversight with defensive monetary strategy.

3. Hong Kong and Singapore: Innovation-Oriented Supervision

Hong Kong has pursued a licensing regime designed to attract stablecoin issuers while maintaining risk-based safeguards. Singapore similarly adopts calibrated regulation that encourages fintech experimentation within supervisory frameworks.

These jurisdictions aim to position themselves as digital asset hubs, balancing innovation and systemic stability.

4. Japan in Comparative Context

Japan's model is institutionally conservative but strategically coherent. It aligns with multilateral prudential guidance and avoids fragmentation between banking and digital asset sectors.

However, unlike the United States, Japan has not yet achieved scale in stablecoin issuance. This raises a central strategic question: can prudential foresight translate into ecosystem leadership without scale?

4. Stablecoins and Sovereign Debt Markets: Macro-Financial Feedback Loops

Stablecoins backed by sovereign assets create new macro-financial linkages. Recent estimates suggest that major U.S. dollar stablecoin issuers collectively hold more than USD 150 billion in U.S. Treasury bills and related short-term instruments, making them non-negligible participants in sovereign debt markets. This development introduces a structural linkage between digital liquidity expansion and public debt financing.

a. Reserve Composition and Duration Risk

Stablecoin issuers typically hold reserves in cash equivalents, short-term government securities, or money market instruments. As issuance scales, reserve portfolios grow correspondingly.

If reserves are concentrated in sovereign bonds, stablecoin growth may:

- Increase demand for short-duration government securities
- Influence yield curves
- Create new liquidity channels in secondary markets

In the U.S., the accumulation of Treasury bills by major stablecoin issuers has become economically significant.

b. Implications for Japan

If yen-denominated stablecoins scale meaningfully, reserve allocation could affect the Japanese Government Bond (JGB) market.

Possible dynamics include:

- Increased demand for short-term JGBs
- Interaction with Bank of Japan yield curve control policies
- Liquidity effects during redemption cycles

Given Japan's large sovereign debt stock and central bank asset purchases, the integration of private digital reserve holders introduces novel complexity.

c. Redemption Stress Scenarios

Large-scale redemptions could force liquidation of reserve assets. While Japan's prudential framework mandates reserve quality, liquidity mismatches cannot be entirely eliminated.

Thus, stablecoins create new feedback channels between digital asset markets and sovereign debt stability.

5. Tokenised Deposits versus Stablecoins: Convergence or Competition?

A critical conceptual question is whether stablecoins and tokenised deposits represent competing models or converging forms.

a. Tokenised Deposits

Tokenised deposits are commercial bank liabilities represented on distributed ledgers. They remain within traditional banking balance sheets and are subject to capital and liquidity regulation.

b. Stablecoins

Stablecoins may be issued by regulated financial institutions but are structurally distinct digital instruments backed by segregated reserves.

c. Convergence Dynamics

As regulatory frameworks mature, distinctions may narrow:

- Both instruments represent claims on fiat currency
- Both may operate on programmable infrastructure
- Both require compliance with AML and prudential safeguards

Japan's framework, by limiting issuance to supervised institutions, accelerates this convergence. Rather than replacing deposits, stablecoins may evolve as interoperable settlement layers.

In Japan, this convergence is likely to be accelerated by regulatory design. Because stablecoin issuance is restricted to supervised institutions, the functional distinction between tokenised deposits and stablecoins may narrow more rapidly than in other jurisdictions. Over time, both instruments may be integrated within bank-led digital platforms, supporting programmable settlement without displacing traditional deposit structures.

CBDC Interaction Scenarios: Japan, like many jurisdictions, has explored central bank digital currency experimentation. Three possible interaction models exist:

<u>1. Competitive Model</u>

CBDC displaces stablecoins as the dominant digital settlement asset.

<u>2. Complementary Model</u>

CBDC serves as wholesale settlement anchor, while stablecoins operate at retail or enterprise level.

<u>3. Layered Hybrid Model</u>

CBDC, tokenised deposits, and stablecoins coexist within unified ledger environments.

Japan's prudential integration approach suggests the third scenario is most plausible. For example, the Bank of Japan has adopted a cautious and exploratory approach to CBDC development, focusing on technical feasibility and institutional implications rather than immediate issuance. This cautious stance reinforces the likelihood that private-sector stablecoins and tokenised deposits will play a significant role in early-stage digital money innovation.

Cross-Border Settlement and Asian Trade Corridors: Digital currencies may reshape cross-border trade settlement. Yen-denominated stablecoins could:

- Facilitate settlement in regional supply chains

- Reduce reliance on correspondent banking
- Enable programmable trade finance

However, network effects favour early movers. Dollar-denominated stablecoins already dominate global digital liquidity.

Japan must therefore consider:

- Bilateral interoperability agreements
- Regional digital currency corridors
- Integration with Asian fintech ecosystems

Without cross-border adoption, domestic stablecoin frameworks risk remaining inward-looking. In this context, regional initiatives such as cross-border payment connectivity in Asia and potential interoperability frameworks among digital currencies will be critical. Without such integration, yen-denominated stablecoins may remain confined to domestic use cases, limiting their strategic impact.

Geoeconomic Competition and Digital Currency Strategy: Stablecoins increasingly intersect with geopolitical considerations. Digital currency dominance may influence:

- Global trade invoicing patterns
- Financial sanctions architecture
- Sovereign liquidity preferences

The expansion of dollar stablecoins strengthens the digital footprint of the U.S. currency. And for Japan, maintaining yen relevance requires strategic engagement rather than passive alignment. Digital monetary architecture is becoming an element of statecraft.

6. Strategic Options for Japan

Japan has been developing a legal framework based on the premise of an evolving hybrid digital money system where fiat currency, stablecoins, and CBDCs coexist. However, financial systems featuring a mix of various digital currencies are still in the early stages of development worldwide, and research into them has only just begun. Consequently, there is a growing need for Japan to formulate policies that adapt to the advancement of such a hybrid digital monetary ecosystem.

Japan faces three broad strategic pathways:

a. Conservative Prudential Stability

Maintain strict supervision and gradual scaling.
Advantage: systemic resilience. Risk: marginalisation in global digital liquidity networks.

b. Regional Digital Integration

Position yen stablecoins within Asian trade ecosystems.
Advantage: regional influence. Risk: coordination complexity.

c. Hybrid Leadership Model

Leverage prudential credibility while enabling scalable ecosystem development through targeted measures such as:

- API standardisation for bank–stablecoin interoperability
- Integration with tokenised securities settlement (e.g. DvP frameworks)
- Pilot projects for cross-border yen-denominated digital settlement

Advantage: balanced resilience and competitiveness. Risk: execution complexity and coordination challenges.

Policy Roadmap for Hybrid Digital Money Architecture: A coherent roadmap could include:

- Enhancing interoperability standards across banks and digital asset platforms
- Encouraging tokenised deposit experimentation within regulated banking environment
- Coordinating CBDC pilot programs with private-sector stablecoin initiatives
- Promoting cross-border pilot projects in Asian trade corridors
- Establishing common technical standards for programmable settlement (e.g. API and smart contract frameworks)

The objective should not be digital currency dominance, but digital currency relevance.

7. Conclusion: Toward Programmable Monetary Infrastructure

Stablecoins have evolved into structural components of global financial architecture. Japan's regulatory framework demonstrates foresight and institutional coherence. However, digital currency competition is accelerating. Prudential clarity alone is insufficient, scale and interoperability matter.

The evidence suggests Japan is constructing a hybrid digital money architecture integrating stablecoins, tokenised deposits, and CBDC experimentation. This layered approach preserves monetary hierarchy and financial stability. Yet maintaining strategic relevance will require proactive engagement in shaping international digital financial governance. The digital monetary order is no longer emerging - it is consolidating.

Japan's next phase will determine whether its early regulatory leadership translates into enduring influence. In particular, Japan's ability will depend on whether yen-denominated digital money can achieve meaningful adoption beyond domestic use cases. Future empirical analysis will be necessary as transaction data accumulates and practical use cases emerge.

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THE JOURNAL OF FINTECH & DIGITAL ASSETS

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| Research Paper

The Legal Regimes of Bitcoin: "A Form of Order Without Law"? A Comparative Study Between El Salvador and the United States.

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Abstract
On September 7, 2021, El Salvador became the first country to adopt Bitcoin as its legal tender by establishing the "Bitcoin Law."[1] The Bitcoin Law is the first statute that describes its main objectives and endows Bitcoin with the status of a legal tender in El Salvador.[2] Pursuant to the Bitcoin Law, El Salvador not only accepts Bitcoin as a means of payment methods for taxes and outstanding debts, but also requires all business enterprises to adopt Bitcoin as a medium of exchange for all commercial transactions.[3] However, the soul of Bitcoin is not the state; instead, it belongs to a decentralized entity with incentives to maintain this currency.[4] Therefore, the essence of Bitcoin is "a form of order without law."[5] A successful Bitcoin ecosystem would generate a mixture of law and nonlegal orders.[6] In the midst of growing literature on digital currency, El Salvador offers a rare opportunity to understand the functions and limitations of Bitcoin as a legal tender in a monetary sovereignty.[7]

Keywords: Bitcoin Law, Digital Currency, Blockchain, El Salvador, United States, Comparative Study.
JEL Classification: E00, F00, K00, K1.

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1. Introduction

Currency is a creature of law.[8] As the father of monetary theory, Georg Friedrich Knapp put it in 1924, "*the soul of currency is not in the material of the pieces, but in the legal ordinances which regulate their use*."[9] Knapp contends that currency must be constituted by law because only central governments have the right to confer the requisite legitimacy to gain inclusion of the public.[10] Consequently, the underlying value of a currency is intrinsically tied to the trust of the public in that legal system.[11] Bitcoin is the first decentralized

[1] F. Alvarez et al., *Are Cryptocurrencies Currencies? Bitcoin as Legal Tender in El Salvador*, Science 382, (2023).
[2] Ibid.
[3] Ibid.
[4] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[5] Ibid.
[6] Ibid.
[7] F. Alvarez et al., *Are Cryptocurrencies Currencies? Bitcoin as Legal Tender in El Salvador*, Science 382, (2023).
[8] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[9] Ibid.
[10] Ibid.
[11] Ibid.

cryptocurrency that bases on peer-to-peer technology and is essentially an innovative payment method with unique properties that are different from other online payment systems.[12] However, Bitcoin transactions are often conducted in a manner that circumvents traditional contract and tax law.[13]

On September 7, 2021, El Salvador became the first country to adopt Bitcoin as its legal tender by establishing the "Bitcoin Law."[14] The Bitcoin Law is the first statute that describes its main objectives and endows Bitcoin with the status of a legal tender in El Salvador.[15] Pursuant to the Bitcoin Law, El Salvador not only accepts Bitcoin as a means of payment methods for taxes and outstanding debts, but also requires all business enterprises to adopt Bitcoin as a medium of exchange for all commercial transactions.[16] However, the soul of Bitcoin is not the state; instead, it belongs to a decentralized entity with incentives to maintain this currency.[17] Therefore, the essence of Bitcoin is "a form of order without law."[18] As Bitcoin includes more users by competing against other monetary regimes, it may at some point transform into other more established regimes, leading to the direct result of a currency law.[19] A successful Bitcoin ecosystem would generate a mixture of law and nonlegal orders.[20] In the midst of growing literature on digital currency, El Salvador offers a rare opportunity to understand the functions and limitations of Bitcoin as a legal tender in a monetary sovereignty.[21]

This research summarizes, compares, and contrasts a wide range of relevant articles. The structure of the research is as follows. In introduction, the author provides background information on money theory. Section 2 presents literature review. And section 3 encompasses the current situation of Bitcoin as a legal tender and Bitcoin regulation in El Salvador. In section 4, the author counts the current regulatory regimes of Bitcoin in the United States. In this section, the author advocates the legality of Bitcoin[22] and proposes a mixture of legal regimes for Bitcoin regulation. The conclusion summarizes the findings and concludes the paper.[23]

2. Literature Review and Contributions of the Research

This research examines relevant articles concerning the regulation of Bitcoin and forms a literature review. Bitcoin is structured based on cryptocurrency, which stems from Satoshi Nakamoto and his work "Bitcoin: A Peer-to-Peer Electronic Cash System."[24] Kaponda summarizes the five traits of Bitcoin as the opposite to traditional currency.[25] Caldararo analyzes the advantages and disadvantages of Bitcoin as contrasted to traditional currency.[26] Baur carefully analyzes trading data generated by Bitcoin users.[27] Gandal examines the price control of Bitcoin trading.[28] Makarov analyzes the trading data from 15 digital currency trading platform from different areas around the world.[29] Surda contends that Bitcoin is an exchange medium of commercial

[12] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
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[14] F. Alvarez et al., *Are Cryptocurrencies Currencies? Bitcoin as Legal Tender in El Salvador*, Science 382, (2023).
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[18] Ibid.
[19] Ibid.
[20] Ibid.
[21] F. Alvarez et al., *Are Cryptocurrencies Currencies? Bitcoin as Legal Tender in El Salvador*, Science 382, (2023).
[22] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
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[24] Wu Linxiu. A Review of Bitcoin Research Literature: From the Perspective of Monetary Standard Theory [J]. Journal of Jixi University, 2015, 15(07): 80-83. DOI: 10.16792/j.cnki.1672-6758.2015.07.024
[25] Liu Xin. A Literature Review on Bitcoin Research [J]. Economic Data Translation Series, 2018, (04): 17-31
[26] Ibid.
[27] Ibid.
[28] Ibid.
[29] Ibid.

transaction.[30] Pavel and Miroslava points out to analyze Bitcoin from three aspects - exchange, value, and storage.[31] Folkinshtely denies the notion that "Bitcoin is merely a mirage" and believes that it contains value as a type of currency.[32] Luther, White, and Yermack notes that Bitcoin is a type of investment tool.[33] Brauneis examines three Bitcoin trading platforms in Asia, United States, and Europe—Bitfinex, Bitstamp, and GDAX.[34] Jafari points out that lawmakers should legislate to curb cybersecurity risk and tax avoidance that associate with Bitcoin transaction.[35] Charles Feremdna contends that digital currency cannot take place of central banks and their services.[36] Easley researches on the costs of Bitcoin transaction and its transformation.[37] Kaponda contends that it is essential to regulate Bitcoin transaction and to aware users about the risks of Bitcoin trading.[38]

2.1. Research Methodology

The methodologies used in this research contain: comparative study, theoretical and empirical study, legislative study, statutory analysis, textual analysis, and historical study.

2.2. Monetary Theory, Payment System and Currency Law

As society developed, civilizations flourished, and money evolved with time, legal philosopher Montesquieu wrote in 1748 that money is a sign that represents the value of all merchandise.[39] Although money has been a different commodity in different societies, it has always maintained primarily the same function.[40] Basically, there are three types of money: "commodity money, representative money, and fiat money."[41] Commodity money constitutes the oldest form of money.[42] Silver or ancient gold coins are examples of commodity money.[43] It has intrinsic value that can be used for something other than mere money—for instance, food grain.[44] Food grain not only can be used to sustain life, but also to evaluate other goods and services.[45] Regarding representative money, tokens or certificates that can be traded for a fixed quantity of gold constitute representative money.[46] Nowadays, fiat money constitutes the cornerstone of modern economies.[47] For instance, currency is a form of fiat money and it a "fungible, transferable, divisible, and recognizable legal tender."[48] Cash is the most common form of tangible currency.[49]

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[48] Ibid.
[49] Ibid.

Historically, there have been various uses of different forms of money.[50] Since the dawn of trade and civilization, money has been a characteristic of most commercial transactions.[51] With the advancement of money, people have reshaped how they conduct their commercial transactions and have introduced new variations.[52] The basic four functions of money include: "a medium of exchange, an overall standard, a measure of value, as well as a store of wealth."[53] There are two major theories of how money emerged.[54] The dominant theory advocates that money creates the market, by arising out of swaps and fundamentally serving to facilitate commodity exchange.[55] On the contrary, the alternative theory argues that money is a deliberate and positive creation of the state.[56]

Digital currencies are monetary currencies that evidenced electronically but not in physically tangible form.[57] One category includes digital currencies that are sponsored by governmental central banks.[58] Another category belongs to privately issued digital currencies.[59] These currencies, such as blockchain, take a token-based digital form is "secured by cryptography."[60] For this reason, privately issued digital currencies are commonly referred to as "cryptocurrencies."[61] Those privately issued digital currencies that are not backed by assets with intrinsic value constitute simply generic cryptocurrencies, as exemplified by Bitcoin.[62]

Bitcoin is the first decentralized cryptocurrency that bases upon blockchain technology[63] and a peer-to-peer network.[64] It is a novel online payment method with unique properties that substantially distinguish it from other online payment systems.[65] Bitcoin is essentially a "digital asset," of which the transfer and ownership is "recorded on blockchain."[66] The value of Bitcoin does not derive from any commodity or government, but only from what people believe they are worth.[67] Sovereignty only embraces currency because of the power they confer to the currencies, such as the monopoly to issue a legal tender.[68] The term "legal tender" refers to the form of money that has been recognized by a legal system, usually a central government.[69] Legal tender means that this payment method has been accepted by the legal authority of the land, and government dues that are paid in this form will be accepted.[70]

Legal regimes can generate a framework of order to preserve the value of currency.[71] Georg Friedrich Knapp, the father of monetary theory, wrote in 1924 that "the soul of currency is not in the materials of the

[50] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[51] Ibid.
[52] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[53] Ibid.
[54] Ibid.
[55] Ibid.
[56] Ibid.
[57] Steven L. Schwarcz, Regulating Digital Currencies: Towards an Analytical Framework, 102 B.U. L. REV. 1037 (2022).
[58] Ibid.
[59] Ibid.
[60] Ibid.
[61] Ibid.
[62] Ibid.
[63] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[64] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
[65] Ibid.
[66] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[67] Sean Greenwalt, Bitcoin: The Conflicting Currency, 4 LINCOLN MEM'l U. L. REV. 81 (Fall 2016).
[68] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[69] Ibid.
[70] Ibid.
[71] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).

pieces, but in the legal ordinances which regulate their use."[72] Knapp argues that "currency must be constituted by law since only governments can confer the requisite legitimacy to gain acceptance. Thus, the underlying value of a currency is intrinsically tied to the public's trust in that legal system."[73]

Modern currency is a creature of law[74] - "when money is created by the rule of law, it inherits the same strengths and weaknesses of law."[75] John Locke contends the theoretical justifications for the limited yet important function of the law on regulating currency - that is to maintain a stable value to facilitate market activities.[76] He argues that the primary function of government is not to manipulate interest rates, but to maintain a stable currency, and to fix the value of the currency to a stable commodity - for instance, gold or silver.[77] In contrast, the theory of modern central banking contends that modern government is supposed to maintain the economy for the benefits of its people.[78] The powers conferred to a modern central bank raise the question as to whether the government should use its power over currency to help the regulators.[79]

The objective of financial regulation is and should be to correct market failures.[80] Cryptocurrencies can pose externalities to central governments that undermine the government's ability to affect monetary policy with its fiat currency.[81] We can understand the promise of Bitcoin only by understanding the limits of currency law on Bitcoin regulation - an innovation that reflects neither a private nor public law of currency.[82] The uncertainty and vagueness of existing Bitcoin regulation post a substantial amount of legal risks to Bitcoin stakeholders and regulatory authorities.[83]

The regulatory approaches to virtual currencies vary widely across the world.[84] Legal regimes have not only embraced different definitions of what constitutes a "digital currency," they have also encountered other legal and policy questions brought by this financial technology.[85] These questions range from financial privacy, tax treatment, anti-money laundering, to corporate and institution compliances.[86] Many central authorities have attempted to include virtual currencies into existing regulatory frameworks, by explicitly or implicitly extending the boundary of existing laws.[87] For this reason, some states have established currency-friendly frameworks based on a wholesale virtual currency approach.[88] By contrast, others are actively considering how to encourage controlled growth of cryptocurrency sector.[89] Lacking clarity about the legal status of cryptocurrency may lead to the application of unexpected laws.[90]

When concerning the question whether a country would adopt a cryptocurrency like Bitcoin as its legal tender, D.G Thomas and D.S Bywaters state that "Different forms of money are evolving as virtual currencies like Bitcoin, although this format has limitations because it is not legal tender in any economy. States and

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[72] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[73] Ibid.
[74] Ibid.
[75] Ibid.
[76] Ibid.
[77] Ibid.
[78] Ibid.
[79] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[80] Steven L. Schwarcz, Regulating Digital Currencies: Towards an Analytical Framework, 102 B.U. L. REV. 1037 (2022).
[81] Ibid.
[82] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[83] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
[84] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[85] Ibid.
[86] Ibid.
[87] Ibid.
[88] Ibid.
[89] Ibid.
[90] Ibid.

monetary authorities have no control over the supply, which is costly to generate by private agents in terms of computer power, which means high transaction costs. The technology of transactions is not transparent, so it is liked by agents who operate in the criminal sector. It is the monetary monitoring and recording of the deposit base of retail banks as a medium of exchange and a store of value that is usually efficient and not too expensive to administer. Therefore, the credit creation-destruction technology of bank liabilities sustains production and trade at low transaction costs and provides a memory of records."[91]

3. Bitcoin as Legal Tender and The Legal Regimes of Bitcoin Law[92] in El Salvador

El Salvador, officially called the Republic of El Salvador, is located in Central America and "bordered on the northwest by Guatemala, on the Northeast by Honduras, and on the south by the Pacific Ocean."[93] On September 7, 2021, El Salvador became the first country to adopt Bitcoin as its legal tender by establishing the "Bitcoin Law."[94] Since this date, bitcoin can be used to conduct tax payments or buy goods and services in El Salvador.[95] With the adoption of bitcoin, the nation operates two currencies as legal tender.[96] The official currencies in El Salvador are Bitcoin and the United States Dollar.[97] El Salvador adopted Bitcoin as its legal tender partially because Bitcoin can stem from one of the most precious energy resources in the country—geothermal energy.[98]

How did El Salvador's government facilitate and promote the adoption of Bitcoin?[99] The government's response was "Chivo Wallet."[100] Additionally, El Salvador government also launched an app called "Chivo Wallet" that allows users to digitally trade both bitcoins and US Dollars, both of which are official currencies within the territory without paying transaction fees.[101] The "big push" policy exerted by El Salvador's government include: granting bitcoin with legal tender status through the Bitcoin Law, $30 bonus, gas price discounts, and no user fees.[102] Many people in the world are still unbanked.[103] Two billion people, or thirty percent of the world population, do not have accesses to bank accounts.[104] In developing countries, and even in some developed countries, many people lack bank accounts.[105] These unbanked individuals represent a huge opportunity for bitcoin.[106]

The Bitcoin system is designed as a traditional money system that bases off precious metals or commodity because the amount of Bitcoin that can be mined has been limited to 21 million as portion of the software's parameters.[107] Bitcoin was originally designed as an alternative system to traditional centralized payment system that suffers "from the inherent weakness of the trust-based model."[108] The beauty of bitcoin system's

[91] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[92] F. Alvarez et al., *Are Cryptocurrencies Currencies? Bitcoin as Legal Tender in El Salvador*, Science 382, (2023).
[93] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[94] F. Alvarez et al., *Are Cryptocurrencies Currencies? Bitcoin as Legal Tender in El Salvador*, Science 382, (2023).
[95] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[96] Ibid.
[97] Ibid.
[98] Ibid.
[99] Ibid.
[100] Ibid.
[101] F. Alvarez et al., *Are Cryptocurrencies Currencies? Bitcoin as Legal Tender in El Salvador*, Science 382, (2023).
[102] Ibid.
[103] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[104] Ibid.
[105] Ibid.
[106] Ibid.
[107] Sean Greenwalt, Bitcoin: The Conflicting Currency, 4 LINCOLN MEM'l U. L. REV. 81 (Fall 2016).
[108] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).

design is that its enforcement mechanism can not only be more powerful than the informal mechanism to enforce social norms, but also be more powerful, in certain aspects, than the formal mechanism of rule of law.[109] This system opposes to most government monetary structures that operate under fiat currency where the number of currencies in circulation can be continuously created.[110] However, Bitcoin system is similar to the mechanism of fiat currency is that fact that the value of Bitcoin is merely as much as the public ascribes to it.[111]

The main categories of Bitcoin stakeholders include users, miners, exchanges, and merchants.[112] The Bitcoin miners are those Bitcoin stakeholders who contribute to the power of their computer systems to the mining process.[113] Bitcoin miners are now compensated with newly minted bitcoins.[114] Another category of Bitcoin stakeholders constitutes Bitcoin exchanges that provide the online trading platforms where the registered members can trade their Bitcoins for traditional money or vice versa.[115] The exchange rate of bitcoin is determined exclusively by supply and demand, and therefore, the network of bitcoin buyers and sellers determine what bitcoin is worth.[116]

Bitcoin system now resembles a modern version of privately issued currencies that operated by the rule of law.[117] We are witnessing the beginning of an "economy of cryptocurrencies."[118] As various types of cryptocurrencies evolve to meet different market demands, individuals may complete the commercial transactions with different cryptocurrencies, while in this process, rely less and less on the use of traditional fiat currency.[119] The emergence of Bitcoin addresses some fundamental issues of monetary theory.[120] For example, many commentators note that Bitcoin's high volatility constitutes the structural flaws that underlie in bitcoin itself.[121]

Creating a decentralized currency based on a peer-to-peer network poses a unique problem—How can a Bitcoin user trust that a unit of virtual currency has any value without a certain sort of tangible note or coin for which it can be ultimately redeemable by the rule of law?[122] This is one of the issues that the inventors of Bitcoin set to solve.[123] At its core, a Bitcoin is merely a string of computer code.[124] The blockchain is decentralized, meaning that there is not an absolute "correct" chain.[125] Ultimately, the market of cryptocurrency users has the power to determine the relative value of bitcoin cash—a decision that the market will make in order to be free from a centralized state authority.[126] Many bitcoin critics incorrectly conflate bitcoin's high volatility with the structural, underlying flaw in bitcoin itself.[127] Consequently, some commentators have speculated that the advent of bitcoin will lead to massive market suppression and manipulation by bitcoin whales.[128]

[109] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[110] Sean Greenwalt, Bitcoin: The Conflicting Currency, 4 LINCOLN MEM'l U. L. REV. 81 (Fall 2016).
[111] Ibid.
[112] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
[113] Ibid.
[114] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[115] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
[116] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[117] Ibid.
[118] Ibid.
[119] Ibid.
[120] Ibid.
[121] Ibid.
[122] Ibid.
[123] Ibid.
[124] Ibid.
[125] Ibid.
[126] Ibid.
[127] Ibid.
[128] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).

The Bitcoin Law is the first statute that describes its main objectives and endows Bitcoin with the status of a legal tender in El Salvador.[129] Pursuant to the Bitcoin Law, El Salvador not only accepts Bitcoin as a means of payment methods for taxes and outstanding debts, but also requires all business enterprises to adopt Bitcoin as a medium of exchange for all commercial transactions.[130] The Bitcoin Law provides that all economic agents in El Salvador must accept Bitcoin, but this statute does not necessarily translate into all firms effectively that are compliance with the legislation.[131] In April 2022, the Central African Republic (CAF) was the second country, after El Salvador, to make bitcoin legal tender, the same month in which Panama approved its own Crypto Law.[132]

The first Article of the Bitcoin Law provides the main objective of the statute and endows Bitcoin as legal tender status in El Salvador.[133] Article 7 of the statute reads: "Every economic agent must accept bitcoin as payment when offered to him by however acquires a good or service."[134] Article 8 of the statute is related to how bitcoin will be implemented in the country by mandating the government to provide payment methods of bitcoin to conduct transactions.[135] In addition to accepting bitcoin as legal tender, El Salvador's Bitcoin Law generally requires "every economic agent" to "accept bitcoin as payment when offered to him by whoever acquires goods and services."[136] Outside of the country, a seller's willingness to accept this form of payment method is essential to the transaction.[137] However, under El Salvador's new rule, a seller must accept bitcoin as payment, even when receiving value in this form is opposite to his will.[138] However, an exception to this compliance rule for those who "do not have access to the technologies that allow them to carry out transactions in bitcoin" has created ambiguity as to whether businesses are required to adopt bitcoin as payment methods.[139]

The World Bank stands at a crossroads as to whether it should recognize El Salvador's adoption of Bitcoin as legal tender.[140] However, the World Bank has already manifested that it does not intend to support El Salvador's adoption of bitcoin as legal tender for "environment and transparency" concerns.[141] The International Monetary Fund indicated that it has economic and legal concerns over the adoption of bitcoin as a parallel legal tender with US Dollar in El Salvador.[142]

4. The Legal Regimes of Bitcoin in the United States: A Mixture of Currency Laws[143] and Nonlegal Orders[144]

4.1. The Legal Classifications of Bitcoin

The United States legislatures have not passed any definitive law concerning bitcoin regulation at this time.[145] A central power of the Congress, conferred power by the U.S. Constitution, is the authority to "coin

[129] F. Alvarez et al., *Are Cryptocurrencies Currencies? Bitcoin as Legal Tender in El Salvador*, Science 382, (2023).
[130] Ibid.
[131] Ibid.
[132] Ibid.
[133] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[134] Ibid.
[135] F. Alvarez et al., *Are Cryptocurrencies Currencies? Bitcoin as Legal Tender in El Salvador*, Science 382, (2023).
[136] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[137] Ibid.
[138] Ibid.
[139] Ibid.
[140] Ibid.
[141] Ibid.
[142] Ibid.
[143] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[144] Ibid.
[145] Sean Greenwalt, Bitcoin: The Conflicting Currency, 4 LINCOLN MEM'l U. L. REV. 81 (Fall 2016).

money and regulate the value thereof."[146] Federal courts are unlikely to classify Bitcoins as money.[147] However, the logical question following is: why should they?[148] Since Bitcoins are a new invention, it is the lawmakers' job to "discover" the law through a multitude of factors, including legal instrument, public policy, and social norms.[149]

The legal classifications of Bitcoin and Bitcoin stakeholders are very complex.[150] Bitcoin may be considered as a good, a commodity, a security, a payment method, so on and so forth.[151] At the same time, it has been proved that Bitcoin cannot be classified as an e-money/e-money institution, a payment instrument, an investment firm, a credit institution, or a payment service/payment service provider.[152] Also, they can be classified as financial assets transforming from a pure medium of exchange advantages to a pure store of value advantages.[153] Bitcoin system poses considerable risks and challenges to users and regulators when they try to fit the new technology into the older legal framework.[154]

We should also take historical perspectives into consideration when thinking about the appropriate regulatory framework for bitcoin regulation.[155] Currencies have changed forms over centuries, with currency laws evolving to adapt to the changes.[156] In the United States, early currencies were gold or silver coins, and therefore currency itself has intrinsic value as a commodity.[157] These forms change into "silver certificate," which is theoretically exchangeable for silver.[158]

As noted above, Bitcoin has all the essential functions of money.[159] Like fiat currency, Bitcoin has no intrinsic value that is backed by commodity.[160] However, Bitcoin is scarce and endowed with deflationary properties at the same time, since its supply is limited by the Bitcoin protocol.[161] It can be argued that, like a legal tender, Bitcoin is "fungible, transferable, divisible, and recognizable."[162] While Bitcoin's volatility is more than that of gold or silver, its absolute return has far more value beyond the precious metal.[163] In addition, Bitcoin can be classified as a payment service system, a financial instrument, or e-commerce.[164]

4.2. The Current Legal Regimes of Bitcoin Regulation in the United States

The current U.S. government regulates Bitcoins by breaking the topic into subparts for each government branch: Subpart A for judicial branch, Subpart B for executive branch, Subpart C for legislative branch, and Subpart D for state sovereign Bitcoin treatment.[165] Currently, although no federal legislation has been created on virtual currencies, there are various regulatory instruments and entities concerning bitcoin regulation.[166]

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[146] Sean Greenwalt, Bitcoin: The Conflicting Currency, 4 LINCOLN MEM'l U. L. REV. 81 (Fall 2016).
[147] Ibid.
[148] Ibid.
[149] Sean Greenwalt, Bitcoin: The Conflicting Currency, 4 LINCOLN MEM'l U. L. REV. 81 (Fall 2016).
[150] Ibid.
[151] Ibid.
[152] Ibid.
[153] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[154] Ibid.
[155] Steven L. Schwarcz, Regulating Digital Currencies: Towards an Analytical Framework, 102 B.U. L. REV. 1037 (2022).
[156] Ibid.
[157] Ibid.
[158] Ibid.
[159] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
[160] Ibid.
[161] Ibid.
[162] Ibid.
[163] Ibid.
[164] Ibid.
[165] Sean Greenwalt, Bitcoin: The Conflicting Currency, 4 LINCOLN MEM'l U. L. REV. 81 (Fall 2016).
[166] Ibid.

These regulatory bodies include the Internal Revenue Service ("IRS"), the U.S. Securities and Exchange Commission ("SEC"), and the U.S. Department of Treasury and Financial Crime Enforcement Network ("FinCEN"), just to name a few.[167] They have been established and reached to interpret existing legislation against this new form of monetary medium.[168]

Although no specific law has been passed to regulate Bitcoin in the United States, Bitcoin legislations are commonly finding treatment under two major fields of law: federal anti-money laundering and tax legislation.[169] Federal Anti-Money Laundering Law such as 18 U.S.C. Section 1956 and 1957, are issued to prohibit engagement in financial transactions that are designed to finance illegal activities.[170]

4.2.1. The Bitcoin Protocol[171]

Created in 2008 and launched in 2009, Bitcoin constitutes both virtual currency and digital payment system within which transaction in this form of currency are made.[172] Under the Bitcoin Protocol, this payment method is based on a peer-to-peer network system and is not controlled or owned by any entity.[173] The Bitcoin protocol determines the primary rules under which the Bitcoin system operates, the same way as any Internet protocol determines rules for any specific technology.[174] The Bitcoin protocol is open-source, however, the open-source nature of Bitcoin protocol does not mean that any modification of the protocol will instantaneously become an effective rule for the Bitcoin system.[175]

4.2.2. Uniform Commercial Code[176]

The definition of "money" is contained in Article 1 of UCC Section 1-201(b)(24).[177] Article 1 defines "money" as "a medium of exchange *currently authorized or adopted by* a domestic or *foreign government*. The term includes a monetary unit of account established by an intergovernmental organization or by agreement between two or more countries."[178] The provision of Article 1 provides that UCC applies to transactions that are subject to the scope of the rest of the Articles of the Code.[179] To address the regulatory challenges of digital currencies, UCC epitomizes a uniform model law that is enacted into national law and designed to facilitate various commercial legislation of U.S. states in multistate commercial transactions.[180] As a result of the specific definition of money in UCC, El Salvador's adoption of Bitcoin as its legal tender has brought changes to the commercial law of all U.S. states that accepted the UCC.[181]

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[167] Sean Greenwalt, Bitcoin: The Conflicting Currency, 4 LINCOLN MEM'l U. L. REV. 81 (Fall 2016).
[168] Ibid.
[169] Ibid.
[170] Ibid.
[171] Ibid.
[172] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
[173] Ibid.
[174] Ibid.
[175] Ibid.
[176] Brian M. McCall, How El Salvador Has Changed U.S. Law by a Bit: The Consequences for the UCC of Bitcoin Becoming Legal Tender, 74 OKLA. L. REV. 313 (Spring 2022).
[177] Ibid.
[178] Ibid.
[179] Ibid.
[180] Steven L. Schwarcz, Regulating Digital Currencies: Towards an Analytical Framework, 102 B.U. L. REV. 1037 (2022).
[181] Ibid.

4.2.3. A Trilogy of Cases: *SEC v. Shavers*, *U.S. v. Ulbrict*, and *Faiella*[182]

On August 6, 2013, in *SEC v. Shavers*, the Eastern District of Texas decided whether investments in a Bitcoin Trust should be considered as securities under federal securities law.[183] This case was the first bitcoin definition case around the world.[184] The Court held that the Bitcoin Trust investment amounts to an investment of money, and, more importantly, the Court specifically classified Bitcoins as a "currency or form of money."[185] The Court notes that "it is clear the bitcoins can be used as money."[186] Bitcoins can be "used to purchase goods or services, and the Defendant stated, used to pay for living expenses."[187] While the Court notes that Bitcoins are limited to "those places that accept it as currency," the Court also reasoned that bitcoins can also be exchanged for many strong currencies, and therefore, the Court decides that Bitcoins qualify as a "form of money."[188]

The *Ulbrict* was the second case in a line of trilogy of District Court cases that resists any persuasive authority regarding to the monetary status of Bitcoins.[189] On July 9, 2014, the Southern District of New York, in *United States v. Ulbrict*, charged the Defendant under 18 U.S.C. Section 1956(h) for participation in a money laundering conspiracy.[190] Pursuant to 18 U.S.C. Section 1956(h), a financial transaction is defined as "the movement of funds by wire or other means…or involving one or other means…or involving one or more monetary instruments."[191] The term "monetary instrument" include: personal checks, bank checks, coinage or banknote of a country, money orders, investment securities, or negotiable instruments.[192] 18 U.S.C. Section 1960 refers to the terms "money" and "funds."[193] Pursuant to Section 1960, "money transmitting" means the "transferring funds on behalf of the public by any and all means."[194] Consequently, the Defendant argues that Bitcoins do not qualify as money pursuant to Section 1960, and FinCEN Guidance ruling states that bitcoins are not classified as a currency.[195]

Faiella was the final case of three U.S. District Court to address the issue on how to classify Bitcoins, and it was the first case that starts using persuasive judicial and legislative authority.[196] However, what makes the *Faiella* case unique, as compared to *Ulbrict* and *Shavers*, is that the "ordinary" definition of Bitcoin is much more comprehensive than either of the previous cases.[197] Where *Shavers* simply states that a practical common knowledge view that Bitcoins are money because they act like money, in *Ulbrict*, judges seem to solidify the notion that Bitcoins are money by suing a dictionary definition by not citing to *Shavers*.[198]

The governance model of bitcoin has drawn significant amount of criticism.[199] Compared with other traditional payment systems, bitcoin lacks a regulatory structure other than its underlying software.[200] Commonly, the ordinary processes of criminal law are used to reinforce bitcoin's order with the lack of a

[182] Sean Greenwalt, Bitcoin: The Conflicting Currency, 4 LINCOLN MEM'l U. L. REV. 81 (Fall 2016).
[183] Ibid.
[184] Ibid.
[185] Sean Greenwalt, Bitcoin: The Conflicting Currency, 4 LINCOLN MEM'l U. L. REV. 81 (Fall 2016).
[186] Ibid.
[187] Ibid.
[188] Ibid.
[189] Ibid.
[190] Ibid.
[191] Ibid.
[192] Ibid.
[193] Ibid.
[194] Ibid.
[195] Ibid.
[196] Ibid.
[197] Ibid.
[198] Ibid.
[199] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
[200] Ibid.

currency law.[201] Bitcoin payment has already been debated and criticized because it is frequently connected with criminal activities.[202]

How a balanced regulation can be achieved?[203] The answer is: optimizing a possible balance between the interests of Bitcoin shareholders and regulatory entities.[204] As has been concluded above, a full regulation is achievable only through the issuance of a conceptually new legislation that, as we have already seen, would not have any practical effect.[205] At conceptual level, Bitcoin may be considered by analogy with other decentralized neutral technologies such as Internet and email.[206] These technologies are decentralized, not owned or controlled by any central entities, and are unregulated or underregulated.[207] Nearly all central authorities manage their money supply in the form of central banking under the shadow of public law.[208] However, bitcoin represents a potential third currency system that is far more resistant to state control, since it mints monetary units that do not exist in any physical place, and relies on scientific principles from cryptography to ensure a numerical ceiling and verify any peer-to-peer transfer.[209]

5. Conclusion

Consequently, there is a necessity for a clear strategy for bitcoin's regulation that maintains the maximum balance between the interests of bitcoin users and financial regulators.[210] However, bitcoin's legal framework is still unclear, and sufficient clarity in the legal regulation of bitcoin has not yet achieved.[211] These vagueness and uncertainty have posted a substantial amount of legal risks to Bitcoin users and stakeholders, resulting challenges for regulatory authorities: for instance, bitcoin users are legally unprotected as consumers; bitcoin transactions are often conducted out of traditional contract and tax law; and the properties and the lack of clear regulation of bitcoin are often exploited by criminals who often use bitcoin for the purpose of money laundering.[212] In this paper, the author develops a legal regime of balanced regulation of bitcoin.[213] When currency is created by the rule of law, at the same time, it inherits the strengths and weaknesses of law.[214] Legal regimes can create a pattern of order to preserve the value of currency.[215]

Since money is a creature of law, government control over currency is a form of oppression.[216] The advent of cryptocurrencies, exemplified by bitcoin, poses both a theoretical challenge to the view that currency law is the necessary foundation of monetary system, and a practical challenge to the sovereign regimes that are monetarily oppressive.[217] If the El Salvador's Bitcoin Law is notable for its brevity, U.S. legislations on Bitcoin regulation is exemplified for its complexity.[218] Because of this multi-faceted approach to Bitcoin regulation in

[201] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[202] Ibid.
[203] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
[204] Ibid.
[205] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
[206] Ibid.
[207] Ibid.
[208] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[209] Ibid.
[210] Sergii Shcherbak, *How Should Bitcoin Be Regulated*, 7 EUR. J. LEGAL STUD. 41 (Summer 2014).
[211] Ibid.
[212] Ibid.
[213] Ibid.
[214] John O. McGinnis & Kyle Roche, *Bitcoin: Order without Law in the Digital Age*, 94 IND. L.J. 1497 (Fall 2019).
[215] Ibid.
[216] Ibid.
[217] Ibid.
[218] Joseph Parampathu, From Securities to Currencies: The Regulatory Consequences of Adopting Cryptocurrencies as Legal Tender, 31 ASIAN BUS. LAW. 35 (2023).

the United States, it is necessary to examine a series of currency laws that play a role in Bitcoin regulation within the U.S. before discussing the potential effects of the Bitcoin Law in El Salvador.[219]

The legislative branch locates in a unique position because they will ultimately act lastly on Bitcoin law, however, will have the final authority on the subject as well.[220] The question is how, and will these Bitcoin legislations be constitutional?[221] The potential order of bitcoin contrasts with the legal regimes that have already laid the foundation of all currencies—the theoretical and historical practice of the so-called "free banking."[222] Consequently, bitcoin represents a third currency regime that is different from both theories of central banking and free banking.[223]

However, the soul of Bitcoin is not the state; instead, it belongs to a decentralized entity with incentives to maintain this currency.[224] Therefore, the essence of Bitcoin is "a form of order without law."[225] As Bitcoin includes more users by competing against other monetary regimes, it may at some point transform into other more established regimes, leading to the direct result of a currency law.[226] A successful Bitcoin ecosystem would generate a mixture of law and nonlegal orders.[227] In the midst of growing literature on digital currency, El Salvador offers a rare opportunity to understand the functions and limitations of Bitcoin as a legal tender in a monetary sovereignty.[228] Just as the Internet, Bitcoin is multijurisdictional, and moreover, we are witnessing that some central authorities are embracing bitcoin system.[229] The strategy of balanced regulation determines the legal issues on the concept of Bitcoin, clarifies the legal rules applicable to Bitcoin stakeholders, and provides regulatory authorities to supervise Bitcoin compliance with these applicable laws.[230]

Declaration of the Use of Generative AI

During the preparation of this work, the author(s) did not use any tools related to AI.

Conflicts of Interest

No conflict of interest.

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| Research Paper

Value-at-Risk (VaR) Based Portfolio Optimization and Risk Decomposition.

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Abstract

This study investigates portfolio optimization using the Value-at-Risk (VaR) as the risk measure to identify the sources of portfolio risk. Optimized portfolios under 95% and 99% VaR constraints were compared with an equal-weight portfolio, using a portfolio of 11 Standard & Poor's Depositary Receipt (SPDR) sector Exchange-Traded Funds (ETFs) representing the S&P 500 sectors (XLB, XLE, XLF, XLI, XLK, XLP, XLU, XLV, XLY, XLRE, XLC) over the period from 2018 to 2025. The delta-normal model was applied for VaR computation, and total portfolio risk was decomposed into marginal, component, and incremental VaR. Results show that VaR-based optimization enhances risk-return efficiency compared to the equal-weight benchmark, with minimal performance difference between 95% and 99% confidence levels. Risk decomposition further reveals that portfolio risk is highly concentrated in technology (XLK), consumer staples (XLP), and utilities (XLU) sectors, with XLK contributing the most to total portfolio risk. This suggests that optimization tends to favor a mix of growth and defensive assets. Overall, the findings highlight the trade-off between diversification and efficiency in risk-based portfolio construction. This study underscores the practicality of using VaR in portfolio optimization and risk attribution, and future research may explore extensions using conditional VaR (CVaR) or alternative market regimes to capture extreme risk dynamics more accurately.

Keywords: Value-at-Risk (VaR), marginal VaR, component VaR, incremental VaR, portfolio optimization.

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1. Introduction

Identifying and quantifying portfolio risk sources is crucial for effective risk management and capital allocation. For institutional investors and portfolio managers, understanding where risk originates within a portfolio helps guide asset allocation decisions, risk budgeting, and regulatory capital management. In particular, decomposing portfolio risk enables investors to identify dominant risk drivers and evaluate how individual assets contribute to overall downside exposure. Traditionally, variance and the standard deviation and variance have been widely used as measures of portfolio risk within Markowitz's mean-variance framework. However, a well-known limitation of variance is that it penalizes both upside and downside fluctuations symmetrically, treating both favorable and unfavorable deviations as risk, which may not accurately reflect investors' primary concern with potential losses. Moreover, variance as a risk measure was inadequate due to its assumption that returns are normally distributed (Ayodeji & Ingram, 2015). In practice, financial returns often deviate from the normal distribution and frequently exhibit fat-tailed distributions (Hallerbach, 1999), making variance-based risk measures less informative in capturing extreme downside events.

In the 1980's, Value-at-Risk (VaR), an alternative risk measure, emerged as a concept and grew popular in the early 1990's owing to J.P. Morgan. VaR indicates the greatest potential loss of a portfolio at a given confidence level over a defined time horizon (Tardivo, 2002), which is considered the financial industry's standard for measuring exposure to financial price risks (Dubofsky & Miller, 2003). Contrary to variance, VaR has the advantage of focusing solely on downside outcomes; its capability in addressing worst-case scenarios makes it appealing for investors, regulators, and risk managers who are more concerned with catastrophic losses.

However, the non-coherent property of VaR is inherently problematic for modeling financial risks, as the risk of the overall portfolio is not simply the total sum of the individual risks (Duc et al., 2018). For example, despite the positive expected returns of each portfolio, at 95% confidence, an investor of this portfolio is still subjected to a risk of -1.9% returns (Duc et al., 2018). Relying on VaR may not help build an optimal portfolio in terms of investment selection. Given that, conditional Value-at-Risk (CVaR) came up by Rockafellar and Uryasev (2000) as an alternative measure that considers the losses that will be held when the VaR threshold is exceeded. Different from the VaR, CVaR is a coherent risk measurement (Pflug, 2000), which propelled its popularity as an efficient measure of risk. CVaR is considered superior to VaR in portfolio optimization (Sarykalin et al., 2008). Nonetheless, VaR remains widely used by institutions and regulators, and it is valuable to understand the implications of using VaR directly in asset selection. In this paper, the focus will be solely on the VaR.

However, VaR does not identify how individual assets contribute to the total; it only measures the overall portfolio risk. An efficient method of decomposing overall risk will then be a useful tool for managing portfolio risk, which allows the risk managers to select assets that provide the best risk-return trade-off to individual risk factors (Yamai & Yoshiba, 2002). Hallerbach (1999) developed a method of decomposing VaR into individual factors - marginal VaR, component VaR, and incremental VaR. The risk decomposing technique can identify the 'hot spots' of risk in the portfolio, enabling effective risk budgeting and better-informed asset allocation (GARP, 2024), which will contribute to constructing an optimal minimum-risk portfolio. The results will be beneficial for the financial institutions or individual investors who need to mitigate effectively against the potential risks. Effective risk management would offer a platform for future policy and strategic decision-making (Duc et al., 2018).

The Sharpe Ratio is a classic metric for risk-adjusted performance, which is defined as expected excess return divided by standard deviation. An alternative is the Reward-to-VaR Ratio, introduced by Alexander and Baptista (2003), which is defined as the expected portfolio excess return divided by the portfolio VaR at a given confidence level. Thus, this measure evaluates portfolio performance by scaling expected excess return with VaR, thereby explicitly incorporating downside risk into the efficiency criterion. Although this measure is closely related to the Sharpe Ratio, it is particularly attractive for investors concerned with extreme losses, since VaR captures tail risk rather than symmetric volatility.

Inspired by this concept, this project adopts a Return/VaR ratio as the optimization objective. This measure is essentially equivalent to the Reward-to-VaR Ratio, with the simplifying assumption of a zero risk-free rate. By maximizing the ratio of expected portfolio return to portfolio VaR, the optimization framework ensures that asset allocations are chosen to maximize reward relative to downside risk exposure. Thus, this paper aimed to 1) construct portfolio that maximize the Sharpe Ratio under VaR-based risk constraints, thereby demonstrating the role of VaR in risk management; 2) compute and analyze marginal, component, and incremental VaR in order to decompose overall portfolio risk and identify the risk sources, which will provide insights into the relative contributions of individual assets and help identify the main drivers of portfolio risk under different market conditions.

To achieve these objectives, an optimal long-only sector ETF portfolio was constructed, and results between 95% and 99% VaR confidence levels were compared to examine how a stricter tail-risk constraint affects asset selection. A full VaR decomposition was then conducted, including marginal VaR - the sensitivity of portfolio VaR to a marginal increase in asset weight, component VaR - each asset's actual contribution to total portfolio VaR, and incremental VaR - the change in portfolio VaR if an asset is removed. This bridges the gap between abstract risk-adjusted performance measures and practical portfolio construction, illustrating how optimizing for Return/VaR can shift the portfolio toward safe and more efficient territory in terms of downside risk.

The remainder of this study is organized as follows: Section 2 reviews relevant literature on VaR and risk decomposition. Section 3 describes the dataset and asset selection criteria, and outlines the methodology, including definitions of risk measures and the optimization approach. Section 4 presents the empirical results, including the optimal portfolios under 95% and 99% VaR, their performance, and a detailed risk decomposition analysis. Finally, Section 5 concludes the study with a discussion of the findings and their implications for risk-focused portfolio management.

2. Literature Review

Research integrating VaR into portfolio optimization builds on the recognition that investors may care more about downside extremes than average volatility. Roy (1952) first introduced the "safety-first" criterion, focusing on minimizing the probability of disaster falling below a certain threshold. This idea had then evolved into downside risk measures and influenced the later development of VaR. By the late 1990s, VaR had become a standard risk metric in the finance industry and was popularised by the release of RiskMetricsTM by J.P.Morgan in October 1994.

The greatest advantage of VaR is that it summarizes risk in a single and understandable number (Horcher, 2011). In other words, VaR is the maximum amount of money that can be lost in portfolio investment, over a specific time horizon window and a given confidence level (Koziorowska, 2012). This definition highlights VaR's focus on tail risk by providing a clear cut-off point that separates typical portfolio fluctuations from extreme loss outcomes. For example, a 99% VaR calculated over a 10-day holding period implies that the maximum portfolio loss over the next 10 days is expected to be exceeded with a probability of only 1%.

2.1. Value at Risk - Delta Normal Model

VaR can be calculated using the methods of historical, Monte Carlo, Risk Metrics, and Variance-Covariance approach (Duc et al., 2018). These methods differ in terms of market data needs, computational demands, and modelling capacity for diverse instruments (Koziorowska, 2012). Historical and Monte Carlo simulation methods are preferred for non-linear portfolios such as options. However, these methods are not intended to be discussed as this paper focuses on ETFs only. The variance-covariance approach (also known as the parametric approach) is the most used and the closest one to the definitions and concepts from the Modern Portfolio Theory, as it expresses the VaR as a multiple of the portfolio deviations (Tardivo, 2002). This approach is computationally efficient, as it only requires matrix multiplication. By approximating each position with its linear exposure, the approach can be applied even to a portfolio with a large number of assets and updated in real time as positions change (Jorion, 1997).

The Delta Normal model, one of the main variance-covariance models, was originally introduced by J.P. Morgan in the RiskMetrics document and will be adopted in this project to analyse the volatility of the returns of the market factors. The risk of a portfolio, quantified through multivariate statistical techniques, depends on both the volatility and the correlation (Tardivo, 2002). This model exactly defines the relations among the financial positions and the market risk factors (e.g., the exchange quotations, rates, and shares) (Tardivo, 2002). It assumes that asset returns are normally distributed, allowing volatilities and correlations to be calculated directly from the underlying time series (Koziorowska, 2012). Under this approach, the expected return and standard deviation of a portfolio are expressed as:

$$\mu_p = \sum_{i=1}^{n} x_i \overline{R_i}, \tag{1}$$

$$\sigma_p = \sqrt{x'\Sigma x}, \tag{2}$$

where x_i represents the value of the i-th asset, $\overline{R_i}$ its expected return, x the portfolio weight vector, and Σ the covariance matrix.

The VaR for an individual financial instrument can then be defined as:

$$VaR_i = -(\mu - \alpha\sigma w_i), \tag{3}$$

where μ denotes the expected return, σ the standard deviation of returns, w_i is the value of the i-th asset, and α is the quantile corresponding to the chosen confidence level (e.g., α = 1.65 for 95% and α = 2.32 for 99%) (Koziorowska, 2012). Assuming μ = 0, then the VaR equation simplifies to:

$$VaR_i = \alpha\sigma w_i. \tag{4}$$

The confidence range describes the probability level with which a loss in a specific time horizon, its choice depends on the aversion level to the risk (Tardivo, 2002).

2.2. Risk Decomposition

Portfolio optimization aims to allocate limited capital efficiently in order to achieve the desired objectives, subject to decision variables, the objective function, and constraints (Ayodeji & Ingram, 2015). Introducing VaR as a shortfall constraint into the portfolio optimization is more consistent with individuals' intuitive perception of risk, as this approach allows the investors or the portfolio managers to focus on the probability of portfolio value falling below a specific VaR threshold (Campbell et al., 2001). In other words, the goal of portfolio optimization is to find optimal solutions that allocate more resources to different assets in a portfolio that investors believe are less risky or that will yield the highest return with respect to some constraints (Ayodeji & Ingram, 2015). Among different categories of risk, market risk is of primary concern, as it arises from fluctuations in market prices influenced by factors such as interest rates, stock indices, and foreign exchange rates, etc. (Ayodeji & Ingram, 2015). Recent studies continue to examine VaR-based portfolio risk management and risk-return evaluation frameworks, highlighting their practical value in asset allocation and financial risk monitoring (Campbell et al., 2001; Huisman et al., 1999; Jiménez et al., 2020; Leduc & Perera, 2025; Tsao & Liu, 2006)

However, as mentioned above, a single VaR only provides the overall portfolio risk and does not indicate how individual assets contribute to that risk. Over time, risk managers refined VaR not only as a measure of total exposure but also to identify sources of risk and set appropriate limits in order to improve portfolio allocation (Koziorowska, 2012). The practical challenge lies in determining which portfolio elements should be adjusted or replaced to make VaR more effective. To operationalise this refinement, VaR can be decomposed into marginal VaR, component VaR, and incremental VaR, which provides insights into how individual assets contribute to overall portfolio risk.

2.2.1 Marginal VaR

Marginal VaR (MVaR) measures the sensitivity of the total portfolio VaR to a small change in the position of a particular asset. In other words, it captures how the overall portfolio risk would change if the weight of one asset were increased or decreased infinitesimally. Formally, it is defined as the partial derivative of the portfolio VaR with respect to the exposure of the asset i (Dowd, 2007):

$$MVaR_i = \frac{\partial VaR}{\partial x_i}. \tag{5}$$

From a practical perspective, MVaR can be expressed as a function of the covariance between the return of asset i (R_i) and the portfolio return (R_p):

$$MVaR_i = \alpha \frac{\text{cov}(R_i, R_p)}{\sigma_p}, \tag{6}$$

where α is the quantile of the standard normal distribution corresponding to the chosen confidence level, and σ_p is the standard deviation of the portfolio return.

Furthermore, MVaR is closely related to the asset's beta coefficient with respect to the portfolio:

$$\beta_i = \frac{\text{cov}(R_i, R_p)}{\sigma_p^2} = \rho_{ip} \frac{\sigma_i}{\sigma_p}, \tag{7}$$

where ρ_{ip} is the correlation coefficient between the asset i and a portfolio p.

The beta coefficient is the basis for the capital asset pricing model (CAPM) developed by Sharpe (1964), describing the relation of its returns with those of the financial market. It can be estimated for individual companies using regression analysis against a stock market index (Koziorowska, 2012).

Finally, by linking to the total portfolio, MVaR is therefore expressed as:

$$MVaR_i = \alpha(\beta_i \cdot \sigma_p) = \frac{VaR}{W} \cdot \beta_i, \tag{8}$$

where W is the total value of the portfolio.

Thus, MVaR reflects the marginal contribution of asset i to portfolio risk. This measure provides useful information for portfolio managers by identifying which assets exert the largest marginal effect on total risk. For example, to lower the portfolio VaR, the investors or managers should pick the asset with the largest MVaR as its greatest hedging effect (GARP, 2024).

2.2.2 Incremental VaR

Incremental VaR (IVaR) quantifies the change in total portfolio VaR when a new position is added. It measures the discrete effect of trading decisions on portfolio risk. Formally, IVR is defined as the difference between the VaR of the portfolio with the new position and the VaR of the initial portfolio p (Dowd, 2007):

$$IVaR = VaR(p + a) - VaR(a), \tag{9}$$

where $VaR(p)$is the VaR of the original portfolio, and VaR($p + a$) is the VaR after including a new position a. Alternatively, for an approximation in the case of large portfolios where a full revaluation requires a large number of computations, IVaR can be estimated using MVaR (Koziorowska, 2012):

$$IVaR = (MVaR)' \cdot a. \tag{10}$$

This simplified VaR method has been proven to perform well for large portfolio especially where a proposed trade is likely to be of a relatively small size, and thus it allows real-time trading limits (GARP, 2024).

A positive IVaR indicates that the new position increases the portfolio risk, while a negative IVaR implies that the new trade is risk-reducing and functions as a natural hedge against the existing portfolio (Koziorowska, 2012). This hedging effect, however, is limited to a certain range of position sizes. To determine optimal hedging strategies, when a new position a is added to a single risk factor i, the portfolio variance of dollar returns can be expressed as (GARP, 2024):

$$\sigma_{p+a}^2 W_{p+a}^2 = \sigma_p^2 W^2 + 2aW\sigma_{ip} + a^2\sigma_i^2, \tag{11}$$

where σ_{ip} is the covariance between the asset i and the portfolio p.

Differentiating with respect to a yields the condition for the variance-minimising position:

$$a^* = -W\frac{\sigma_{ip}}{\sigma_i^2} = -W\beta_i\frac{\sigma_p^2}{\sigma_i^2}. \tag{12}$$

This solution represents the best hedge, i.e., the additional amount to invest in an asset i that minimises the overall portfolio risk. The concept of best hedge illustrates how IVaR can be used not only for risk measurement but also for designing effective hedging strategies within portfolio management.

2.2.3 Component VaR

Component Value at Risk (CoVaR) indicates how the portfolio VaR would change if the component were deleted. It decomposes total portfolio VaR into additive contributions from individual assets. By construction, component VaRs sum to the portfolio VaR. Unlike simply summing up stand-alone VaRs, which neglects diversification benefits, CoVaR also captures the power of diversification (GARP, 2024). Thus, CoVaR for an asset i was defined as (Koziorowska, 2012):

$$CoVaR_i = w_i \frac{\sigma VaR}{\sigma w_i}, \quad (13)$$

$$VaR = \sum_{i=1}^{n} CoVaR_i, \quad (14)$$

where w_i is the portfolio weight of the asset i.

Moreover, CovaR can be computed via MVaR:

$$CoVaR_i = w_i W \cdot MVaR_i, \quad (15)$$

where w_i is the portfolio weight of the asset i, W is the portfolio value.

This formulation implies that CoVaR represents the risk contribution of the current dollar position of asset i to the portfolio's total VaR. However, this decomposition is more useful with large portfolios containing many small positions, as the quality of this linear approximation improves when the VaR components are small (GARP, 2024). In a nutshell, assets with negative CoVaR act as natural hedges, while those with positive CoVaR increase the overall portfolio risk. Hence, CoVaR provides investors or risk managers with a practical tool for identifying key risk contributors and guiding portfolio rebalancing decisions. In sum, MVaR and CoVaR are extremely useful tools for identifying risk sources, finding natural hedges, defining risk limits, reporting risk, and improving portfolio allocations (Koziorowska, 2012).

These three VaR-based risk decomposition tools are closely related and provide complementary perspectives on how individual assets contribute to overall portfolio risk (Koziorowska, 2012). MVaR captures the sensitivity of portfolio VaR to an infinitesimal change in an asset's position, reflecting the local slope of the VaR function with respect to asset weights. In this sense, MVaR measures how small adjustments in each asset's allocation affect total portfolio risk. CoVaR extends this concept by quantifying the contribution of each asset to total portfolio VaR as the product of the asset's portfolio weight and its marginal VaR. CoVaR therefore provides an additive decomposition of portfolio risk, allowing total VaR to be allocated back to individual assets in proportion to their risk contributions. IVaR, in contrast, measures the discrete change in portfolio VaR resulting from the complete removal of an asset from the portfolio. IVaR, thus, reflects the overall risk impact of including a particular asset, capturing both marginal sensitivity and portfolio interactions. Together, these three measures offer a comprehensive framework for understanding portfolio risk structure.

MVaR highlights marginal sensitivity, CoVaR enables additive risk attribution, and IVaR captures the total effect of asset inclusion or exclusion.

In summary, the literature review suggests VaR-based optimization is inherently aligned with investors' concern for tail risks. This paper provides an empirical case study on implementing VaR within portfolio optimization, emphasizing the application of three VaR decomposition tools. Together, these elements aim to bridge the gap between theoretical portfolio optimization and practical risk management.

3. Data and Methodology

The daily close prices of selected 11 Standard & Poor's Depositary Receipt (SPDR) sector ETFs - materials (XLB), energy (XLE), financials (XLF), industrials (XLI), technology (XLK), consumer staples (XLP), utilities (XLU), health care (XLV), consumer discretionary (XLY), real estate (XLRE), and communication services (XLC) between 1st January, 2015 and 22nd August, 2025 were downloaded from Yahoo Finance. To reflect realistic portfolio construction, long-only constraints, and a full investment requirement ($\sum w_i = 1$) were imposed. No leverage or short selling is typical for many investment funds.

Sector-focused ETFs allow us to observe how different portions of the equity market contribute to portfolio risk. It also limits the impact that any single stock's extreme move may have on a sector ETF. Thus, using sector ETFs is ideal for a sector-level risk decomposition. Besides, these stocks selected collectively represent all major sectors of the S&P 500, providing a well-diversified and comprehensive market coverage, covering cyclical sectors (e.g., technology and financials) and defensive sectors (e.g., staples and utilities), which is ideal for analyzing how a tail-risk-focused optimization allocates between high-risk/high-return and low-risk/low-return assets. Additionally, the ETFs' long trading histories with sufficient liquidity reduce data quality issues. A ten-year period ensures robustness across diverse market conditions, including bull and bear markets, especially the COVID-19 shock.

However, the actual data time-window acquired spans from 19th June 2018 to 22nd August, 2025, since the XLC sector was launched in June 2018. To maintain a consistent comparison across all 11 sectors, the effective sample period to the same start date was restricted. This means roughly 7 years of daily data (1,805 observations/trading days) were used, which is sufficient for our analysis. Log daily returns were used and computed from the close prices, a transformation commonly adopted due to its ability to generate a return distribution that better conforms to the normality assumption underlying VaR models. The obtained data was checked for quality to make sure a complete dataset without missing values.

The basic statistics, including count, mean, std, min, 25%, 50%, 75%, and max, were summarized in Table 1 and showed substantial cross-sector differences in mean and volatility (std). Over the 2018-2025 period, the average daily return ranged from 0.03%, mainly in the defensive sectors, to 0.08% (XLK, the technology sector). The volatilities spanned from 1.00% (XLP) to 2.09% (XLE). As expected, the defensive sectors are less volatile, and the cyclical sectors are more volatile.

Table 1. Descriptive Statistics of 11 Sector Daily Returns

	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY	XLRE	XLC
Mean	0.03%	0.03%	0.04%	0.05%	0.08%	0.04%	0.04%	0.03%	0.04%	0.03%	0.05%
Std	1.42%	2.09%	1.53%	1.38%	1.70%	1.00%	1.32%	1.12%	1.55%	1.44%	1.45%
Min	-11.66%	-22.49%	-14.74%	-12.04%	-14.87%	-9.87%	-12.06%	-10.38%	-13.55%	-17.44%	-11.97%
25%	-0.71%	-0.92%	-0.61%	-0.56%	-0.74%	-0.41%	-0.59%	-0.50%	-0.64%	-0.63%	-0.61%
50%	0.07%	0.10%	0.09%	0.09%	0.15%	0.06%	0.11%	0.06%	0.13%	0.10%	0.12%
75%	0.80%	1.02%	0.78%	0.73%	0.97%	0.54%	0.69%	0.60%	0.86%	0.75%	0.79%
Max	11.12%	14.87%	12.36%	11.91%	12.60%	8.17%	12.04%	7.42%	10.34%	8.42%	8.61%

3.1. Optimization Objective

The portfolio optimization goal is to maximize the Sharpe Ratio, where risk is measured by VaR instead of variance. Thus, the optimization problem is formulated to maximize the ratio of expected excess return to VaR. VaR was calculated using a delta-normal (parametric) approach. This assumes returns are normally distributed and uses the portfolio's mean and covariance to calculate VaR. For a one-day horizon and confidence level α (95% or 99%), the VaR is defined as the loss threshold such that the probability of a larger loss is 1- α. Mathematically, for a portfolio with daily mean return μp and standard deviation σ_pVaR is calculated as:

$$VaR_\alpha = -\mu_p + z_\alpha \sigma_p, \tag{16}$$

where zα is the α quantile of the standard normal distribution (e.g., z0.95 = 1.65, z0.99 = 2.33).

Therefore, the optimization objective is expressed as:

$$\max_w \frac{w^\top \mu - r_f}{-w^\top \mu + z_\alpha \sqrt{w^\top \Sigma w}}, \tag{17}$$

where w denotes the vector of portfolio weights, μ the vector of expected asset returns, Σ the covariance matrix of returns, rf the risk-free rate, and zα the critical value of the standard normal distribution corresponding to confidence level α.

The numerator $w^\top \mu - r_f$ represents the expected excess return of the portfolio, where $-w^\top \mu$ adjusts for mean return and $z_\alpha \sqrt{w^\top \Sigma w}$ scales the risk by the confidence quantile. For simplicity, the risk-free rate was set as zero. This formulation ensures that the optimization is explicitly aligned with downside risk consideration, rewarding portfolios that generate higher returns for a given VaR exposure.

3.2. Portfolio Construction

Using the formula described above, two optimized portfolios were constructed: 1) Opt95: Optimized to maximize $\frac{w^\top \mu - r_f}{VaR_{95\%}(w)}$. This portfolio internalizes the 95% VaR in its construction, effectively balancing expected return against the 95% downside risk; 2) Opt99: Optimized to maximize $\frac{w^\top \mu - r_f}{VaR_{99\%}(w)}$. This portfolio gives more weight to extreme-tail risk (99% VaR) in the optimization, likely leading to a more conservative allocation compared to Opt95. In practice, the implementation was carried out in Python by defining the function directly according to the formulas outlined in Section 3.1. No short selling is allowed (weights were constrained to [0,1]), and full investment was assumed (weights summing to 100%). The Equal-Weight Portfolio (EWP) was constructed by assigning $w_i = \frac{1}{11}$ to each sector ETF at the start, which was used as an undiversified benchmark to evaluate the performance of the optimized portfolios.

After obtaining the weight solutions, the overall VaR and return/VaR were calculated under a common confidence level at 95%. This ensures that the portfolio risk decomposition and performance metrics are evaluated consistently across all portfolios.

3.3. VaR Decomposition Metrics

Marginal VaR (MVaR), component VaR (CoVaR), and incremental VaR (IVaR) were employed together to attribute the total portfolio VaR to each asset. All the computations were realized in Python by defining the function using the formulas listed below.

3.3.1 Marginal VaR

MVaR estimates the changes in total VaR when the asset's position is infinitesimally increased. For asset i, $MVaR_i$ is the partial derivative of portfolio VaR with respect to a small change in the weight of i (formally, $MVaR_i = \partial VaR_p / \partial w_i$), so under the delta-normal model, MVaR was calculated as:

$$MVaR_i = \frac{\partial VaR_p}{\partial w_i} = z_\alpha \frac{\mathrm{Cov}(R_i, R_p)}{\sigma_p} - \mu_i, \quad (18)$$

where R_i is the return of asset i, R_p is the portfolio return, σ_p is the portfolio volatility, μ_i is the expected return of asset i, and z_α is the critical value of the standard normal distribution. A higher $MVaR_i$ indicates that increasing the exposure to asset i will increase the overall portfolio VaR more significantly.

3.3.2 Component VaR

CoVaR represents the amount of the total VaR attributed to asset i, it can be decomposed into the sum of individual component contributions. In other words, CoVaR shows how much of the portfolio's tail risk comes from asset i. Larger values mean that the asset is a major driver of extreme losses. Here, it was obtained by scaling the marginal VaR with the asset's portfolio weight:

$$CVaR_i = w_i \cdot MVaR_i. \quad (19)$$

The percentage contribution of asset i to portfolio VaR was given by:

$$\%Contri_i = \frac{CVaR_i}{VaR_p}, \quad (20)$$

which will help identify which assets dominate portfolio risk.

3.3.3 Incremental VaR

IVaR measures the discrete change in total portfolio VaR if asset i is removed. Here, IVaR was evaluated by hypothetically removing each asset from the portfolio and recalculating the portfolio VaR.

So, VaR was calculated as:

$$IVaR_i = VaR_p - VaR_{p\setminus i}, \tag{21}$$

where $VaR_{p\setminus i}$ is the VaR of the portfolio without asset i. If $IVaR_i$ is positive, removing asset i reduces the VaR, so asset i was making the portfolio riskier - a net risk contributor. On the contrary, a negative $IVaR_i$ means that asset i was providing diversification benefits by reducing overall portfolio risk. Therefore, the sign and magnitude of IVaR help identify natural hedges versus risk amplifiers, as assets with negative IVaR would help stabilize the portfolio in extreme scenarios.

4. Empirical Results and Discussion

4.1. Portfolio Performance

Table 2 summarizes the portfolio performance of Equal-Weight Portfolios (EWP) and two optimized portfolios (Opt95 and Opt99). Figure 1 presents a clear comparison of final portfolio VaR and Return/Ratio Ratio between EWP and two optimized portfolios. As expected, both optimized portfolios consistently achieve higher Return/VaR ratios than EWP, representing a roughly 36% improvement in risk-adjusted performance. Although they both have slightly higher volatility and VaR, their expected returns increased more than enough to offset the higher risk. This indicates that the optimized portfolios generate substantially higher returns per unit of downside risk compared with the equal-weight benchmark.

Table 2. Portfolio Performance Summary

	Mean Return(%)	Volatility(%)	VaR(95%)	Return/VaR(95%)
EWP	0.0421	1.1983	0.0193	0.021829
Opt95	0.0596	1.2585	0.0201	0.029644
Opt99	0.0588	1.2427	0.0199	0.029617

Notes: Mean Return and Volatility are daily figures. VaR(95%) denotes the one-day VaR at 95% confidence level. Return/VaR(95%) is the ratio of Mean Return to 95% VaR. All values are rounded to four decimal places, except the Return/VaR(95%) ratios, which are given to six decimal places for precision.

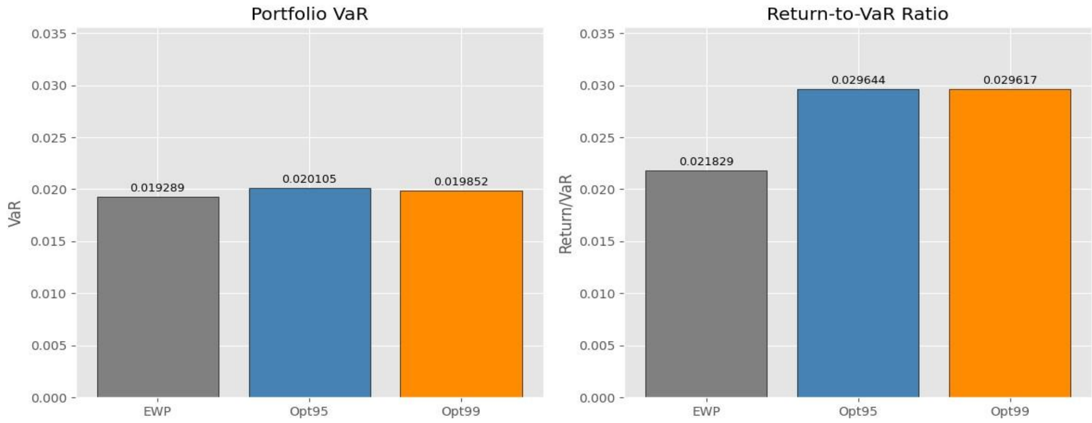

Figure 1. Comparison of Equal-Weight and Optimized Portfolio under 95% and 99% VaR constraints. The left panel reports the Portfolio VaR evaluated at 95% confidence level, while the right panel shows the Return-to-VaR ratio.

In comparison with Opt95, Opt99 has marginally lower volatility and VaR. However, its Return/VaR (95%) is essentially equal to Opt95, though an Opt99 strategy was expected to be more conservative, potentially sacrificing some expected return to reduce extreme-tail risk. A higher confidence level could penalize risky exposure more - the 99% VaR is roughly 1.41 times (2.33/1.65) than the 95% VaR, demanding more caution in asset selection and allocation. Indeed, the different confidence levels can lead to different portfolio ranking performance (Alexander & Baptista, 2003). A stricter VaR constraint will tilt the portfolio towards safety. Nonetheless, in our case, the trade-off was mild, so both optimized portfolios ended up similarly efficient. In sum, the optimization process successfully reallocated the portfolio to achieve greater return per unit of downside risk.

4.2. Allocation and Diversification

The different risk-return profiles of the portfolios are derived from the distinct weight allocations. Figure 2 shows pie charts of the asset weight allocation for the EPS, Opt95, and Opt99 portfolios, respectively. It is evident that the optimized portfolios are far from EWP. The equal-weight strategy invests uniformly across assets, meaning all the 11 sectors were evenly allocated (9.09%). In contrast, both VaR-optimized portfolios concentrated over 50% of the total weight in the technology sector (XLK), with supplementary allocations to consumer staples (XLP) and utilities (XLU), while excluding all other sectors (i.e., 0.00% weight). This is not surprising because assets that are attractive under a 95% VaR criterion often remain the same under a 99% VaR criterion. These assets are selected likely with either strong returns and acceptable risks or with diversification power that lowers portfolio VaR when combined. The subtle differences may include slightly higher weight on assets that are low risk to curtail the 99% tail risk, which was proved in the risk decomposition analysis.

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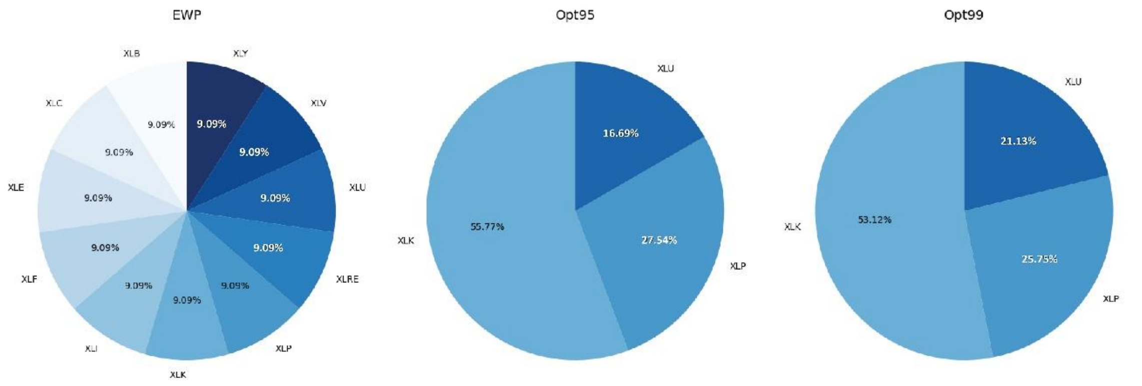

Figure 2. Asset allocations of the EPS, Opt95, and Opt99.

Specifically, in the Opt95 portfolio, XLK accounts for 55.77%, followed by XLP (27.53%) and XLU (16.69%). The Opt99 portfolio is similar, with slightly less dominated by XLK (53.12%), XLP (25.75%), and XLU (21.13%). In effect, the Opt99 portfolio could be seen as a "de-risked" version of Opt95. However, in our results, the difference was marginal, indicating that the chosen assets were consistently favourable under both risk levels. The allocation is reasonable as the technology sector often offers the highest excess return potential but also high volatility, whereas staples and utilities are more defensive and help offset the high risk brought by technology.

In sum, these concentrated allocations show that VaR-based optimization prefers allocations that maximize return per unit of downside risk, even if that means heavy concentration in a few assets.

The presence of staples and utilities in the optimized portfolios underscores that including some low-risk and defensive assets can allow the portfolio to take larger positions in high-return/high-risk assets without violating the VaR limit. In essence, the optimization seeks to find an efficient trade-off that sacrifices the diversification (focused on only three sectors) to achieve the best return per unit outcome.

4.3. Risk Decomposition and Contribution

A detailed VaR decomposition analysis of the portfolios (Tables 3, 4, and 5) provides further insights into how each asset contributes to the overall VaR (i.e., Portfolio risk). MVaR, CoVaR, and IVaR for each asset were analyzed, based on which we will understand which assets are the riskiest on the margin, how much each asset contributes to total VaR, and how the total VaR would change if an asset is removed.

For the EWP (Table 3), although each sector has the same position, its contribution to the total VaR spans from 5.81% to 11.49%. Also, the MVaR values differ across assets, reflecting different risk characteristics. Assets with the highest MVaR are the riskiest at the margin, assets with the lowest MVaR adds comparatively little risk, which are aligned with their highest CoVaR values and risk contribution. Higher-volatility sectors like energy (XLE), technology (XLK) naturally contributed more, whereas defensive sectors like utilities (XLU) and consumer staples (XLP) are relatively safe or diversifying. This means that even with equal weights, the risk contribution is not necessarily equally distributed. Therefore, diversification by capital does not translate to diversification by risk, which makes the importance of risk management self-evident.

Table 3. Risk Decomposition Results for Equal-Weight Portfolio

	Weight(%)	MVaR	CoVaR(%)	Contribution(%)	IVaR
XLE	9.0909	0.0244	0.2217	11.4913	0.000361
XLK	9.0909	0.0225	0.2049	10.6225	0.000264
XLF	9.0909	0.0222	0.2016	10.4514	0.000258
XLY	9.0909	0.0214	0.1943	10.0730	0.000164
XLB	9.0909	0.0208	0.1891	9.8054	0.000127
XLI	9.0909	0.0207	0.1877	9.7333	0.000119
XLRE	9.0909	0.0192	0.1741	9.0272	-0.000059
XLC	9.0909	0.0190	0.1728	8.9597	-0.000076
XLU	9.0909	0.0150	0.1363	7.0674	-0.000488
XLV	9.0909	0.0148	0.1343	6.9632	-0.000478
XLP	9.0909	0.0123	0.1120	5.8055	-0.000724

Notes: All values are rounded to four decimal places, except for IVaR, which is reported to six decimal places due to its very small magnitude.

The IVaR column (Table 3) provides additional insight. Positive IVaR means that removing those assets decreases the total VaR. In other words, those assets are net contributors to risk, which aligns with their high MVaR value - they are "risk drivers" in the portfolio. In contrast, assets having negative IVaR are risk-reducing assets by providing diversification benefits. From the EWP risk decomposition analysis (Table 3), it is clear that assets with positive IVaR are "risk hotspots", while others are risk mitigators. This explains the asset allocation in the optimized portfolios.

Table 4 shows the decomposition for the Opt95 portfolio. The weight distribution, as it was shown in Figure 2, is very concentrated: the technology sector (XLK) carries a 55.77% weight and contributes 71.50% of the total VaR, while consumer staples (XLP) at 27.54% weight contributes 16.69%, and utilities (XLU) at 16.69% weight contributes 11.81%. Almost all the portfolio's VaR comes from XLK. This allocation aligns with the finding above that XLK likely has the best return-to-risk trade-off. Also, XLK remains a positive IVaR value, whereas XLP and XLU have negative values. This means that XLK is still the major risk contributor in Opt95, XLP, and XLU play the diversifier roles.

In sum, the Opt95 portfolio's risk decomposition highlights a key point that it chose to tolerate concentrated risk in XLK because it offers a superior return-to-risk trade-off. XLP has the highest daily mean return of 0.08% with relatively high volatility of 1.70% (Table 1). XLP and XLU share a similar mean return of approximately 0.04%; the bigger proportion allocated to XLP is presumably due to it being the safest asset (lowest MVaRs and volatility). Comparing Opt99 to Opt95, the differences are minor (Table 5).

Table 4. Risk Decomposition Results for Optimized Portfolios at 95% Confidence Level

	Weight(%)	Active	MVaR	CoVaR(%)	Contribution(%)	IVaR
XLK	55.7742	Yes	0.0258	1.4375	71.5002	0.0033
XLP	27.5350	Yes	0.0122	0.3355	16.6890	-0.0033
XLU	16.6909	Yes	0.0142	0.2375	11.8109	-0.0014
XLY	0.0000	No	0.0210	0.0000	0.0000	0.0000
XLC	0.0000	No	0.0193	0.0000	0.0000	0.0000
XLF	0.0000	No	0.0184	0.0000	0.0000	0.0000
XLI	0.0000	No	0.0180	0.0000	0.0000	0.0000
XLB	0.0000	No	0.0178	0.0000	0.0000	0.0000
XLRE	0.0000	No	0.0172	0.0000	0.0000	0.0000
XLE	0.0000	No	0.0171	0.0000	0.0000	0.0000
XLV	0.0000	No	0.0140	0.0000	0.0000	0.0000

Notes: Active indicates whether the asset is included in this portfolio. Assets not included (Active = No) are displayed in ascending order of their MVaR values. All values are rounded to four decimal places.

The Opt99 gave a slightly higher weight to XLU, a relatively safer asset, and less to XLK, the riskiest asset, which is intuitive for a strategy that cares about extreme tail risk. This led to a marginal reduction in total VaR from 0.0201 (Opt95) to 0.0199 (Opt99). The risk contributions shifted such that XLU rose from 11.81% to 15.82%, while XLP decreased slightly from 16.69% to 16.02% and XLK from 71.50% to 68.16%. Figure 3 presents the risk contribution comparison between the two optimized portfolios.

Table 5. Risk Decomposition Results for Optimized Portfolios at 99% Confidence Level

	Weight(%)	Active	MVaR	CoVaR(%)	Contribution(%)	IVaR
XLK	53.1212	Yes	0.0255	0.013531	68.1580	0.0027
XLP	25.7451	Yes	0.0124	0.003180	16.0188	-0.0029
XLU	21.1338	Yes	0.0149	0.003141	15.8232	-0.0017
XLY	0.0000	No	0.0209	0.0000	0.0000	0.0000
XLC	0.0000	No	0.0192	0.0000	0.0000	0.0000
XLF	0.0000	No	0.0185	0.0000	0.0000	0.0000
XLI	0.0000	No	0.0180	0.0000	0.0000	0.0000
XLB	0.0000	No	0.0179	0.0000	0.0000	0.0000
XLRE	0.0000	No	0.0175	0.0000	0.0000	0.0000
XLE	0.0000	No	0.0172	0.0000	0.0000	0.0000
XLV	0.0000	No	0.0141	0.0000	0.0000	0.0000

Notes: Active indicates whether the asset is included in this portfolio. Assets not included (Active = No) are displayed in ascending order of their MVaR values. All values are rounded to four decimal places.

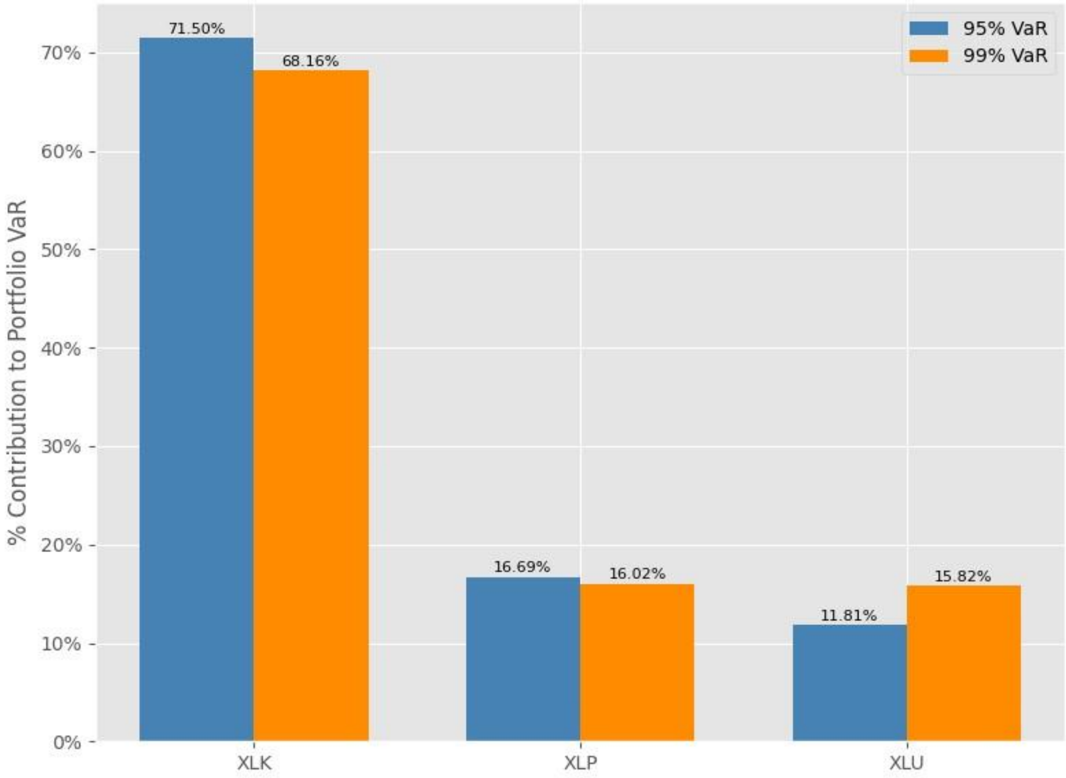

Figure 3. Risk Contribution Comparison under 95% and 99% VaR Confidence Levels.

In summary, from a risk management perspective, this concentrated risk profile means the optimized portfolio is heavily exposed to sector-specific shocks, notably in technology. The inclusion of staples and utilities provides some cushion, as evidenced by their diversifying effect. The risk decomposition confirms the intuitive trade-off anticipated that the VaR-optimized portfolios deliberately select a large exposure to the highest-return/high-risk sector, balanced by allocations to some low-risk sectors to control the overall VaR. Besides, the diversification also plays a key role in this optimization process by adding enough assets to maximize the return/VaR objective while satisfying the VaR constraint, which contrasts with the EWP's broad diversification.

5. Conclusion

This study demonstrated that VaR-based portfolio optimization can significantly enhance the risk-return profile relative to an equal-weight strategy. By explicitly incorporating a VaR constraint, the optimized portfolios achieved higher returns. The return/VaR maximization approach tends to concentrate assets that offer the best trade-off between expected return and VaR. In this study, a large allocation was attributed to the technology sector, mediated by position in defensive sectors (i.e., staple and utility) to satisfy the risk limits. As a result, compared to the equal-weight benchmark, the optimized portfolios delivered superior performance - higher mean returns and return/VaR ratios.

Two optimized portfolios produced comparable results. A stricter 99% VaR constraint led to a slightly more conservative portfolio, with marginally lower returns and risk, but largely the same asset allocation. In other words, increasing the confidence level from 95% to 99% did not fundamentally change the portfolio's structure but the proportions. The 99% portfolio is more towards a higher allocation in safe assets of XLU, as it demands protection against more extreme tail events, thus by sacrificing some return to control risks. This implies that one should set the VaR confidence level in accordance with one's risk tolerance; a higher level (e.g., 99% or beyond) will emphasize stability at the cost of return, whereas a lower level (e.g., 95% or below) allows more return-seeking at the expense of accepting a higher potential loss in extreme cases. However, in this case, the difference was small, likely because the assets did not have behavior in the 99% tail compared to the 95% tail under the normality assumption.

The risk decomposition provides a valuable insight into understanding how the optimized portfolios manage risk. A large portion of the total VaR was attributed to a high-return/high-risk asset (technology, XLK), which is a natural consequence of optimizing the return/VaR ratio. However, the inclusion of other assets with different risk levels is crucial to keep the overall VaR within acceptable bounds - a clear demonstration of diversification's role in a concentrated portfolio. Notably, the other two assets, XLU and XLP, with a negative IVaR value, indicate their inclusion reduced the portfolio's total risk. From a risk management perspective, the decomposition analysis is invaluable, as it allows investors to identify the main drivers of downside risk and confirm whether the portfolio is relying on a broad diversification. In optimized portfolios, it clearly shows that a concentration in one aggressive asset, supplemented by two smaller defensive assets, is used to mitigate the potential risks. In contrast, the EWP allowed the assets to contribute a lot of VaR without sufficiently higher returns, essentially diluting its risk-adjusted performance.

In summary, the VaR-based optimization strategy proved effective in enhancing performance, but it also led to concentrated risk exposures. While VaR optimization aligns the portfolio with a desired risk level, the resulting concentration means that the portfolio could be more vulnerable to unexpected shocks in the heavily weighted sectors. For investors, these results highlight that, though a higher risk-adjusted return and clear focus on downside risk, it demands careful oversight of the concentrated positions. An equal-weight portfolio strategy, by contrast, spreads risk more evenly but forgoes some return potential. In practice, portfolio managers might impose additional constraints or modify certain parameters to avoid such an extreme portfolio allocation. However, the adoption of such an approach largely depends on the investors' comfort with the resulting portfolio profile. By refining the method and rigorously testing under various conditions, one can harness the benefits of VaR-based optimization while mitigating its drawbacks, contributing to more effective risk-aware investment strategies. Therefore, based on current findings, in the future, other methods are worth exploring, for example, the conditional VaR-based (CVaR) optimization. Optimizing portfolios using CVaR could yield different allocations, potentially more diverse.

In conclusion, VaR-based portfolio optimization offers an alternative to mean-variance optimization for investors, particularly concerned with downside risk. The methodology and insights here are valuable for risk management, as they present how VaR can be used not just as a constraint but as a driver of portfolio decisions, and how decomposing VaR helps in understanding those decisions. Risk decomposition into MVaR, CoVaR, and IVaR proved to be a powerful tool to validate the portfolio's risk structure - it confirmed that risk was allocated to the intended assets and quantified how each position would impact the portfolio's tail risk. Portfolio managers can use these insights to understand where risk is coming from and which positions are truly adding value in an optimized portfolio. Ultimately, the combination of Return/VaR optimization and VaR decomposition facilitates a performance-focused portfolio construction process. It exemplifies how modern risk management techniques can be integrated into portfolio optimization to achieve better outcomes, meeting the goals of high returns and controlled downside risk.

Data Availability Statement

The data used in this study are derived from publicly available sources and can be accessed via Yahoo Finance.

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Declaration of the Use of Generative AI

The author declares that no generative AI tools were used in the preparation of this manuscript.

Conflicts of Interest

The author declares that there are no conflicts of interest related to this study.

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| Research Article

Real-Time Fraud Detection at Scale: An Architectural Framework for FinTech Big Data Systems

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Abstract
Digital finance platforms generate massive streams of transactions every second. Alongside convenience and scale, this environment has also enabled more intricate forms of financial fraud. Many institutions still rely on batch analytics that review transactions only after they occur, making timely intervention difficult and increasing exposure to losses and regulatory scrutiny. This study examines structural weaknesses in existing Big Data infrastructures used for fraud detection in FinTech and proposes a framework designed to flag suspicious activity as transactions unfold. The model integrates stream processing, machine-learning–based pattern analysis, and distributed data storage to manage high-volume transaction flows. Tests using simulated workloads and anonymized banking transaction logs show faster detection, higher processing capacity, and improved identification of fraudulent activity, indicating strong potential for deployment in large financial systems.

Keywords: Real-Time fraud detection, FinTech data architecture, Stream processing, Machine learning for fraud detection, Big data analytics.
JEL Classification: C55, C88, G17.

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1. Introduction

Financial technology (FinTech) platforms now operate in environments where enormous volumes of transactional data are generated continuously. Every digital payment, login attempt, device interaction, and behavioral signal contributes to a stream of data that must be processed almost instantly. As global adoption of mobile banking, digital wallets, and online payment gateways accelerates, financial institutions must analyze transaction logs, user behavior telemetry, and external risk signals in real time to safeguard their systems. At the same time, fraud schemes have grown more sophisticated. Fraudsters increasingly rely on automated bots, stolen or synthetic identities, and vulnerabilities within networked infrastructures to execute attacks at scale. The exponential growth of digital payments and mobile banking ecosystems has also enabled complex fraud vectors that exploit automation and adversarial machine learning techniques (Vorobeychik & Rubinstein, 2020; World Bank, 2022). These developments require Big Data infrastructures capable not only of ingesting high-velocity data streams but also of performing machine learning inference quickly enough to intervene before fraudulent transactions are completed.

Recent advances in distributed computing have introduced tools that make such capabilities technically feasible. Frameworks such as Apache Kafka, Flink, and Spark Structured Streaming allow organizations to capture, transport, and process large data streams across distributed clusters with relatively low latency. These technologies support continuous data pipelines where transactions can be evaluated as they occur, enabling the integration of predictive models and rule-based engines into live processing workflows. In principle, these frameworks provide the architectural foundation for scalable fraud detection systems that can keep pace with modern financial data volumes.

However, many financial institutions continue to rely on legacy fraud detection architectures built around offline batch analytics. In these systems, transaction data is accumulated and analyzed periodically rather than continuously, creating delays between the moment a fraudulent action occurs and the moment it is detected. Such delays can allow fraudulent transactions to be completed before intervention is possible, increasing financial losses and undermining customer confidence. Closing this gap requires system architectures that reduce end-to-end processing latency while sustaining accurate fraud detection across terabytes of transaction data generated each hour.

The remainder of this paper is organized as follows. Section 2 reviews existing literature on fraud detection and Big Data systems. Section 3 defines the problem statement, followed by key technical challenges in Section 4. Sections 5 and 6 present the proposed real-time fraud detection architecture and risk scoring model. Section 7 describes the detailed solution approach with the corresponding experimental evaluation and performance analysis. Section 8 presents real-world case studies. Finally, Section 9 concludes the paper.

This paper makes the following contributions:

- Proposes a stream-first architecture for real-time fraud detection in FinTech environments.
- Integrates distributed streaming frameworks with machine learning inference for continuous transaction analysis.
- Demonstrates significant improvements in detection latency, throughput, and predictive accuracy.
- Provides practical validation through real-world case studies and experimental evaluation.

2. Literature Review

Financial fraud detection has been widely studied across the fields of financial analytics, machine learning, and distributed computing. Early fraud detection research relied primarily on statistical anomaly detection techniques that identified irregular transaction behavior in financial datasets. Bolton and Hand demonstrated that statistical monitoring approaches could detect suspicious transaction patterns in credit card systems and provided one of the earliest analytical frameworks for fraud detection in financial services (Bolton & Hand, 2002).

As financial systems evolved and transaction volumes increased, machine learning methods began to play a larger role in fraud detection systems. Supervised learning models including decision trees, logistic regression, and ensemble learning algorithms have been widely applied to identify fraudulent transactions in highly imbalanced financial datasets (Dal Pozzolo et al., 2015). These models analyze transaction attributes such as spending behavior, merchant category codes, temporal transaction patterns, and geographic information.

More recent research has explored deep learning and graph-based machine learning approaches capable of identifying complex relationships among accounts, devices, and transaction networks. Graph neural networks have been shown to effectively detect coordinated fraud activity across interconnected financial accounts by modeling relationships between entities involved in financial transactions (Weber et al., 2019).

At the infrastructure level, distributed stream processing technologies have enabled financial institutions to process high-velocity transaction streams in real time. Platforms such as Apache Kafka and Apache Flink support event-driven architectures capable of processing millions of transaction events per second with low latency (Apache Software Foundation, 2021; Carbone et al., 2015). These technologies provide the foundation for real-time fraud detection systems that integrate predictive models directly into transaction processing pipelines.

Despite these advances, many deployed fraud detection systems continue to rely on hybrid architectures combining batch analytics with partial real-time scoring layers. These architectures introduce delays in fraud detection and limit system scalability. The framework proposed in this paper addresses these limitations by integrating streaming infrastructure, machine learning inference, and adaptive risk scoring mechanisms within a unified real-time processing pipeline.

3. Problem Statement

Current FinTech data infrastructures face several structural limitations that weaken their ability to detect fraud quickly and reliably.

a. Batch-First Analytics: Many financial institutions continue to rely on traditional ETL-based analytics pipelines. In these systems, transaction data is collected, stored, and processed in batches, meaning analysis takes place only after transactions have already been completed. While such systems are useful for reporting and historical analysis, they are ineffective for preventing fraud in real time, as suspicious activity is often detected only after financial damage has occurred.

b. Scalability Constraints: Digital payment ecosystems generate enormous volumes of transactions every second. However, many fraud detection models and supporting data pipelines do not scale proportionally with this growth. As transaction volumes increase, processing delays begin to emerge, creating bottlenecks that slow down model inference and weaken system responsiveness. This mismatch between data velocity and processing capacity limits the effectiveness of existing fraud detection systems.

c. Model Staleness: Fraud detection models are often trained offline using historical datasets and updated only periodically. In a rapidly evolving threat landscape, this approach reduces model relevance. Fraudsters frequently modify their strategies, and models that are not continuously updated struggle to capture new behavioural patterns, leading to declining predictive accuracy over time.

d. Static Rule-Based Detection: Many operational systems still depend on fixed rule sets that flag transactions based on predefined conditions or thresholds. While rule-based approaches can identify known fraud signatures, they lack adaptability. As fraud tactics evolve, static rules become less effective, resulting in model drift and reduced detection performance (Dal Pozzolo et al., 2015; Gama et al., 2014).

Given these limitations, a key question emerges: How can FinTech platforms design a real-time Big Data pipeline capable of sustaining high throughput, low latency, and strong predictive performance for fraud detection?

4. Challenges

Developing real-time fraud detection systems introduces several technical challenges.

a. Transaction Volume and Velocity:

Modern digital payment systems generate extremely large data streams that must be processed with minimal latency. Distributed processing infrastructures are therefore necessary to maintain system responsiveness under high workloads (Apache Software Foundation, 2021).

b. Model Interpretability:

Financial institutions must ensure that automated fraud decisions can be explained to regulators and auditors. Explainable artificial intelligence techniques have been proposed to improve transparency in machine learning models used for financial decision-making (Lin & Chen, 2021).

c. Data Integration:

Fraud detection systems must integrate data from diverse sources including transaction logs, device fingerprints, and behavioral analytics. Data integration across heterogeneous systems remains a major challenge in large-scale financial infrastructures (Baesens, 2014).

d. Latency Constraints:

Fraud detection systems must operate quickly enough to prevent fraudulent transactions before they are completed. Achieving both low latency and high predictive accuracy remains a critical architectural challenge (Akidau et al., 2015).

5. Proposed Real-Time Fraud Detection Architecture

The proposed architecture adopts a stream-first design to process financial transactions in real time, enabling immediate fraud detection.

a. Event Ingestion Layer

Transaction data is ingested through Apache Kafka, which acts as a distributed messaging backbone. Kafka enables high-throughput, fault-tolerant ingestion of transaction streams across multiple partitions, ensuring scalability and reliability.

b. Stream Processing Layer

Apache Flink processes incoming data streams in real time. It performs feature extraction, window-based aggregation, and machine learning inference. Flink supports event-time processing, enabling accurate analysis of transaction sequences and behavioral patterns.

c. Machine Learning Inference

Machine learning models are deployed using TensorFlow Serving. These models evaluate transaction features and generate fraud probability scores in real time.

d. Distributed Storage

The system uses a hybrid storage approach:
- Apache HBase for low-latency access to transactional data
- Data lake (e.g., Delta Lake) for historical analysis

e. Risk Scoring Engine

A composite fraud score is calculated using:
- Machine learning predictions
- Rule-based indicators
- Contextual signals (location, velocity, device anomalies)

f. Feedback and Retraining

Confirmed fraud cases are fed back into the system for continuous model retraining, enabling adaptation to evolving fraud patterns.

Figure 1 below illustrates the complete architecture pipeline from ingestion to fraud detection and feedback.

6. Fraud Risk Scoring Model

Fraud detection decisions are generated using a hybrid scoring framework that combines machine learning predictions with contextual indicators derived from operational data sources.

Let X represent the feature vector associated with a financial transaction.

$$P(Fraud \mid X) = f(X)$$

where $f(X)$ represents the predictive function learned from historical transaction datasets using supervised learning models.

To incorporate contextual indicators, a composite fraud risk score is calculated:

$$R_t = \alpha P_{ML} + \beta R_{rules} + \gamma R_{context}$$

where

P_{ML} = represents the probability of machine learning prediction.

R_{rules} = represents rule-based detection indicators.

$R_{context}$ = represents contextual risk signals such as geolocation anomalies or abnormal transaction velocity.

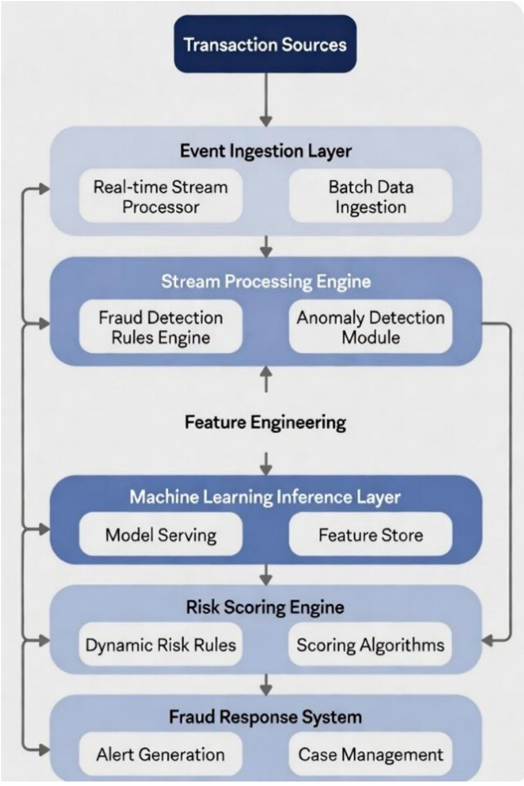

Figure 1. Stream-first fraud detection architecture showing data flow from ingestion (Kafka), processing (Flink), ML inference, storage, and feedback loop.
Source: Author

7. Experimental Evaluation

The architecture was evaluated using both synthetic transaction streams and anonymized banking datasets. Similar evaluation methodologies have been used in large-scale fraud detection research to analyze system scalability and predictive performance (Gartner Research, 2023).

The proposed architecture was evaluated using a combination of synthetic transaction streams and anonymized banking datasets. The synthetic dataset simulated high-volume transaction environments with varying fraud patterns, while the anonymized dataset represented real-world banking transactions. The evaluation environment was configured to simulate streaming conditions with continuous data ingestion and real-time processing. Machine learning models were trained on historical transaction data and deployed within the streaming pipeline for real-time inference. Performance was evaluated using both system-level and model-level metrics, including detection latency, throughput, precision, recall, F1-score, and AUC (Area Under the Receiver Operating Characteristic Curve).

Table 1. System Performance Comparison

Metric	Batch System	Proposed System
Detection latency	15 minutes	350 ms
Throughput	200K tx/sec	1.1M tx/sec
True Positive Rate	87%	93%
False Positive Rate	4.8%	3.2%

Table 1 shows that the proposed system significantly reduces detection latency from 15 minutes in batch systems to 350 milliseconds, representing approximately a 97% improvement. Throughput increased from 200,000 transactions per second to 1.1 million transactions per second, demonstrating strong scalability. These improvements are primarily due to the use of stream processing and distributed event-driven architecture, which eliminates delays associated with batch processing.

Table 2. Machine Learning Model Metrics

Metric	Baseline	Proposed
Precision	0.89	0.92
Recall	0.87	0.93
F1 Score	0.88	0.925
AUC	0.91	0.96

Table 2 presents the performance of the machine learning models. The proposed system improves precision from 0.89 to 0.92 and recall scores from 0.87 to 0.93, resulting in a higher F1 score of 0.925. The AUC (Area Under the Receiver Operating Characteristic Curve) value increased from 0.91 to 0.96, indicating better classification performance.

The baseline model refers to a traditional batch-trained logistic regression classifier applied to historical transaction data without real-time streaming integration. This model represents conventional fraud detection systems where predictions are generated post-transaction using static datasets. In contrast, the proposed model integrates machine learning within a real-time streaming architecture, enabling continuous inference and improved detection performance.

These results demonstrate that integrating machine learning within a streaming architecture improves both detection accuracy and real-time responsiveness.

8. Case Studies

To understand how the proposed architecture performs in practical environments, it was examined through two real-world deployments in digital financial services. These cases illustrate how stream-based fraud detection systems operate when integrated into production payment platforms and banking applications. They also demonstrate how real-time analytics can influence operational outcomes such as loss reduction, faster response to suspicious activity, and improved customer protection.

a. Online Payment Processor

A mid-size payment platform deployed the architecture from January 2025 to June 2025. During this period:

- Fraud-related losses decreased by 22%

- Chargeback rates reduced by approximately 18%
- Detection latency improved to under 1 second

b. Neobank Implementation
A digital bank implemented the framework in a proof-of-concept environment. The system:
- Detected over 1,200 suspicious transactions per month
- Identified anomalies within 2 seconds of transaction initiation
- Triggered automated alerts and account restrictions in real time

These real-time fraud detection systems have been shown to significantly reduce financial losses and improve response times in digital banking environments (World Bank, 2022; McKinsey & Company, 2023).

9. Conclusion

The rapid growth of digital payments and mobile banking has made fraud detection both more urgent and more technically demanding. Traditional batch-based analytics struggle to keep pace with continuous transaction streams, often identifying suspicious activity only after the transaction has already been completed. This paper proposed a scalable architecture centered on real-time stream processing, distributed infrastructure, and continuously updating machine learning models to address these limitations. By processing transactions as they occur and combining streaming analytics with hybrid storage, the framework supports faster detection while maintaining high throughput and reliable predictive performance.

The experimental results and case implementations indicate that such architecture can substantially reduce detection latency while improving overall fraud identification accuracy. At the same time, the study highlights areas that require further attention as FinTech systems continue to evolve. Future work can focus on strengthening explainability in machine learning models and enabling secure information sharing across financial institutions, allowing fraud patterns to be identified more quickly across the broader financial ecosystem.

The proposed framework aligns with prior research on real-time analytics, machine learning–based fraud detection, and distributed data processing systems (Apache Software Foundation, 2021; Carbone et al., 2015; Dal Pozzolo et al., 2015), demonstrating its relevance and applicability in modern FinTech environments.

Although the proposed architecture demonstrates improved performance in fraud detection latency and scalability, several limitations remain. The evaluation presented in this study relies partly on simulated transaction streams designed to replicate large-scale financial workloads. While these simulations provide valuable insights into system performance, additional validation using large real-world financial datasets would strengthen the findings.

Future research may explore federated learning approaches that enable financial institutions to collaborate on fraud detection without sharing sensitive transaction data. Federated machine learning frameworks have shown promising results in privacy-preserving financial analytics systems (Yang et al., 2019).

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Declaration of the Use of Generative AI

During the preparation of this work, the author used ChatGPT for identifying relevant references and improving the structure and clarity of the manuscript. All content was reviewed, validated, and finalized by the author.

Conflicts of Interest

No conflict of interests is identified.

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| Research Papers

Volatility and Risk Spillovers between CBDC and Digital Currency Markets: Evidence from Copula Switching Models.

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Abstract

Central Bank Digital Currency (CBDC), as an innovation in the global monetary system, has attracted significant attention from many countries and researchers. These currencies are digital forms of national money issued and regulated by the central banks of various countries. With the expansion of financial technologies and the increasing popularity of decentralized digital currencies, many countries are exploring and implementing CBDCs as a solution to improve payment systems and increase financial inclusion. In this paper, we aim to examine the impacts and risk spillover from the CBDC market on digital currency markets, particularly the bitcoin market. This research utilizes a combination of copula models and switching models. First, we will analyze marginal models, examining Heston switching and Markov switching models in these markets, and then create a multivariate distribution function using copula models. The data analyzed in this study spans from January 2015 to January 2025 in both the CBDC and Bitcoin markets. This period was chosen to investigate different regimes in these markets and select appropriate marginal models for them. The results indicate that the CBDC market influences the Bitcoin market; therefore, volatility in the CBDC market can also impact the global Bitcoin market. Using the Heston switching model combined with copula models, such as the Gumbel copula, can yield favourable results. Comparing this model with other models, such as Markov switching copulas, confirms this advantage.

Keywords: Heston switching copula model, Gumbel copula, Spillover, Digital currency markets, Fiat currencies.
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1. Introduction

Central Bank Digital Currency (CBDC) is a type of national digital currency issued by a country's central bank, whose status as legal tender depends on the laws or regulations of the issuing country. What has driven central banks to develop national digital currencies is the competition with decentralized encrypted digital currencies. With the advent of blockchain technology, bitcoin, and other cryptocurrencies, governments have realized the importance of these decentralized financial systems.

Moreover, in 2020, with the outbreak of the COVID-19 pandemic, the global financial system showed increased interest in these cryptocurrencies. For this reason, central banks began exploring CBDCs as a suitable alternative to cryptocurrencies. They view CBDCs as a solution to manage the threats posed by cryptocurrencies. In other words, they are trying to offer the benefits of monetary systems like Bitcoin and Ethereum within a framework controlled by themselves.

Unlike decentralized cryptocurrencies, CBDCs are under government supervision and are issued with their backing. Each unit of CBDC acts as a secure digital equivalent of the national currency, so it can be referred to as a fiat currency. As of February 2025, out of a total of 167 CBDC-related projects being carried out by central banks, 160 projects are in various phases of research and implementation.

These currencies offer numerous advantages, such as helping to maintain financial stability, increasing public access to financial services, and addressing issues associated with existing digital currencies. Therefore, policymakers and investors must remain vigilant to ensure market stability and financial growth. Numerous studies have been conducted on CBDCs so far, examining various aspects including their benefits, challenges, and implementation. For instance, the Bank for International Settlements (BIS) concluded in its 2020 research that CBDCs can enhance the efficiency of payment systems, reduce transaction costs, and improve financial inclusion. On the other hand, it is important to note that implementing CBDCs without considering security and privacy challenges could pose risks to the financial system.

One of the areas significantly impacted by the introduction of CBDC is the banking sector, in that CBDCs could lead to the disintermediation of banks (Kim et al., 2022). On the other hand, CBDCs may also affect the lending capacity of banks. Overall, the rise of CBDCs can increase competition and innovation in monetary and banking sectors (Ward and Rochement, 2019).

The implementation of monetary policies can also be influenced by CBDCs. For example, in a financial system with scarce reserves, the central bank must actively manage the flows between reserves, CBDCs, and other liabilities to maintain control over interest rates. On the other hand, in a financial system with abundant reserves, the central bank’s approach may involve increasing the supply of reserves (Kim et al., 2022). Consequently, the risk spillover effects of CBDCs are multifaceted and highly dependent on their design, the structure of the existing financial system, and the central bank's policies. While CBDCs offer potential benefits, significant risks and uncertainties remain that require careful examination. A well-designed CBDC can enhance efficiency and financial inclusion, but if poorly designed, it could lead to instability in financial markets.

Since these currencies are a form of fiat money, it can be predicted that their functionality and spillover effects will resemble those of physical currencies. Research has been conducted on the impact of foreign exchange markets on digital currency markets, including studies by Alsaid et al. (2022), Rahman et al. (2023), and Ubaid et al. (2023).

However, despite the growing body of literature on the operational and macroeconomic implications of CBDCs, the potential risk spillover from CBDC-related uncertainty to cryptocurrency markets remains largely unexplored. Specifically, no study to date has empirically examined whether media-derived sentiment and policy uncertainty surrounding CBDC development transmit volatility to decentralized digital assets such as bitcoin. This gap is significant, given the competitive positioning of CBDCs as sovereign alternatives to cryptocurrencies and the increasing interconnectedness of digital asset markets.

This study aims to address this gap by investigating the risk spillover between CBDC-related uncertainty and the bitcoin market. The primary research objective is to determine whether uncertainty surrounding CBDC development - measured through a text-based index derived from news articles - significantly affects bitcoin's volatility. Unlike previous studies that focus on price-based spillovers between established financial markets, this study introduces a novel theoretical channel: policy-induced uncertainty as a driver of volatility transmission in the absence of a liquid spot market for CBDCs.

Accordingly, we formally test the following hypothesis, the uncertainty regarding CBDC development has a statistically significant positive spillover effect on the volatility of bitcoin. The use of a news-derived uncertainty index alongside a financial price series warrants theoretical justification. In the absence of historical trading data for CBDCs, media coverage and central bank communications constitute the primary channel through which market participants form expectations about the future state of digital fiat competition. Therefore, treating the CBDC Uncertainty Index as a valid proxy for latent policy risk is both conceptually sound and methodologically necessary. To capture the asymmetric and state-dependent nature of volatility transmission, we employ a regime-switching stochastic volatility model, which allows for the identification of spillover effects under different market regimes.

By doing so, this study contributes to the literature in two ways. First, it extends the scope of spillover analysis to include policy-driven uncertainty as a distinct source of risk in cryptocurrency markets. Second, it provides empirical evidence on the interdependence between sovereign digital currencies and decentralized financial assets, offering insights for policymakers and investors regarding the broader risk architecture of the digital economy. The next section provides research background, followed by research methodology. Data and empirical results are presented in section 4, and section 5 concludes the paper.

2. Research Background

The topic of spillover between markets is considered one of the favorite subjects among researchers. As mentioned, with the liberalization of information and the increase in interactions between different markets, the spillover between markets has garnered more attention than ever before. Researchers generally believe that risk spillover can occur due to various factors. For example, factors such as investor behavior and expectations (Mihae and Maria, 2020), market efficiency and the level of information transfer and freedom of information dissemination in the market (Ajaya et al., 2021), regulatory oversight of the market by various institutions, including governments (Fan et al., 2020), and the level of development of financial systems (Alberto et al., 2019) can all influence the level of spillover (Salimi Nasab et al., 2024).

Before the mid-1950s, there were limited studies on the relationship between markets. From the 1960s onward, due to researchers' interest in optimizing investment portfolios, the topic of inter-market relationships began to gain attention. Most of the research conducted during this period utilized statistical models such as simple linear regression, quantile regressions, and vector autoregression. Notable studies include the work of Longin and Solnik (1995) and McQueen et al. (1996).

From the 1990s, nonlinear approaches for examining market spillover and financial market interdependence gained popularity among researchers. Due to the limitations of regression models, copula functions were introduced. Copula models have been explored by various researchers to analyze dependency structures between markets, including studies by Cossin et al. (2000), Patton (2006), and Canela (2006) (Bergkar and Sohrabi, 2020).

The use of copula models marked a significant step in examining the interconnection between markets and assessing the degree of spillover between them. Several studies have investigated spillover between markets using copula models, including Huang et al. (2009), who utilized the Clayton copula; Chang (2017), who employed Gumbel and Clayton copulas to examine the correlation between crude oil markets and futures trading; and Li and Hussain (2018), who analyzed the relationship between the Chinese market and Asian, European, and U.S. markets.

In addition to using copula models, attention must also be paid to marginal models. Many of the aforementioned studies relied on marginal models that were either unable to capture regime changes in the data or used constant-parameter models. The use of switching models, such as the Markov-switching model, as a marginal model can enhance the dynamics of the models. Tan Suchat et al. (2017), Salmi et al. (2019), Tiwari et al. (2020), Mwamba and Mwambi (2021), Suri (2024), Ho et al. (2024), and Ning et al. (2025) have incorporated this dynamism into copula models by using the Markov-switching model as a marginal model.

Although the aforementioned studies have significantly advanced the measurement of spillover effects, they have primarily focused on traditional financial assets and equity markets. The application of these methodologies to sovereign digital currencies -particularly the spillover effects of CBDC-related uncertainty on cryptocurrency markets - remains largely unexplored.

As mentioned, CBDCs can have an impact on various financial and economic sectors. Ward and Rochemont (2019) examined these currencies, discussing their advantages, disadvantages, and the effects they have on the financial sector. Alonso et al. (2021) explored the optimal conditions for creating and launching CBDCs, as well as the countries that are better positioned to implement this monetary system. Wang and colleagues (2022) analyzed the impact of news about these currencies on economic markets and concluded that financial markets react to them. A key point regarding these currencies is their influence on financial and economic sectors, including the cryptocurrency market. Van et al. (2025) investigated the impact of CBDCs on cryptocurrencies and examined risk transmission and spillover using TVP-VAR models.

However, a critical gap remains. While Van et al. (2025) provide preliminary evidence of spillover between CBDCs and cryptocurrencies, their TVP-VAR framework does not explicitly model the volatility transmission channel through which uncertainty regarding CBDC development affects cryptocurrency returns. Furthermore, no study to date has justified theoretically why such a spillover should exist. We argue that in the absence of a liquid spot market for CBDCs, media coverage and central bank communications serve as the primary channel through which market participants form expectations about the future competitive landscape between sovereign and decentralized digital currencies. This information flow shapes investor sentiment and risk appetite, thereby transmitting volatility to cryptocurrency markets. This study provides the first theoretical articulation and empirical test of this uncertainty-driven spillover channel.

To study the spillover between different markets from the CBDC market, a combination of copula models and switching models can be employed. However, considering the limitations of Markov-switching models - such as their performance in short-term intervals with clustered volatility or when data distribution is non-normal - it may be more appropriate to use the Heston-switching model, which addresses some of these limitations. The aim of this research is to examine the relationship between the CBDC market and the bitcoin market. To analyze this relationship, we will utilize a combination of Heston-switching models and different copula functions.

3. Research Methodology

In this study, we will examine the combination of switching models and copula models. First, we will introduce the marginal model, and then we will explore its integration with the copula model. As is well known, regardless of any classification, the task of linking marginal distributions together falls to copula functions. To investigate risk spillover between different markets, we first analyze the marginal distributions and then proceed to examine the multivariate joint model.

In this study, we investigate risk spillover between the CBDC Uncertainty Index - a text-based index derived from news articles - and bitcoin returns. A methodological justification is necessary here. Since CBDCs are still largely in pilot or research phases and no liquid spot market with observable transaction prices exists, media coverage and central bank communications constitute the primary channel through which market participants form expectations about the future of digital fiat currency. Therefore, treating the CBDC Uncertainty Index as a valid proxy for latent policy risk and modeling its volatility dynamics alongside bitcoin returns is both theoretically grounded and methodologically necessary. This approach does not assume equivalence between the two series; rather, it recognizes that uncertainty shocks transmit across heterogeneous asset classes through investor sentiment and expectation formation channels.

Switching models, unlike stochastic volatility models, do not have constant parameters throughout the entire model; instead, their parameters change based on the economic regime. Switching models allow the economy to transition into a regime under any number of constraints and at any point in time. The regime significantly influences the dynamic behavior of time series. Regimes can occur at specific points in time. A Markov-switching model, as shown in Equation (1), allows volatility to shift between regimes, meaning it permits σ to fluctuate and vary between two regimes.

$$\Delta r_t = a_i + b_i r_{t-1} + \sigma_i r_{t-1}^{\gamma} \varepsilon_t \qquad (1)$$

where $i \in \{1,2\}$ is an input for the regime at time t. Here, γ is the diffusion parameter, σ is the volatility parameter, and a and b are constant parameters within each regime. ε_t is a white noise process that is independent of r_t. All ε_t are independent and identically distributed with a mean of zero and variance σ^2. The transition probability from regime i to regime j at time t is defined as $P_{ij} = Pr(S_t = i | S_{t-1} = j)$.

Another model that we will examine as a marginal model is the Heston-switching model[1]. The base Heston model was introduced by Heston in 1993. This model is also defined based on Brownian motion. The base Heston model has a significant weakness because it does not account for different regimes. However, if this model is combined with regime-switching probabilities, it can become a highly effective model.

Consider that we are dealing with a probability space$(\Omega, \mathbb{F} := (\mathcal{F}_t)_{[.,T]}, \mathbb{P})$, where $\mathbb{P}$ represents the risk-neutral measure. We define X_t as a Markov chain on the space $E := \{1, \dots, S\}$ with an initial distribution μ.

[1] Heston

This Markov chain essentially identifies the regime in the data of interest. The generator matrix of X is denoted by Π, where for all $i, j \in E$, we have $\Pi_{ij} \geq 0$ if $i \neq j$, and $\Pi_{ii} = \sum_{i \neq j} \Pi_{ij}$.

We assume that the transition probabilities from state $i \in E$ at time t to state $j \in E$ at time $t + h$ are constant. This assumption leads to the construction of a generator transition function denoted by Π. Let us now denote by $X(h)$ the transition probability matrix, which is defined as follows:

$$X_{ij}(h) = \mathbb{P}(Z_h = j \mid Z_0 = i) \quad (2)$$

Then, for all $i, j \in E$, we will have:

$$\frac{d\, X_{ij}(h)}{d\, h} = \Pi_{ij} \quad for\ all \quad i, j \in E \quad (3)$$

Finally, let us denote the transition matrix as P, similar to the Markov switching model. Therefore, we will have:

$$P_{ij} = \begin{cases} \dfrac{\Pi_{ij}}{\sum_{i \neq j} \Pi_{ij}} & if\ i \neq j \\ 0 & In\ other\ states \end{cases}$$

Now, consider $S = (S_t)$ as a stochastic process in our probability space. This space can exist in any of the markets we are researching. Suppose $V = (V_t)$ is another stochastic process that models the instantaneous variance of S.
It is important to note that all parameters of the stochastic volatility process v, as well as the correlation coefficient between the index of each market and its instantaneous variance v, depend on the state X. In simpler terms, the parameters of each regime are dependent on that specific regime. Consider the baseline Heston model:

$$\mathrm{dS_t} = \mathrm{\mu S_t} + \mathrm{S_t}\sqrt{v_t}\mathrm{d}Z$$
$$\mathrm{d}v_\mathrm{t} = \mathrm{k}(\theta - v_\mathrm{t})\mathrm{dt} + \sigma\sqrt{v_\mathrm{t}}\mathrm{d}B$$

We know that the processes Z and B are Brownian motions. Here, v_t represents the instantaneous variance, θ is the long-term variance, and k denotes the volatility of variance. The two Brownian motions Z and B are independent of each other. Now, we have:

$$\frac{\mathrm{dS_t}}{\mathrm{S_t}} = \mu + \sqrt{v_\mathrm{t}}\mathrm{d}Z \quad (4)$$

And we also have:

$$\mu = rdt$$

where r is the risk-free interest rate. Therefore, we have:

$$\frac{\mathrm{dS_t}}{\mathrm{S_t}} = rdt + \sqrt{v_\mathrm{t}}\mathrm{d}Z \quad (5)$$

Now, consider a situation where we are faced with different regimes. Then, we will have:

$$X_t = \begin{cases} (1,0)^t, & Pos\ \text{Regime} \\ (0,1)^t, & Neg\ \text{Regime} \end{cases}$$

And the transition function between the two regimes follows a Poisson distribution. The transition probabilities in this model are also as follows:

$$P = Pr(S_t = 1|S_{t-1} = 1)$$
$$q = Pr(S_t = 2|S_{t-1} = 2)$$

Now, for each regime, we will have:

$$dv_i = k_{\mathrm{i}}(\theta_{\mathrm{i}} - v_{\mathrm{i}})dt + \sigma_{\mathrm{i}}\sqrt{v_{\mathrm{i}}}dB_{\mathrm{i}} \quad (6)$$
$$dZ_{\mathrm{i}}\, dB_{\mathrm{i}} = \rho_{\mathrm{i}} dt \quad (7)$$
$$dZ_{\mathrm{i}}\, dZ_{\mathrm{j}} = dB_{\mathrm{i}}\, dB_{\mathrm{j}} = 0 \quad (8)$$

Where ρ_{i} is the correlation between the two Brownian processes, θ is the long-term variance of volatility, k is the mean reversion speed of volatility, and r is the interest rate. Now, after introducing the marginal models, we proceed to examine and introduce copula models. A copula function is a linking function for multiple marginal functions, defined on the space $[0,1]^n$. For example, the joint distribution function with marginal distributions $F_x(x)$ and $F_y(y)$ is defined as follows:

$$F_{XY}(x, y) = C\left(F_x(x), F_y(y)\right) \quad (9)$$

If the marginal distributions $F_x(x)$ and $F_y(y)$ are continuous and also specified, then we will have:

$$C(u, v) = H\left(F^{-1}(u), F^{-1}(v)\right) \quad (10)$$

Moreover, their joint distribution will also be as follows:

$$F_{XY}(x, y) = c(u, v)F_x(x)F_y(y) \quad (11)$$

In this way, $c(u, v) = \frac{\partial^2 C(u,v)}{\partial u \partial v}$ serves as the copula density function, and $F_x(x)$ and $F_y(y)$ are the marginal distributions. These equations can be extended to consider N marginal distributions connected by a copula function, which then forms the joint distribution. As mentioned earlier, different types of copulas can be used to create multivariate distributions. The various types of copulas provide a flexible space for identifying joint distributions. One type of copula that performs particularly well in creating joint distributions is the Frank copula. This function was introduced by Frank for the parameter $\theta \in \mathrm{R}$ as follows:

$$\mathrm{C}(u, \mathrm{v}; \theta) = \frac{-1}{\theta} \mathrm{Ln}[1 + \frac{\left(\mathrm{e}^{-\theta_u} - 1\right)\left(\mathrm{e}^{-\theta_v} - 1\right)}{\mathrm{e}^{-\theta} - 1} \quad (12)$$

The copula density function for this family is as follows:

$$\mathrm{C}(\mathrm{u}_1, \mathrm{u}_2; \theta) = \frac{\theta \mathrm{e}^{-\theta(\mathrm{u}_1 + \mathrm{u}_2)}(\mathrm{e}^{-\theta} - 1)}{[\mathrm{e}^{-\theta(\mathrm{u}_1+\mathrm{u}_2)} - \mathrm{e}^{-\theta \mathrm{u}_1} - \mathrm{e}^{-\theta \mathrm{u}_2} + \mathrm{e}^{-\theta}]^4}$$

The Frank copula is used because it is symmetric in both tails and encompasses the full range of correlation limits when analyzing phenomena that exhibit either positive or negative dependence. Due to the symmetry of the Frank copula, the dependence on the upper and lower tails will be equal to zero (Bargkar, 2020).

Another widely used copula is the T- Student copula. In the bivariate case, this copula is expressed as follows:

$$C(u_1,u_2) = T_{\upsilon,\rho}\left(t_v^{-1}(u_1), t_v^{-1}(u_2)\right) = \int_{-\infty}^{t_v^{-1}(u_1)} \int_{-\infty}^{t_v^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \left(1 + \frac{s^2 - t^2 - st\rho}{u_2(1-\rho^2)}\right) \frac{u_2 + 2}{2} dsdt$$

In this model, $T_{\upsilon,\rho}$ represents the bivariate Student's t-distribution, ρ is the correlation coefficient, υ is the degrees of freedom, and t_v^{-1} is the inverse of the univariate Student's t-distribution. This function, like the Gaussian copula, is symmetric, but it considers the upper and lower tail dependencies to be equal.
The Clayton copula was first introduced by Clayton for the parameter $\theta \in [-1,0] \cup [0,\infty)$and is defined as follows:

$$C(u_1,u_2;\theta) = \mathrm{Max}\left\{(u_1^{-\theta} + u_2^{-\theta} - 1)^{\frac{-1}{\theta}}, 0\right\} \qquad (13)$$

For $\theta > 0$, this copula will be expressed as follows:

$$C(u_1,u_2;\theta) = \left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{\frac{-1}{\theta}}$$

The density function of this copula is also as follows:

$$C(u_1,u_2;\theta) = (\theta+1)\left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{\left(\frac{-1}{\theta}-2\right)} (u_1u_2)^{(-\theta-1)}$$

This copula function, for $\theta > 0$, exhibits lower tail dependence, where the upper tail dependence is$\lambda_{U_C} = 0$ and the lower tail dependence is $\lambda_{L_C} = 2^{\theta-1}$.

The Gumbel copula was also defined by Gumbel for the parameter $\theta \geq 1$ as follows:

$$C(u_1,u_2;\theta) = (\theta+1)\left(u_1^{-\theta} + u_2^{-\theta}\right)^{\left(\frac{-1}{\theta}-2\right)} (u_1u_2)^{(-\theta-1)}$$

$$C(u_1,u_2;\theta) = \exp\left\{-[-(\ln u_1)^\theta + (\ln u_2)^\theta]^{\frac{1}{\theta}}\right\} \qquad (14)$$

The copula function for this family is also defined as follows:

$$c(u_1,u_2;\theta) = \frac{[(-\ln u_1)(-\ln u_2)]^{\theta-1}}{u_1u_2}[(-\ln u_1)^\theta + (-\ln u_2)^\theta]^{\left(\frac{2}{\theta}-2\right)}$$
$$\left\{(\theta-1)\left[(-\ln u_1)^\theta + (-\ln u_2)^\theta\right]^{\frac{1}{\theta}} + 1\right\}$$

This copula exhibits tail dependence. In the Gumbel copula, the upper tail dependence is $\lambda_{U_C} = 2 - 2^{-\theta}$, and the lower tail dependence is $\lambda_{L_C} = 0$

Now, if we wish to transform the marginal functions, which include switching models, into a joint function using copula models, we will have:

$$f(u,v \mid S_t = k) = c(u,v \mid \theta_k) \cdot f_U(u) \cdot f_V(v)$$

Since both marginal models are of the switching type and the time series $x_t = (x_{1t}, x_{2t}), t = 1,2, \ldots$ is a two-dimensional vector, the switching copula model can then be defined as follows:

$$RS(\mathrm{X}_t|\mathrm{S_t}) = C_t^{S_t}\big(\mathrm{F}_1(\mathrm{x_{1t}}|\mathrm{S_{1t}}), \mathrm{F}_2(\mathrm{x_{2t}}|\mathrm{S_{2t}})\big) \quad (15)$$

In this equation, $C_t^{S_t}$ represents the Frank copula parameter, and $\mathrm{F}_i(\mathrm{x_{it}})$ denotes the marginal distribution functions. $\mathrm{F}_i(\mathrm{x_{it}})$ in this equation can follow either Markov-switching or Heston-switching distributions. Patton (2006) provided an equation for time-varying copula functions, which is derived from scalar equations. Suppose the copula parameter C can be considered as a simple ARMA function. Then, we will have:

$$C_t = \Lambda(\omega + \varphi C_{t-1} + \psi \Gamma_t) \qquad (16)$$

In this equation, $\Lambda(.)$ is an exponential function, ω, φ, and ψ are constant parameters, and Γ_t represents the pressure variable. This equation allows for mean reversion. The pressure variable Γ_t is also defined as follows:

$$\Gamma_t = \begin{cases} \dfrac{1}{m}\sum_{j=1}^{m} F_1^{-1}(x_{1,t-j})F_2^{-1}(x_{2,t-j}) & \text{elliptical} \\ \dfrac{1}{m}\sum_{j=1}^{m} \left| F_1(x_{1,t-j}) - F_2(x_{2,t-j})\right| & \text{Archimedean} \end{cases} \qquad (17)$$

In the above equation, $F_n^{-1}(u_{n,t})$ is the inverse of the marginal distribution function. Additionally, Patton assumed in this equation that $m = 10$. Now, consider that we are dealing with a regime-switching copula function; then, Patton's equation will be as follows:

$$C_t^{S_t} = \Lambda\big(\omega^{S_t} + \varphi C_{t-1}^{S_{t-1}} + \psi \Gamma_t\big) \qquad (18)$$

In this equation, unlike the first case, the copula behaves differently in each regime and may take on different values in each regime based on the pressure variable. In both Markov-switching and Heston-switching models, we are dealing with a transition probability matrix, where the transition probability $\mathrm{p_{ij}}$ is calculated as follows:

$$\mathrm{p_{ij}} = \Pr(\mathrm{s_t} = \mathrm{j}|\mathrm{s_{t-1}} = \mathrm{i})$$

Now, to estimate the parameters of this model, the maximum likelihood method can be employed. Therefore, we will have: (Filho et al., 2012)

$$l(\vartheta|X_t) = \sum_{t=1}^{T} \log(C_\theta(\mathrm{F}_1(\mathrm{X_{1t}}|\vartheta_1), \mathrm{F}_2(\mathrm{X_{2t}}|\vartheta_2) \times \prod_{i=1}^{2} f_{it}(\mathrm{X_{it}}|\vartheta_i)) \qquad (19)$$

In Equation 19, ϑ_i represents the parameters of the marginal model, such as a_i, b_i, σ_{it}. Estimating the parameters using Equation 19 can be complex; however, since this equation is separable, a two-step maximum likelihood estimation method can be applied. Therefore, the IFM (Inference Functions for Margins) method proposed by Joe and Zhu (1996) can be utilized. Equation 19 can be rewritten as follows:

$$l(\vartheta|X_t) = \sum_{t=1}^{T} \log(C_t^{S_t}(\mathrm{F}_1(\mathrm{X_{1t}}|\vartheta_1), \mathrm{F}_2(\mathrm{X_{2t}}|\vartheta_2) \times \prod_{i=1}^{2} f_{it}(\mathrm{X_{it}}|\vartheta_i)) =$$
$$\sum_{t=1}^{T} \log f_{1t}(\mathrm{X_{1t}}|\vartheta_1) + \sum_{t=1}^{T} \log f_{2t}(\mathrm{X_{2t}}|\vartheta_2) + \sum_{i=1}^{2}\sum_{t=1}^{T} \log C_t^{S_t}(U_{it}|\vartheta_i)$$
$$l(\vartheta|X_t) = \ell_{f_1}(\vartheta_1) + \ell_{f_2}(\vartheta_2) + \ell_C(\vartheta_i) \qquad (20)$$

In this equation, $\ell_{f_1}(\vartheta_1)$ and $\ell_{f_2}(\vartheta_2)$ are the maximum likelihood functions for the marginal distributions. To estimate the parameters, we can start with these two functions and, after estimating the parameters of the marginal distributions, proceed to the next step.

Now, to estimate the third part of Equation 20, represented by $\ell_C(\vartheta_i)$, considering that there are likely two regimes, we can expect to encounter two different copulas. For estimating the parameters of each copula, the parameters can be estimated separately within each regime. Finally, it can be stated that in the first step, the parameters of each marginal model should be estimated using the maximum likelihood method, and then, in the second step, the copula parameter should be estimated for each regime.

4. Data and Empirical Results

First, we examine the statistical data of this research. In this study, we analyze the CBDC market and the Bitcoin market. After statistically examining these two markets, we determine the appropriate marginal distribution for each and, ultimately, use copula models to construct their joint distribution function. Finally, we investigate the risk spillover between these two markets. The data related to the CBDCU market are derived from the research conducted by Wang et al. in 2022.

These data were initially obtained by analyzing 663.9 million news articles related to CBDCs, collected weekly from economic and news sources from January 2015 to the end of 2022. They then continued their observations and calculated the uncertainty index up to the beginning of 2025. The data related to the bitcoin market were extracted from global bitcoin markets over the same period, this data was taken from Yahoo Finance.

The statistical description of these markets is as follows:

Table 1: Statistical description of data for the global bitcoin market and CBDC uncertainty

Title	Bitcoin Market	CBDC Market Uncertainty (CBDCU)
Count	2566	522
Mean	11307.5	100.8739
Median	6442.55	100.2443
Maximum	67566.83	115.1469
Minimum	178.1030	99.1167
Standard Deviation	15985.9	1.8119
Skewness	1.9187	2.2812
Kurtosis	5.52	12.3237
Jarque-Bera Test	2253.5	2343.54
Probability	0.00000	0.00000

The trend of these two markets can be observed in the figures below:

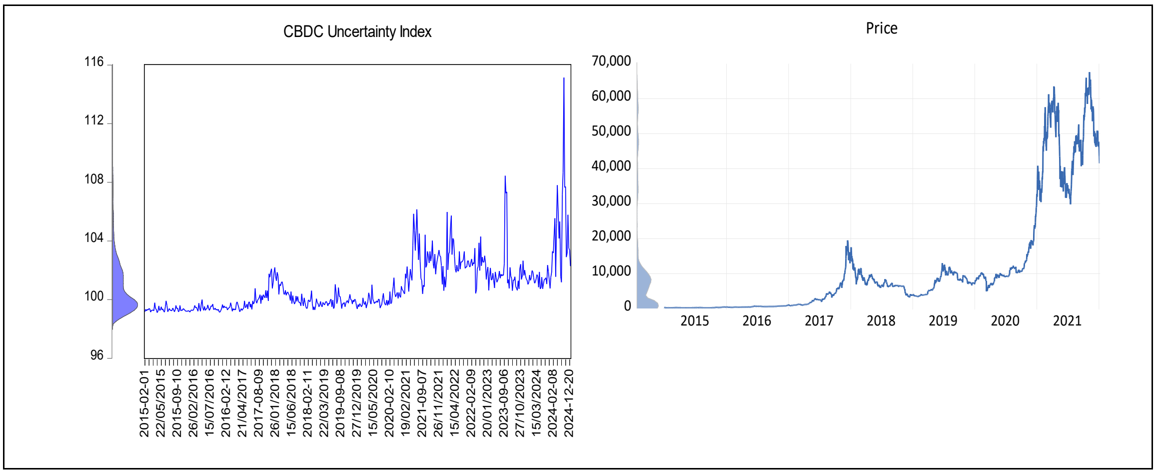

Figure 1: Daily bitcoin price and CBDC uncertainty index

It should be noted that the CBDC Uncertainty Index is a text-based index derived from news articles, while the bitcoin series consists of actual market returns. Since CBDCs are still largely in pilot or research phases and no liquid spot market with observable transaction prices exists, media coverage and central bank communications constitute the primary channel through which market participants form expectations about these currencies. Therefore, treating this index as a proxy for CBDC-related risk and examining its spillover effects on bitcoin is methodologically necessary and theoretically justified.

Time series are one of the most important statistical data used in empirical analysis. It is generally assumed that time series are stationary, and if this assumption does not hold, most statistical tests come into question. Non-stationarity can lead to issues such as spurious regression. Therefore, we use the Dickey-Fuller test to check for stationarity and given the presence of a unit root in the data, we utilize the logarithmic differenced series. Considering that we also observe autocorrelation, it can be concluded that small jumps follow small jumps, and large jumps follow large jumps, which fully supports the assumption of autocorrelation. Now, based on the above evidence, we perform the ARCH test, and we will have:

Table 2: Arch test

Title	F-Statistic	Probability
ARCH Test	61.1611	0.0000

The null hypothesis in this test is that there is no ARCH effect. According to the table, this hypothesis is rejected, and we are faced with the ARCH phenomenon and heteroskedasticity. After determining the coefficients of the GARCH model, we proceed to examine and estimate the parameters of the two switching models in this dataset shown in Table 3 and Figure 2.

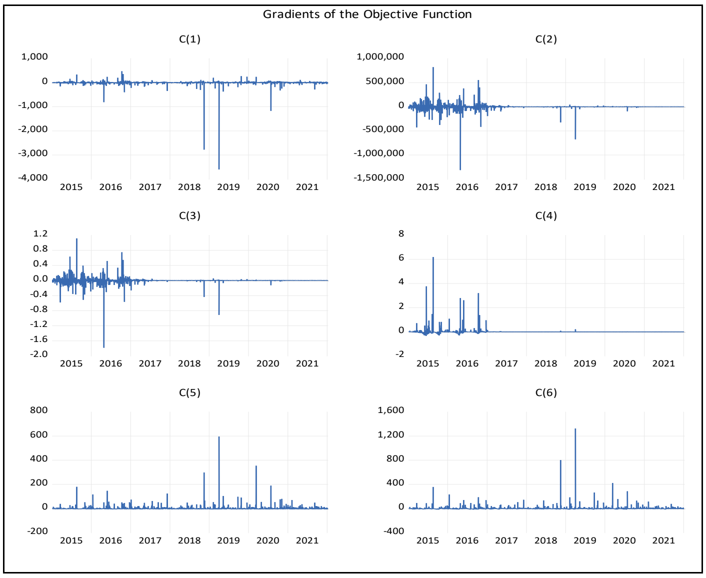

Figure 2: Gradients of the objective functions

Table 3: Estimation of model parameters

Model	Parameters		
Heston Switching Model	Positive Regime	k	0.0643
		θ	5.8654
		v	0.0459
	Negative Regime	k	0.0577
		θ	5.1842
		v	0.0542
	Transition Probability Matrix		$\begin{bmatrix} 0.3151 & 0.6849 \\ 0.6764 & 0.3236 \end{bmatrix}$
Markov Switching Model	Positive Regime	α	-0.0078
		β	-0.0963
		σ	0.9008
	Negative Regime	α	0.0211
		β	-0.0959
		σ	0.8649
	Transition Probability Matrix		$\begin{bmatrix} 0.4976 & 0.5024 \\ 0.5109 & 0.4891 \end{bmatrix}$
Conditional Variance Equation	c		0.55
	$RESID(-1)^2$		0.11
	$GARCH(-1)$		0.91
	$GARCH = C(4) + C(5) \times RESID(-1)^2 + C(6) * GARCH(-1)$		

After estimating the parameters of the two models, the performance of the two marginal models in the bitcoin market, namely Markov switching and Heston switching, is very close to each other. With a slight difference, the Heston switching model performs slightly better. It should also be noted that the variance of these models follows the GARCH model. After examining the marginal models, we can proceed to investigate and select the appropriate copula model.

Table 4: Comparison of copulas in different regimes

Copula	Frank Copula		Clayton Copula		T Student copula		Gumbel Copula	
	Positive Regime	Negative Regime	Positive Regime	Negative Regime	Positive Regime	Negative Regime	Positive Regime	Negative Regime
Copula parameter	17.0996	12.7631	5.0602	4.8106	0.9238	0.8512	2.6395	1.8388
Max likelihood	867.6598	412.0142	793.3967	464.4664	734.0646	294.6065	460.6929	136.1972
AIC	1737.3	826.0284	1588.8	930.9328	1427.1	593.2130	923.3857	274.3943
BIC	1742.1	830.3051	1593.5	935.2094	1481.6	601.7663	928.1310	278.6710

After determining the parameters of the marginal models, the copula parameters have been estimated. Based on the results in Table 4, the best copula is selected according to the Akaike information criterion (AIC) and the lowest information loss. In both the first and second regimes, the Gumbel copula shows the best performance. In the first regime, the value of this index is 2.6395, and in the second regime, it is 1.8388.

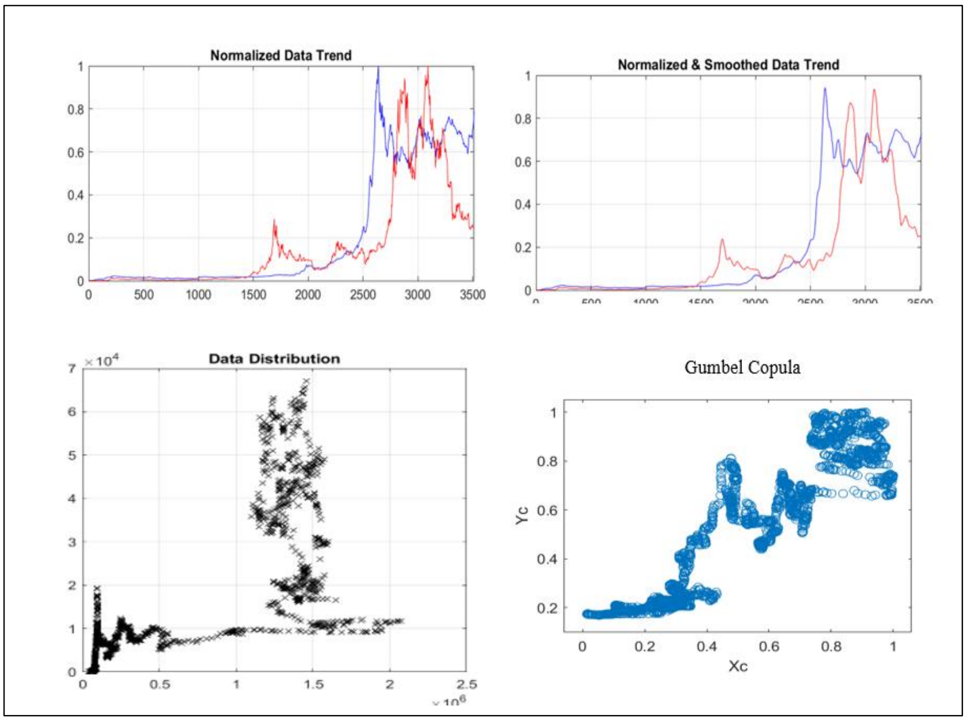

Figure 3: Normalized data trend and copula distribution

The Gumbel copula exhibits upper tail dependence and zero lower tail dependence in Figure 3. This indicates that the two markets are more strongly correlated during periods of high uncertainty and high volatility, while during calm periods they move more independently. This finding is consistent with our theoretical argument that uncertainty shocks - rather than steady-state information - drive spillover effects.

Now, after identifying the appropriate copula index, we need to determine the spillover effect of the bitcoin market from the CBDC market uncertainty index. To examine the spillover effect, we utilize the conditional Value at Risk (VaR). We will now calculate the conditional Value at Risk at the 95% confidence level and the 5% significance level. If we observe volatility at these two levels, it will indicate a spillover effect from the CBDC markets to the bitcoin market.

Table 5: Calculation of Risk Spillover from the CBDC Market to the Bitcoin Market

Title	Positive Domain	Negative Domain
Risk Spillover from the CBDC Market to the Bitcoin Market	9.3	4.21

As shown in Table 5, the positive domain (9.3) is substantially larger than the negative domain (4.21), indicating that spillover effects are asymmetric and stronger during periods of increased CBDC-related uncertainty. This asymmetry is consistent with the Gumbel copula results and supports our research hypothesis.

This finding has several economic implications. First, investors react more strongly to bad news about CBDCs than to good news, consistent with loss aversion in behavioral finance. Second, it validates our theoretical channel that in the absence of a liquid CBDC spot market, media and central bank communications transmit uncertainty shocks to bitcoin through investor sentiment. Third, the Gumbel copula's upper tail dependence confirms that co-movement intensifies precisely during high-uncertainty periods.

For investors, symmetric risk models underestimate tail risk during CBDC news spikes. For policymakers, abrupt policy signals even if benign can generate disproportionate spillover; transparent communication helps mitigate this.

The correlation coefficient (0.78) is consistent with our findings, but correlation alone misses the asymmetric dependence captured by CoVaR and copula analyses, which are the novel contribution of this study. Therefore, CBDC-related news has a significant and asymmetric impact on the bitcoin markets, supporting the hypothesis that CBDC uncertainty constitutes a distinct source of risk spillover to decentralized digital assets.

5. Conclusion

In this paper, we examined the relationship and risk spillover from the emerging CBDC market to digital currency markets, particularly the bitcoin market. Initially, we analyzed marginal models and tested Markov-switching and Heston-switching models in these markets. Ultimately, due to the superior performance of the Heston-switching model, we utilized it as the marginal model. After identifying the regimes in these markets and estimating the regime transition probabilities, we estimated the parameters of this model. Subsequently, to determine the multivariate function, we estimated various copulas such as Frank, Clayton, Gumbel, and Student's t copulas, and selected the best copula based on Akaike information criteria and lost information metrics. The combination of marginal models and the proposed copulas form the final model.

The primary contribution of this study is twofold. First, we provide a theoretical framework explaining why and how CBDC-related uncertainty should transmit volatility to cryptocurrency markets. We argue that in the absence of a liquid spot market for CBDCs, media coverage and central bank communications serve as the primary channel through which market participants form expectations about the future competitive landscape between sovereign and decentralized digital currencies. Second, we empirically validate this channel by demonstrating significant and asymmetric risk spillover from a text-based CBDC Uncertainty Index to bitcoin returns. This addresses a critical gap in the literature, as prior studies have focused primarily on the operational and macroeconomic implications of CBDCs while neglecting their financial market externalities.

In the past, researchers such as Tan Sotchot et al. (2017), Jamal Bouoiyour et al. (2019), Pat Chalok et al. (2019), and Wistras et al. (2021) had explored the combination of copulas with Markov-switching models. However, the limitations of the Markov model - particularly its performance in short-term intervals with clustered volatility and under non-normal data distributions - compelled us to test the Heston-switching model as the marginal model. Our results indicate that the Heston-switching model performs slightly better than the Markov-switching alternative, and its combination with the Gumbel copula yields superior fit and more plausible economic interpretations.

Our empirical findings reveal three key insights. First, the Gumbel copula consistently outperforms other copula specifications in both positive and negative regimes. This dominance indicates the presence of upper tail dependence, meaning that CBDC uncertainty and bitcoin volatility exhibit stronger co-movement during periods of high uncertainty and high volatility, while moving more independently during calm periods. Second, the conditional Value-at-Risk (CoVaR) analysis confirms significant asymmetric spillover effects, meaning that positive uncertainty shocks generate spillover effects more than twice the magnitude of negative shocks. This asymmetry is consistent with behavioral finance theories of loss aversion and confirms that market participants react more intensely to the emergence of new risks than to their resolution. Third, the correlation coefficient of 0.78 between the two data series provides additional validation, though correlation alone fails to capture the asymmetric dependence structure revealed by our copula and CoVaR approaches.

These findings carry important implications. For investors and portfolio managers, conventional risk models that assume symmetric spillover or constant correlations may substantially underestimate tail risk during periods of heightened CBDC-related news activity. Dynamic, regime-aware risk management frameworks are therefore necessary. For policymakers and central banks, the asymmetry documented here implies that abrupt, ambiguous, or contradictory policy signals, even if ultimately benign, can generate disproportionate and potentially destabilizing risk transmission to adjacent markets. Transparent, consistent, and forward-looking communication strategies can help mitigate these unintended spillover effects.

One of the key points to consider regarding the spillover effects of the CBDC market on various markets, including cryptocurrency markets, is the role of government policies concerning CBDCs. Political and social factors play a significant role in these markets. Although CBDCs have not yet been fully implemented, they could play an important role in the future in terms of inter-market relationships. The risk spillover from these markets will be somewhat similar to that of foreign exchange markets, with the difference that the speed of reactions will likely be faster. In such conditions, a robust model is one that can account for sudden jumps, instantaneous changes, and regime shifts. The combination of switching models and copula models provides flexible tools for addressing these fluctuations.

This study is not without limitations. First, the CBDC Uncertainty Index, while methodologically necessary, remains an imperfect proxy for latent policy risk. As CBDC projects mature and spot markets potentially emerge, future research should re-examine these spillover effects using actual transaction data. Second, our analysis focuses exclusively on bitcoin; extending this framework to other cryptocurrencies and digital assets would provide a more comprehensive understanding of spillover dynamics. Third, the specific mechanism through which uncertainty transmits to volatility, whether through retail investor sentiment, institutional portfolio rebalancing, or algorithmic trading, remains unidentified. Future studies employing survey data, trading volume disaggregation, or high-frequency identification strategies could help open this black box. Finally, comparative studies examining CBDC spillovers across different countries with varying policy approaches and institutional frameworks would enrich our understanding of how institutional context moderates these effects.

Despite these limitations, this study provides the first theoretical articulation and empirical evidence of risk spillover from CBDC-related uncertainty to cryptocurrency markets. By demonstrating that policy-driven information flow constitutes a distinct and economically meaningful source of volatility transmission, we hope to open a new avenue of research at the intersection of sovereign digital currency policy and decentralized financial markets.

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Conflicts of Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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