Cryptocurrency’s Societal Impact: ESG Compliance, Gaming Economies, and Political Finance

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Abstract

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This dissertation investigates the transformative role of cryptocurrency across three critical domains: environmental, social, and governance (ESG) compliance, blockchain-integrated gaming (GameFi), and political finance (PolitiFi). Through a thesis-by-article structure, it presents three complementary studies that together explore cryptocurrency’s broader societal impact and its implications for innovation in finance and governance.

The first article critically evaluates Bitcoin’s alignment with ESG criteria, challenging the dominant narrative that emphasizes its environmental footprint. Utilizing a novel forecast model, the study projects Bitcoin’s energy consumption and highlights overlooked contributions to financial inclusion, renewable energy integration, and governance transparency. This work offers insights into how Bitcoin’s environmental criticisms may be mitigated through technological advancements and innovative mining practices.

The second article examines the emerging GameFi sector, which bridges decentralized finance (DeFi), non-fungible tokens (NFTs), and gaming. By analyzing key developments such as play-to-earn models and blockchain gaming’s evolution, the study uses empirical methods to explore GameFi’s independence from traditional cryptocurrency markets. It reveals how GameFi redefines digital economies, providing new monetization opportunities and reshaping value exchange between players and developers.

The third article introduces PolitiFi, a novel category of cryptocurrencies linked to political campaigns and figures. Employing a Vector Autoregressive (VAR) model, the study investigates PolitiFi’s market dynamics and its rapid decoupling from traditional meme coins. It demonstrates PolitiFi’s potential to engage underrepresented voters, influence campaign strategies, and disrupt traditional political finance.

Together, these studies provide a cohesive examination of cryptocurrency’s societal contributions, addressing critical challenges and uncovering opportunities for its application in diverse fields. The findings contribute to academic discourse on decentralized technologies while offering practical implications for policy-making, sustainable finance, and digital innovation.

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Dedication

To my father, mother, and sister—your unwavering support and belief in me have shaped who I am today.

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Contribution of Authors

This thesis consists of three research papers that I have co-authored with my co-supervisors, Dr. Juliane Proelss and Dr. Denis Schweizer.

1. Proelss, J., Schweizer, D., & Sévigny, S. (2023). Is bitcoin ESG-compliant? A sober look. *European Financial Management*, 30(2), 680–726.

2. Proelss, J., Sévigny, S., & Denis Schweizer. (2023). GameFi: The perfect symbiosis of blockchain, tokens, DeFi, and NFTs? *International Review of Financial Analysis*, *90*(102916), 102916.

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Juliane Proelss: Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Funding acquisition

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Introduction

The sophisticated centralized system dominating today's financial infrastructure is the result of significant transformations, evolving from its earliest forms of barter-based exchanges of goods and services. While effective in small, localized economies, this system was inherently limited by the "double coincidence of wants"—the need for two parties to have mutually desired goods at the same time (Jevons, 1875; Smith, 1776). The introduction of commodity money, such as gold, silver, and other valuable materials, addressed these inefficiencies by providing a standardized medium of exchange and enabling more flexible trade (Davies, 2002). However, the physical nature of commodity money presented challenges, including difficulties in transportation, storage, and valuation (Graeber, 2011).

As economies grew more complex, representative money emerged to address these limitations. Banknotes backed by tangible assets like gold reserves allowed for more portable and divisible financial transactions, making trade and commerce more efficient (Davies, 2002; Redish, 1993). This innovation also enabled the development of early financial services, such as lending and borrowing, which had been cumbersome with physical commodities (Quinn & Roberds, 2014). The eventual transition to fiat currencies, which is money that derives its value from government decree rather than physical backing, marked another pivotal shift. Fiat currencies offered greater flexibility in managing monetary policy and responding to economic crises, becoming the foundation of modern financial systems (Goodhart, 1998; Eichengreen, 2019).

Fiat-based systems, however, come with their own set of vulnerabilities. Although centralized control by governments and central banks has facilitated global commerce by providing stability, scalability, and liquidity (Goodhart, 1998; Eichengreen, 2019), it also introduces systemic risks. Centralized systems often struggle to adapt to rapid economic changes or crises, highlighting their fragility (Allen & Gale, 2000; Gorton & Metrick, 2012). Exacerbating these issues are high transaction costs, limited accessibility for the unbanked, and a lack of transparency in monetary policies (World Bank, 2021). According to the World Bank, over 1.4 billion adults worldwide remain unbanked, disproportionately affecting populations in developing economies.

The 2008 financial crisis brought these inefficiencies into focus. Driven by excessive risk-taking, opaque financial instruments, and inadequate regulatory oversight, the crisis led to widespread economic disruption and a loss of public trust in financial institutions (Brunnermeier, 2009; Allen & Carletti, 2010). As Gorton and Metrick (2012) observe, the lack of transparency in complex financial products like mortgage-backed securities amplified systemic risks. The crisis underscored the limitations of centralized systems, particularly their reliance on a small number of institutions that can fail due to poor decision-making or mismanagement (Reinhart & Rogoff, 2008).

In the aftermath of the crisis, fintech innovations emerged as a potential solution (Arner et al., 2015). Mobile payment platforms like M-Pesa, peer-to-peer lending networks such as LendingClub, and robo-advisors like Betterment have democratized access to financial services, addressing key challenges of traditional finance, including high costs and limited accessibility (Jack & Suri, 2011; Frame et al., 2018; Philippon, 2017). However, fintech innovations rely on intermediaries to function, binding them to centralized frameworks (Arner et al., 2015). This dependency reintroduces issues of control and trust, ultimately limiting their potential to fully transform financial systems.

Parallel to these developments, the financial industry sought to create digital money capable of blending the accessibility and efficiency of fintech with a decentralized framework (Downey, 1996). Early attempts, such as David Chaum's eCash in the 1990s, failed to gain traction due to reliance on centralized intermediaries, limited security, and scalability issues (Chaum, 1983; Green & Miers, 2017). These failures highlighted the need for a trustless system that could operate without centralized oversight (Maurer et al., 2013; Nakamoto, 2008).

The invention of blockchain technology in 2008 enabled the introduction of Bitcoin as the first truly decentralized digital currency, solving the longstanding 'double-spend' problem and enabling digital scarcity (Nakamoto, 2008). Blockchain's decentralized, transparent, and trustless design addressed many limitations inherent in centralized financial systems, marking a revolutionary shift in the financial landscape (Antonopoulos, 2014; Barber et al., 2012).

Subsequent innovations in blockchain technology, such as the introduction of smart contracts, further expanded its potential. Smart contracts, which are self-executing contracts with terms directly written into code, allow for automated and trustless execution of complex transactions without intermediaries (Szabo, 1997; Buterin, 2014). This innovation set the stage for decentralized finance (DeFi), which seeks to reimagine financial services such as lending, borrowing, and trading without relying on traditional intermediaries (Schär, 2021). Unlike previous fintech innovations, blockchain-based systems offer not only efficiency but also resilience against central points of failure, redefining the possibilities for financial inclusion and transparency (Narayanan et al., 2016; Gudgeon et al., 2020).

Within DeFi, decentralized exchanges (DEXs) like Uniswap have emerged as transformative platforms, leveraging automated market maker (AMM) models to replace traditional order books. As Lehar and Parlour (2023) highlight, Uniswap's innovative liquidity pool mechanism has demonstrated remarkable scalability and stability, handling daily trading volumes of up to $7 billion while addressing inefficiencies in traditional trading systems. These developments showcase DeFi's potential to challenge and complement existing financial structures while raising questions around governance and sustainability.

While blockchain technology and cryptocurrencies have garnered significant attention for their potential to transform the financial system, this promise is accompanied by substantial challenges. Emerging innovations like Bitcoin and decentralized finance (DeFi) aim to address limitations in centralized systems but simultaneously introduce new complexities. Technical inefficiencies, environmental impact, regulatory uncertainty, and the pseudonymity that facilitates illicit activities remain central barriers to broader adoption. These multifaceted issues underscore the importance of critically evaluating cryptocurrencies' viability as transformative financial instruments.

A core challenge lies in demonstrating the utility and scalability of cryptocurrencies beyond their current perception as speculative assets. While Bitcoin is often heralded as "digital gold," its adoption as a medium of exchange remains limited. Merchant adoption is hindered by price volatility, regulatory uncertainty, and integration difficulties with existing financial systems. Hileman and Rauchs (2017) highlight the lack of standardized payment solutions and banking relationships as critical barriers to broader adoption. Furthermore, speculative trading amplifies price instability, reducing cryptocurrencies' appeal as stable financial tools and hindering their scalability beyond emerging applications like decentralized finance (DeFi) and non-fungible tokens (NFTs) (Gandal & Halaburda, 2016; Aramonte et al. 2021).

Bitcoin's proof-of-work (PoW) consensus mechanism has also attracted substantial criticism for its environmental impact. Estimates suggest that global cryptocurrency electricity usage in 2022 ranged between 120 and 240 billion kilowatt-hours (kWh), comparable to that of Argentina or Australia (OSTP, 2022). Bitcoin alone accounts for 60-77% of this consumption and is responsible for an estimated 25-50 million metric tons of greenhouse gas emissions annually, comparable to emissions from diesel railroads (OSTP, 2022). Additionally, localized challenges such as electronic waste and grid strain exacerbate environmental concerns, even in renewable-powered mining operations. These issues highlight the urgent need for more sustainable alternatives, such as proof-of-stake (PoS) mechanisms, which consume significantly less energy (OSTP, 2022).

The inherent volatility of cryptocurrencies further hampers their adoption. Extreme price fluctuations, driven by speculative trading and investor herding behavior, undermine their role as a stable store of value or reliable medium of exchange. Yermack (2015) notes Bitcoin's annualized volatility rate of 142% in 2013, illustrating the risks associated with integrating cryptocurrencies into routine financial activities. Tools like the Cryptocurrency Volatility Index (CVIX) (Bonaparte, 2023) underscore the persistent unpredictability of these markets, deterring both consumers and institutions from embracing cryptocurrencies for everyday use.

Compounding these issues is the association of cryptocurrencies with illicit activities. Their pseudonymous nature facilitates money laundering, ransomware, and darknet transactions. Foley, Karlsen, and Putniņš (2019) estimate that nearly half of Bitcoin transactions are linked to illegal activity. The growing sophistication of criminal tools, such as mixers and cross-chain bridges, further complicates law enforcement efforts (Tziakouris, 2021). High-profile scandals like the collapse of FTX in 2022 erode public trust, despite advancements in blockchain analysis tools aimed at combating illicit use.

Finally, regulatory uncertainty remains a major barrier to cryptocurrency adoption. Inconsistent global policies create a fragmented regulatory landscape, complicating compliance for businesses and investors. Decentralized finance participants face legal and operational risks due to unclear regulations, as highlighted by Schär (2021). Moreover, resistance from traditional financial institutions exacerbates these challenges, with central banks perceiving cryptocurrencies as threats to monetary policy and financial stability (Auer & Claessens, 2022). The exploration of central bank digital currencies (CBDCs) reflects an institutional response to these disruptions but further delays the integration of cryptocurrencies into the financial mainstream.

Together, these challenges illustrate the complexities of integrating cryptocurrencies into broader financial systems. Addressing these barriers requires a nuanced understanding of their limitations and risks, balanced against their potential to revolutionize finance. This thesis contributes to this critical discourse by examining the societal and financial impacts of cryptocurrencies, focusing on environmental concerns, utility limitations, and governance issues. Through three distinct yet interconnected chapters, it provides insights into the transformative potential of cryptocurrencies while highlighting associated risks.

The first chapter evaluates Bitcoin's compliance with Environmental, Social, and Governance (ESG) criteria. While Bitcoin's energy-intensive Proof-of-Work (PoW) mechanism has drawn widespread environmental criticism, this chapter reexamines these claims using a novel forecasting model to project carbon emissions. It highlights the potential for renewable energy adoption and improved mining practices, showing how Bitcoin mining can stabilize energy grids by utilizing excess energy. The chapter also emphasizes Bitcoin's social benefits, such as promoting financial inclusion for unbanked populations, and its governance strengths, rooted in decentralized decision-making and transparency.

The second chapter explores GameFi as a case study in expanding cryptocurrency utility and adoption. By integrating blockchain technology, decentralized finance (DeFi), and non-fungible tokens (NFTs), GameFi creates decentralized digital economies where players and developers can monetize in-game interactions and assets. This chapter demonstrates how GameFi introduces real-world applications for cryptocurrencies, decouples blockchain use cases from speculative trading, and fosters sustainable economic activity through decentralized gaming ecosystems.

The final chapter examines PolitiFi, a novel application of cryptocurrencies in political finance. PolitiFi tokens engage underrepresented voter demographics, particularly younger, tech-savvy individuals, by simplifying political participation through decentralized platforms. By leveraging blockchain for campaign finance, these tokens enhance transparency, reduce reliance on elite donors, and offer innovative tools for real-time voter engagement and campaign strategy. This chapter also highlights how PolitiFi reflects and shapes voter sentiment, positioning these tokens as both financial instruments and vehicles for political narratives.

By bridging interdisciplinary approaches to sustainable finance, digital innovation, and governance, this thesis addresses pressing issues in cryptocurrency adoption and impact. Its findings contribute to academic discourse and policy-making by offering solutions to key challenges while uncovering opportunities for innovation in cryptocurrency and blockchain technologies.

Chapter 1: Is bitcoin ESG-compliant? A sober look

1.1. Citation

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1.2. Abstract

Much of the media focus surrounding Bitcoin (BTC) has been on the 'E' (environmental) element of the ESG investing approach. Given the amount of electricity consumed by BTC mining, and the resulting large carbon emissions, BTC has faced substantial criticism of its overly negative environmental impact, which is critically reviewed in this article. This one-sided discussion, however, ignores the 'S' (social) and 'G' (governance) elements entirely. To remedy that, we explore BTC's positive impact on the 'S' (user satisfaction, data protection and privacy, human rights, and criminal activity), and 'G' (accounting integrity and transparency, compensation, and principles of good governance) components.

1.3. Introduction

On October 28, 2008, a mailing list of known cryptographers received a white paper, entitled "Bitcoin: A Peer-to-Peer Electronic Cash System," from the pseudonymous Satoshi Nakamoto (Nakamoto, 2008). The idea of electronic cash (i.e., digital currency) was not exactly novel, as it had first been introduced by Chaum (1982). In the years since, many iterations of digital currency have been created, but all failed due to their inability to solve the "double-spend" problem. Digital assets (e.g., images, video, music) are simply unique combinations of binary code, and can thus be easily replicated by duplicating the code. The problem of how to prevent a digital asset representing a monetary value (i.e., a digital currency) from being duplicated and spent twice (the double-spend problem), however, was extremely difficult to resolve.

The underlying technology described in the Bitcoin[1] white paper had existed for some time. However, it was not until the creation of a unique combination, which led to the invention of blockchain technology and the discovery of true digital scarcity, that the double-spend problem was satisfactorily solved. As such, Bitcoin is the first functional digital currency that has not yet been hacked. Besides this remarkable innovation, Bitcoin also has numerous unique features: It is decentralized, permissionless, and fully transparent. Moreover, it requires no intermediaries, and follows a strict monetary policy, with a fixed maximum supply of 21 million bitcoin.

[1] Bitcoin: Denoted with a capital "B," it refers to the concept of Bitcoin – the technology, protocol, network, etc. Denoted with a lower case "b," it refers to the asset, or monetary unit of Bitcoin.

At its genesis, Bitcoin was broadly dismissed by the financial world. And, although its adoption has accelerated significantly, there remains fierce opposition. A multitude of narratives continue to dominate news cycles, articles, and even governmental debates (e.g., U.S. congressional hearings), including that it is used for criminal activity (Foley, Karlsen, and Putniņš, 2019), has no intrinsic value (García-Monleón, Danvila-del-Valle, and Lara, 2021; Hanley, 2015), is overly volatile (Yermack, 2015), involves too few transactions per second (Lee, 2019); is overly vulnerable to attacks (Malhotra et al., 2022), and, lastly, is environmentally harmful (Truby et al., 2022).

The latter narrative is of critical importance to ESG institutional investors interested in Bitcoin who may expect higher returns if the "E" is not tackled (Cornell, 2021) or simply be prevented from investing due to concerns of the potential valuation effect (Cornell and Shapiro, 2021; Krueger, Sautner, and Starks, 2020). Some of the negative narratives persist due to the broad lack of understanding of Bitcoin and how it functions. Although the proof-of-work (PoW) mechanism used by Bitcoin does consume enormous amounts of energy, it is instructive to evaluate the real environmental impact of this consumption against that of the industries it displaces. We should also consider the additional benefits it provides. The environmental narrative is a "low hanging fruit," so to speak, because it can more easily be estimated due to the digital and transparent nature of Bitcoin (vs. that of traditional industries). Common criticisms are that Bitcoin emissions alone could push global warming above 2°C, and that Bitcoin alone consumes as much electricity as a medium-sized European country. These critiques are not entirely unfounded, but nevertheless ignore Bitcoin's important social and governance contributions to the ESG discussion.

In this paper, we aim to evaluate Bitcoin's influence on the three ESG components (environmental, social, and governance) separately. By doing so, we contribute to the empirical evidence regarding ESG performance, enabling investors to make more informed and conscious decisions about investing in BTC from an ESG perspective (Larcker, Tayan, and Watts, 2022). Moreover, we consider the implications of observed governance structures on stakeholder welfare, as it relates to the decision-making process for Bitcoin's governance component, which aligns with Fama's examination of contract structures and stakeholder welfare in organizations (Fama, 2021). We begin with an assessment of Bitcoin's direct energy consumption, to estimate current and historical levels, and direct carbon emission as a proxy for the "E" (e.g., conserving natural resources). Next, we project a range for future energy consumption to determine how it may evolve (assuming Bitcoin mining continues in its current form). We note, however, that new methods may use less energy, reduce net carbon emissions (or achieve net negative carbon emissions), and even find uses for unwanted excess energy. Therefore, we posit that Bitcoin's current "E" score is underestimated, and that predictions about mining-related carbon emissions are most likely overrated.

We also develop a novel forecast model to estimate the Bitcoin mining-related carbon footprint to gauge its environmental impact. When relating it to the literature, we find that previous estimations of the carbon footprint have most likely been substantially overestimated for various reasons, such as unrealistic assumptions or inadequate prediction models.

In focusing on the "S", Bitcoin's extensive network allows for vast opportunities. For example, Bitcoin may be used to supply unbanked populations with financial services, such as storing wealth, transferring and receiving funds, and serving as an inexpensive remittance alternative. Furthermore, Bitcoin mining's probabilistic nature, and instant "*flip of a switch*" response feature, allows for the consumption of curtailed excess energy while providing a rapid demand response. This can aid greatly in stabilizing the grid and energy prices. By improving the economics of variable energy production, we believe Bitcoin mining will greatly facilitate the overall transition to renewables.

Within the "G" factor, two primary components significantly impact Bitcoin's governance: accounting integrity and transparency, as well as compensation. Accounting integrity ensures the accuracy, completeness, and consistency of financial information within the Bitcoin ecosystem. The mechanisms underlying Bitcoin's blockchain, including digital signatures and time-stamping, provide cryptographic proof of authenticity, effectively preventing fraudulent transactions. Furthermore, the blockchain maintains an immutable and comprehensive record of all transactions, allowing for comprehensive audits at any given time. Consistency is achieved through code that establishes a consistent set of rules for validating transactions, ensuring the integrity of the ledger. Transparency, a fundamental aspect of governance, is exemplified by Bitcoin's public and distributed ledger, enabling independent verification and auditing of transactions. Bitcoin's governance operates in a decentralized manner, with decisions made through consensus among network participants. The protocol facilitates proposals and voting on changes, granting participants a voice in the system's direction and evolution. By embodying accounting integrity, transparency, and decentralized decision-making, Bitcoin's governance aligns with the principles of good governance, including transparency, responsibility, accountability, participation, and responsiveness. Thus, accounting integrity and transparency play vital roles in evaluating Bitcoin's governance from an ESG perspective.

Moreover, Bitcoin aligns well with several of the United Nations' Sustainability Development Goals (U.N. SDGs). For example, #1: Ending poverty in all its forms everywhere; #7: Providing affordable and clean energy; and #10: Reducing inequality within and among countries. Bitcoin also scores high on the "G" (operating standards) factor. In fact, Bitcoin's governance is an almost ideal implementation of the U.N.'s Human Rights Council's five key attributes of good governance: transparency, responsibility, accountability, participation, and responsiveness. Therefore, it also supports U.N. SDG #16: Peace, justice, and strong institutions.

This paper is organized as follows. Section 1.4 describes how Bitcoin's overall ESG performance is assessed. Sections 1.5, 1.6, and 1.7 provide in-depth discussions of Bitcoin's contributions to the "E," "S," and "G" factors, respectively. Section 1.8 concludes.

1.4. Assessing Bitcoin's ESG Performance

Measuring an organization's ESG performance is never straightforward. But it is even more complex for a peer-to-peer network like Bitcoin. As of today, there is no universally accepted approach or method to measure ESG metrics. Companies are increasingly including disclosures in their annual reports or in standalone sustainability reports, but these metrics are not yet part of mandatory financial reporting. Several institutions, such as the Sustainability Accounting Standards Board (SASB), the Global Reporting Initiative (GRI), and the Sustainable Finance Disclosure Regulation (SFDR), are working to develop standards and define materiality to facilitate incorporating these factors into disclosure and reporting requirements. However, none of these standards or frameworks precisely defines ESG. As a result, a definitive taxonomy of ESG factors is lacking. ESG factors are also often interconnected, so it can be challenging to classify an ESG issue as solely an environmental, social, or governance issue.

To explore Bitcoin's performance on the "E," "S," and "G" factors, we first aim to find a common denominator with which to measure Bitcoin's contributions. To this end, we research numerous sources, such as the UN's definition of ESG, in order to ensure consistency with the UN's Sustainable Development Goals. During this process, we adjusted some elements of the factors to better fit the context of Bitcoin, which is a network, not a company. We note that the ESG factors were originally designed to fit companies.

We categorize the elements as follows, and discuss the factors in the subsequent sections.

- "E": 1. Energy, 2. Pollution, 2.a. Emissions, 2.b. Water, 2.c. Waste
- "S": 1. User Satisfaction, 2. Criminal Activity, 3. Data Protection and Privacy, 4. Human Rights
- "G": 1. Accounting Integrity and Transparency, 2. Compensation, 3. Principles of Governance

1.5. Environmental, “E”

A longstanding criticism of Bitcoin and its underlying mechanism, which is referred to as “proof-of-work” (PoW), is the amount of energy it consumes. Critics argue that the huge energy consumption needed to secure a distributed network and prevent fraud is wasteful. Total transaction value per year is a small fraction of total cash transactions, but Bitcoin consumes many magnitudes more energy, at about 100 TWh per year (or about 0.16% of global consumption). Mora et al. (2018) posit that, if Bitcoin were to scale at the median rate of several other technologies, its emissions could unilaterally warm the planet by 2 degrees Celsius within one to two decades. The network’s energy consumption is continuously monitored by the Cambridge Bitcoin Electricity Consumption Index (CBECI).

In 2012, amid mounting concerns about the energy consumption of nascent proof-of-work blockchains, Scott Nadal and Sunny King (pseudonym) designed the proof-of-stake (PoS) consensus mechanism for their competing blockchain, Peercoin. PoS uses only a fraction of PoW’s energy output because no physical or complex work is required to successfully append a block. In PoS, miners are replaced by validators or minters, which are essentially nodes that hold a pool of native blockchain coins. Owners allocate their coins to a node, and the node’s chance of being selected to append a block to the chain is proportional to the total percent of coins it is holding. Since its development, many PoS blockchains have emerged, such as Cardano, Avalanche, Solana, Algorand, Cosmos, Polkadot, and Tezos. The literature on PoS blockchains confirms they can generate consensus and maintain network security while achieving many more transactions per second for only a fraction of the energy consumption of a PoW blockchain. Nevertheless, there remain some nuances and caveats surrounding PoS.

First, the advantages of PoS come at a cost, one of which is neatly illustrated by the CAP theorem, which was developed by computer scientist Eric Brewer in the 1980s. The CAP theorem holds that, in any distributed data store, a compromise must always be made among consistency, availability, and partition tolerance (CAP). All three are necessary at different times, but only two can be guaranteed at all times. Blockchain technology, which constitutes an iteration of distributed data stores, suffers from a similar compromise, known as the Blockchain Trilemma: Security, decentralization, and scalability are all necessary, but only two can exist at any given time. Although each PoS blockchain approaches the trilemma differently, they sacrifice on security and decentralization at varying degrees for scalability and reduced energy consumption. It therefore becomes important to consider the objective and the use case of the blockchain.

Bitcoin, on the other hand, was designed as digital money, without a governing body. Therefore, a decentralized trustless digital currency system is essential to maintaining the integrity of the network and ensuring that transactions are valid and irreversible. Prioritizing security not only protects against malicious actors, but it also strengthens trust, the resilience of its independent network, resistance to censorship, and protects users from theft or fraud. Bitcoin's security feature aligns with the "G" (Governance) aspect by promoting transparency, accountability, and resilience. Bitcoin demonstrates a commitment to maintaining a robust and trustworthy financial system that can withstand external threats and ensure the integrity of its transactions. This aligns with the principles of good governance and responsible management of resources (see section 5).

In subsection *3.1. Bitcoin Mining*, we describe the mining process, and explain why it requires substantial energy resources. In subsection *3.2. Forecasting Bitcoin-Related Energy Consumption and Carbon Emissions* as well as *3.3. Energy and Emissions, 3.4. Water*, and *3.5. Waste*, we evaluate the "E" factor, under which we define how the Bitcoin network impacts the environment: 1. Energy, 2. Pollution, 2.a) Emissions, 2.b) Water, and 2.c) Waste.

1.5.1. Bitcoin Mining

Mining, performed by nodes, is the process of assembling blocks of Bitcoin transactions and hashing the data of that block. The SHA-256 algorithm is used to generate an output, with the number of leading zeros determined by current network difficulty. Difficulty in turn is determined by targeting an average number of blocks per hour. If blocks are produced too quickly, difficulty is increased. Therefore, because every additional leading zero increases difficulty exponentially, either more time or more computational power to perform hashing is required. With the shift from hashing using CPUs to application-specific integrated circuits (ASICs), rapid technological innovation in computing, and a strong economic incentive, the amount of active miners and total difficulty have skyrocketed.

For perspective, as of December 31, 2022, the total Bitcoin network had a hash rate of 253.1 million tera hashes per second (TH/s). This means, on average, 2.53×10^{20} hashes are required before a miner creates a block (~10 minutes) that meets the target difficulty and is accepted to be appended to the blockchain. The hash rate is a measure of the computing power provided by the miners in the Bitcoin network. It is estimated from the number of blocks being mined and current block difficulty, since the exact hashing power is unknown. This process is often referred to as "solving a math problem," and is commonly viewed as trivial and a waste of resources. However, it is what makes transactions final and Bitcoin's blockchain immutable. Note that, to modify a past transaction, the work (hashing) for that block, along with all subsequent blocks, needs to be redone in order to supplant the work done by the honest mining nodes. But, as subsequent blocks are added, and total network hash rate increases, modifying past transactions becomes virtually impossible.

Arguably, one reason Bitcoin has survived this long is due to its seemingly perfectly balanced incentive structure and underlying game theory (Han et al., 2012; Bengtsson and Gustafsson, 2022). Unlike equity, or other crypto currencies (alt coins), where early investors are afforded favorable terms, Bitcoin's supply is fairly awarded at a predetermined rate to the miner that successfully appends a new block. Initially, miners were awarded 50 BTC per block, which has halved every 210,000 blocks (~4 years) until today, where they currently receive 6.25 BTC. The limited supply and predictable issuance schedule have played an important part in the meteoric rise of bitcoin's price, which provides a strong incentive to contribute to the network by mining.

At its core, mining is a simple process that only requires a computer to run a mining node (program) and perform hashing computations. For a small-scale miner, the costs are just the hardware and the electricity it consumes. Revenue can be generated from the coinbase reward (for successfully appending a block), as well as from transaction fees for all the transactions included in the block.

Once in operation, two other variables can influence the economics: 1) the difficulty adjustment, which "tunes" the total difficulty based on total network hash rate and occurs every 2,016 blocks (approximately two weeks), and 2) the variable price. Miners do not earn revenue unless they successfully append a block, so an increase in network difficulty reduces the probability of success, despite the continuing costs of operation. Therefore, the average cost to mine a Bitcoin can theoretically be determined. And, if the bitcoin price remains above it, it is economically viable to mine.

However, generating a block that meets the difficulty target is purely probabilistic. As the network size grows, the average cost to mine a block becomes increasingly unreliable and may become economically unviable. To circumvent this problem, miners can contribute hash rate to a mining pool to generate scale. If the pool succeeds at mining a block, they will be compensated accordingly, minus a fee (Cong et al. 2019). Because of all these factors, scaling up a mining operation can be extremely lucrative. Larger-scale operations resemble data centers, with special electrical infrastructure to power the miners, a large area to house racks of miners, ventilation and cooling to mitigate heat waste, and an inexpensive energy source.

However, establishing a large mining operation, although lucrative, is also very capital-intensive. This is exacerbated by the fact that revenue is generated in bitcoin. Because of bitcoin's aggressive price appreciation during each so-called bull cycle, miners seek to maximize bitcoin accumulation, and only sell when necessary or most opportune. Thus, liquidating bitcoin to secure operating cash flow can hinder long-term earning potential.

This has led large mining operations to go public, particularly since 2021, mainly via SPACs, to gain ready access to capital (Cumming, Haß, and Schweizer, 2014). In these cases, the sizes of their operations have grown exponentially. For example, Bitfarms reported an average of 1.2 EH/s in Q1 2021, which grew to 4.5 EH/s by 2022 year-end (see Bitfarms, 2023). The megawatt capacity of their facilities has evolved from 14 MW in 2017, to 69 MW in 2020, 106 MW in 2021, and 188 MW in 2022.

The mining process by design tethers the digital network to the physical world by requiring costly real work be done. The method is both simplistic and designed to be scalable. The incentive mechanism for miners ensures that new coin supply is issued as transactions are processed. Moreover, as the value of the network (market capitalization) grows, the security of the network must also scale up. Network security is encompassed by total network hash rate and network difficulty, which ultimately means more hashing is needed to successfully append a block. This results in higher costs in electricity consumption per block, meaning that any dishonest actors must expend increasing amounts of capital to modify a block or include an invalid transaction. The cost of conducting a fraudulent transaction has grown to the extent that it would only really be possible for select nation states, and only for a short time. However, the network is further protected by its incentives. In this way, more favorable economic outcomes accrue for honest contributions to the network.

1.5.2. Forecasting Bitcoin-Related Energy Consumption and Carbon Emissions

In this section, we explore the future energy consumption and carbon footprint of the Bitcoin network by developing a forecast model that links bitcoin price distribution to the mining hash rate. The latter approximates the computational power of the Bitcoin network that can be used to estimate related energy consumption and CO_2 emissions.

Note that prior studies that attempted to estimate Bitcoin's energy consumption and related carbon footprint either used incorrect assumptions and/or made manual mistakes. These resulted in highly overstated numbers. However, these studies were frequently picked up by the popular media, and have contributed to the negative narrative surrounding Bitcoin. We aim to counter the prior false assumptions by providing recent and more accurate estimates and forecasts about Bitcoin's energy consumption and carbon emissions.

1.5.2.1. Methodology

Previous studies have researched the connection between hash rate and bitcoin prices and often used hash rate movements to predict bitcoin prices, and vice versa (e.g., Fantazzini and Kolodin, 2020; Hayes, 2019; Aoyagi and Hattori, 2019). Hash rate, energy efficiency, and production cost are the input factors. We build our prediction model following Fantazzini and Kolodin (2020), who find evidence for the existence of a unidirectional Granger causality and cointegration from bitcoin price to hash rate. This type of relationship between the commodity price and extraction/excavation equipment is well established in energy economics.

Economic reasoning suggests that the commodity price (for example, oil prices/returns) affects demand for the equipment (for example, drilling rigs), but not vice versa (see, e.g., Khalifa, Caporin, and Hammoudeh, 2017). Following previous research, we focus on the bivariate relationship between hash rate and bitcoin price, rather than using multivariate models such as production cost models. To model the relationship, we estimate a bivariate VAR model, as an extension to AR or ARIMA models allowing for multiple independent variables but without enforcing a causal relationship between hash rate and bitcoin price. Past research found a long-run relationship between bitcoin price and various factors, including bitcoin supply, investor sentiment, hash rate, market capitalization, and gold prices (see, e.g., Zwick and Syed, 2019; Dubey, 2022; Gaies et al., 2023). To allow for a possible long-run relationship between bitcoin price and hash rate, we also consider a VECM model as an extension to the VAR model, as follows (see also Fantazzini and Kolodin, 2020; and Sa-ngasoongsong et al., 2012):

1. We test for structural breaks in the data, which could result from, e.g., the three previous halving events that led to a reduction in the mining reward (November 28, 2012; July 9, 2016; May 11, 2020).

2. We then test for stationarity, and identify the order of integration and optimal VAR lag-length using information criteria. We also test for the existence of a long-run relationship using a cointegration rank test. We determine the optimal VECM model in case of such a relationship.

If we find evidence for a statistically significant unidirectional relationship between the bitcoin price and hash rate, we use bootstrapping (random sampling with replacement) of actual biweekly bitcoin returns. Based on our results for structural breaks, we are able to determine the start date of the observation period for the bootstrapping. Furthermore, applying a Monte Carlo bootstrapping technique allows us to simulate a bitcoin price trajectory distribution.[2] We can then use dynamic one-step-ahead forecasting with our

[2] We bootstrap 5,000 x 100 biweekly Bitcoin returns, which will be used to generate 5,000 possible Bitcoin price trajectories for a 200-week forecast period.

model framework (VAR or VECM) to estimate 100 subsequent biweekly expected hash rates, depending on simulated bitcoin prices. We roll the window for the model parameter estimation forward so that the latest bootstrapped bitcoin return is included in the parameter estimation for the subsequent forecast.

The advantage here is that we can avoid long forecast periods without updating estimation parameters or bitcoin prices. We can then convert the hash rate to energy consumption, based on miner efficiency. Finally, we can convert into a CO_2 consumption estimate based on the respective country's contribution to the hash rate (using data from the Cambridge Centre for Alternative Finance). The carbon footprint in turn is based on the energy production sources (e.g., hydro or nuclear) in the countries that contribute to the hash rate (using data from IEA statistics).

1.5.2.2. Data

Average hash rate is measured in exa hashes per second (EH/s), and has been obtained from www.BTC.com on a biweekly basis since the first block was mined on January 3, 2009. Bitcoin (BTC) prices in USD are obtained from CoinGecko, and are based on the global volume-weighted average beginning April 30, 2013, and ending July 7, 2022. Combining both datasets, we obtain a sample of 254 biweekly observations.

Table Chapter 1-1 describes our data and sources. Figure Chapter 1-1 shows the development of average hash rate in EH/s (blue line) compared to BTC price in USD (red line). We calculate CO_2 emissions per EH/s by country based on data from the International Energy Agency.

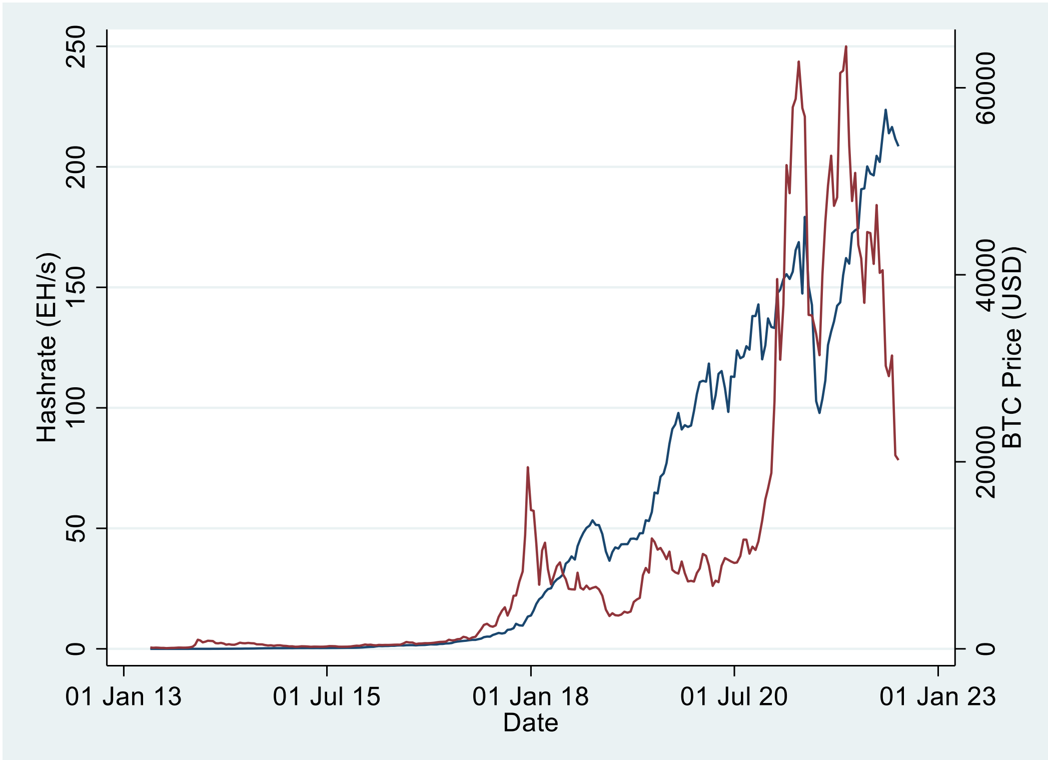
Table Chapter 1-1: Variable Description

This table summarizes the data used and provides a description of their calculations as well as the database from which it is obtained.

Variable Name	Description / Calculation	Database
Bitcoin price (USD)	CoinGecko provides the Bitcoin price based on a global volume-weighted average price, beginning April 30, 2013 (see https://www.coingecko.com/en/coins/bitcoin).	CoinGecko
Average Hash Rate	BTC.com provides biweekly statistics for average hash rate beginning January 27, 2009 (see https://btc.com/stats/diff).	BTC.com
CO_2 Emissions	International Energy Agency (IEA) Emissions Factors – CO_2 emissions per kwh of electricity only (gCO2/kWh) (see https://www.iea.org/data-and-statistics).	IEA Emissions Factors
Hash Rate Country Split	Average monthly hash rate share by country and region, based on geolocation of mining pool data (see https://ccaf.io/cbeci/mining_map).	Cambridge Centre for Alternative Finance

Figure Chapter 1-1: Hash Rate and BTC Price

This figure shows average hash rate development (in EH/s) and average Bitcoin price (in USD) from April 30, 2013 to July 7, 2022.



1.5.2.3. Results

In line with the literature, we use log-transformed variables in our analysis, as both EH/s and BTC are highly skewed. We first analyze whether the log-transformed hash rate and the bitcoin price time series are stationary and have structural breakpoints. To this end, we employ a series of tests, including the traditional Dickey-Fuller test (DF); the Zivot and Andrews test (ZA), which allows for one structural break; and the Clemente-Montañés-Reyes test (CMR), which allows for two structural breaks (see Clemente, Montañés, and Reyes, 1998; Perron and Vogelsang, 1992; Zivot and Andrews, 1992).

The bitcoin price literature shows that testing for structural breaks is important in the crypto asset space. Such events include halving approximately every four years, the introduction of derivatives (2011), the introduction of Bitcoin ETFs (2021), and bitcoin booms, such as in 2013 (2014-2015 crash), 2017 (2018 crash), and 2020 (2022 crash). These events could cause a structural break in the time series, which may bias models and forecasts (see, for example, Corbet, Lucey, and Yarovaya, 2018; Fry, 2018; and Fantazzini and Kolodin, 2020). Test results are in Table Chapter 1-2.

The Dickey-Fuller test statistics show that the bitcoin price time series was not stationary over the sample period. This is in line with the literature on bitcoin prices, and with the findings of Fantazzini and Kolodin (2020) (see Table Chapter 1-2, and Figure Chapter 1-8 in Appendix A). However, we cannot reject the stationary hypothesis for the hash rate for all tests. Based on the structural break tests by Zivot-Andrews (1992) and Clemente-Montañés-Reyes (1998), we find support for at least one structural break for bitcoin prices. However, both suggest that the first break occurred in Spring 2017.

We opt to use the Clemente-Montañés-Reyes test to begin our sample period, which indicates a breakpoint on March 17, 2017. This is very close to that identified by Zivot-Andrews (see Table Chapter 1-2). We choose Clemente-Montañés-Reyes's test because it is an "innovation outlier" test and therefore allows for a gradual shift in time series data. Because we use bootstrapping to forecast a bitcoin price distribution in our later analysis, we should only consider historical observations. These do not feature any break in their overall trends. We therefore believe this test provides the most useful breakpoint information for our purposes.

We establish a subsample beginning after the breakpoint, from March 17, 2017, to July 7, 2022, for further analysis. This is the most recent period. It is arguably the most representative for future bitcoin price development, because it includes periods of steep price appreciation and depreciation as well as periods of stability.

Table Chapter 1-2: Test for (Trend) Stationarity and Structural Breaks

This table shows the results for different unit root tests for the log-transformed variables and their differences in order to test for level of integration $I(1)$, allowing for breakpoint(s) with the null hypothesis (H0): The time series variable has a unit root ("Dickey-Fuller with trend"). Clemente-Montañés-Reyes (IO) refers to the "innovation outlier" test, allowing for a gradual shift in the mean of the series. ***, **, * indicate we cannot reject H0 of the unit root at the 1%, 5%, 10% significance levels, respectively.

Test	Variable	Test statistics	crit. value 5%	Break Date(s)
Dickey-Fuller with trend	Log(EH/s)	-6.908***	-3.43	./.
Dickey-Fuller with trend	Log(BTC)	-1,757	-3.43	./.
Zivot-Andrews	Log(BTC)	-3.432	-4.80	Apr 13, 2017
Clemente-Montañés-Reyes (IO)	Log(BTC)	-4.581	-5.49	Mar 17, 2017 Oct 4, 2020
Dickey-Fuller with trend	D.Log(EH/s)	-11.089***	-3.43	./.
Dickey-Fuller with trend	D.Log(BTC)	-13.366***	-3.43	./.

In the next step, we determine the optimal lag structure to estimate a stationary VAR model. We also test for causality, as per Toda and Yamamoto's (1995) approach, to account for integration. We use the following equations for log-transformed variables, EH/s_t and BTC_t:

$$EH/s_t = \mu_1 + \sum_{i=1}^{p+m} \alpha_i EH/s_{t-1} + \sum_{i=1}^{p+m} \beta_i BTC_{t-1} + u_{1t}, \quad (1)$$

$$BTC_t = \mu_2 + \sum_{i=1}^{p+m} \gamma_i BTC_{t-1} + \sum_{i=1}^{p+m} \delta_i EH/s_{t-1} + u_{2t}, \quad (2)$$

where μ is the constant term, m is the maximal order of integration of the variable, and p is the optimal lag lengths for the hash rate (EH/s_t) and bitcoin price (BTC_t). $\alpha_i, \beta_i, \gamma_i,$ and δ_i are the short-run dynamic coefficients. The error terms are assumed to be white noise.

To perform the Toda and Yamamoto (1995) test, we need to determine the order of integration for each variable. For the full sample, we find that the bitcoin price is integrated at $I(1)$, but the hash rate is not (see Table Chapter 1-2). In unreported results, however, we find that both variables are integrated at $I(1)$ for the subsample period according to a DF test. So we set $m = 1$ for both the full sample and the subsample. We use the Final Prediction Error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC) to identify the optimal lag-order for the VAR model (see results in Table Chapter 1-3). We find ambiguous results for our full sample, so we opt for both $p = 3$ and $p = 1$, and test for any remaining autocorrelation in the VAR model by using a Lagrange multiplier test. The test shows that H0 (no autocorrelation) cannot be rejected if we use $p = 3$, but it is rejected at the 1% level if we set $p = 1$. We also cannot reject H0 for our subsample with $p = 1$.

Table Chapter 1-3: Optimal Lag

This table summarizes the outcome for optimal lag choice according to AIC, HQIC, and SBIC for the full sample and subsample.

Variable	Optimal Lag (FPI)	Optimal Lag (AIC)	Optimal Lag (HQIC)	Optimal Lag (SBIC)
Full sample	3 (-0.0001)	3 (-3.4424)	1 (-3.3783)	1 (-3.3269)
Subsample	1 (-0.0001)	1 (-3.1800)	1 (-3.1292)	1 (-3.0551)

In sum, for the full sample, we set $p + m = 4$, and, for our subsample, we set $p + m = 2$. Following Toda and Yamamoto (1995), we perform Granger causality (the Wald test) on the unrestricted [restricted] VAR using $p + m$ [p only]. We find a significant causal relationship from hash rate to bitcoin price (p = 0.0002) [p = 0.0000] for our full sample, and for our subsample (p = 0.0986) [p = 0.0408]. We also observe a significant causal relationship from bitcoin price to hash rate for our full sample (p = 0.0686) [p = 0.0222], but not the subsample (p = 0.2553) [p = 0.6274] using the (unrestricted) [restricted] VAR models.

Next, we test for cointegration using a Johansen test. We consider VECM as an alternative to the previous VAR model in case of a long-run relationship between hash rate and bitcoin. We use the following equations for log-transformed variables EH/s_t and BTC_t:

$$\Delta EH/s_t = \mu_1 + \sum_{i=1}^{p-1} \alpha_i \Delta EH/s_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta BTC_{t-1} + \lambda_1 ECT_{t-1} + \tau_1 t + u_{1t}, \qquad (3)$$

$$\Delta BTC_t = \mu_2 + \sum_{i=1}^{p-1} \gamma_i \Delta BTC_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta EH/s_{t-1} + \lambda_2 ECT_{t-1} + \tau_2 t + u_{2t}, \qquad (4)$$

$$ECT_{t-1} = \mu_3 + \zeta_j BTC_{t-1} + \rho_1 t, \qquad (5)$$

where μ is the constant term, p is the optimal lag lengths, $\alpha_i, \beta_i, \gamma_i, \delta_i,$ and ζ_j are the dynamic coefficients of the model's adjustment to long-run equilibrium, λ_i is the speed of the adjustment with negative sign, and ECT_{t-1} is the error correction term (the lagged value of residuals obtained from cointegrated regression). It contains the long-run cointegration relationship, with ρ representing the trend.

Following our results for the VAR model, we assume a maximum lag of three for the full model, and one for the subsample on which we perform the Johansen test of cointegration with trend. For our full sample, the trace value (73.14) for rank = 0 exceeds its critical value at the 1% level (30.45), and we can reject the null hypothesis of no cointegration. At rank = 1, the trace value (6.26) is less than its critical value at the 1% level (16.26). Thus, we fail to reject the null hypothesis. Based on the Johansen test, there is one cointegration relationship between our two variables. For our subsample, we fail to reject the null hypothesis for no cointegration assuming a trend (trace value = 16.28, with critical value = 23.46) at the 1% level, but not the 10% level.

Table Chapter 1-4 reports the estimation results for our full sample, using the VECM model with trend (and the VAR model as a robustness check), and the VAR model for our subsample (with the VECM with trend as a robustness check). We also conduct a series of post-estimation tests, and find no remaining autocorrelation. Our estimation fulfills the unit root requirement. However, error terms for some equations are non-normally distributed.

In the final step, we conduct an out-of-sample forecast on the average hash rate to test respective forecast quality using dynamic forecasting. To this end, we re-estimate our models in Table Chapter 1-4, removing the last thirteen (seven) observations, half a year (three months) from the estimation. We then compare the actual observed values with the forecasted values for the hash rate to visualize forecast accuracy.

Figure Chapter 1-2 plots the average observed hash rate and the respective forecasts.

Furthermore, we calculate a series of measures of forecast accuracy, including root mean squared error (RMSE), mean absolute error (MAE), mean absolute percent error (MAPE), and Theil's U. According to these measures, our preferred models, which outperform the other choices on average, are the VEC for the full sample and the VAR for the subsample. Overall, the VAR model for the subsample seems to produce the best short-term forecasts (see Table Chapter 1-5).

Subsequently, we use bootstrapping of biweekly bitcoin returns to estimate 5,000 bitcoin price trajectories for a 200-week period (four years). This allows us to estimate the bitcoin price distribution at any point over the next four years. One advantage of this method is that we do not need any distribution assumptions. The technique is well established in the financial literature for estimating, e.g., a distribution of returns, or for assessing the predictive ability of technical trading rules.

Table Chapter 1-4: Estimation Results

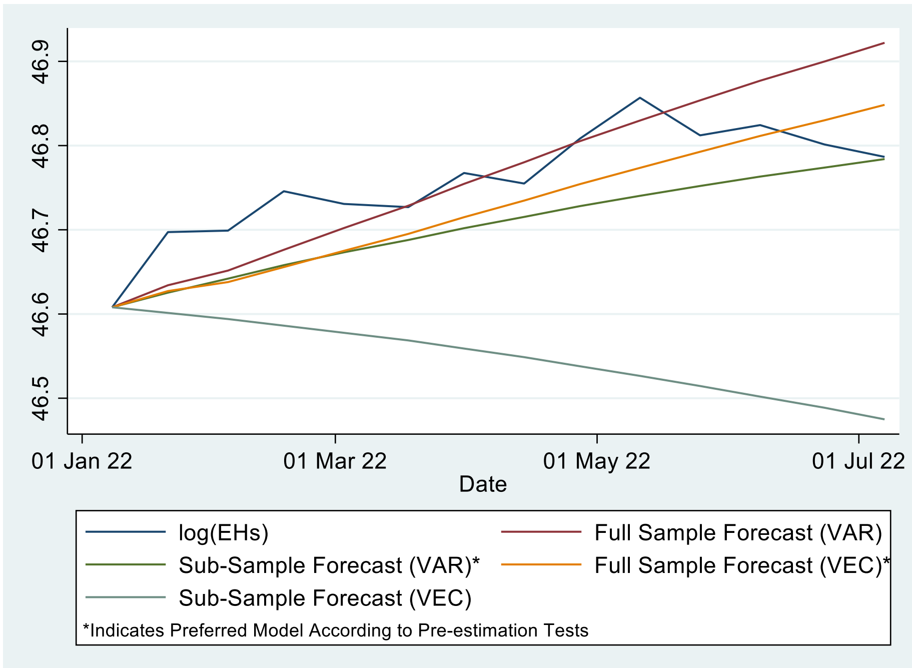
This table shows the estimation results for our VAR and VECM models for the full sample (April 30, 2013-July 7, 2022) and subsample (March 17, 2017-July 7, 2022). Formatting in "bold" indicates the main model is based on the pre-estimation test. If a variable estimate is not filled, it means it was not estimated based on the pre-estimation test, or is not required for the model. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample		**Subsample**	
VAR / VECM	**VAR** $(p=3, m=1)$	**VECM** $(p=3, r=1)$	**VAR** $(p=1, m=1)$	**VEC-Model** $(p=1, r=1)$
		Eq. (1), (3), (5)		
L1.EH/s / ΔL1.EHs	1.0605***	0.0791	0.9681***	
L2.EH/s/ ΔL2.EHs	0.0310	0.1071*		
L3.EH/s	-0.1145*			
L1.BTC/ ΔL1.BTC	0.0389	0.0127	0.0190**	
L2.BTC/ ΔL2.BTC	0.0322	0.0439*		
L3.BTC	-0.0476*			
μ_1	-0.1067***	0.02476*	-0.01935	-0.0006***
τ_1		-0.0001		0.0710***
λ_1		-0.0205***		-0.0004**
ζ_j		-1.5111***		-62.1496***
μ_3		7.4913	-0.01935	510.9624
p_j		0.0109		0.9843
		Eq. (2), (4)		
L1.EH/s / ΔL1.EHs	0.0189	0.0327	-0.0095	
L2.EH/s/ ΔL2.EHs	0.4279*	0.4599***		
L3.EH/s	-0.4299***			
L1.BTC/ ΔL1.BTC	1.16867***	0.1950***	0.9771***	
L2.BTC/ ΔL2.BTC	-0.2413**	-0.0492		
L3.BTC	0.0456			
μ_2	-0.1067**	0.0302	0.2712*	0.0352
τ_2		-0.0001		-0.0003
λ_2		0.0171**		0.0008*
Nobs	251	251	142	142
R^2 (Eq1) / R^2(Eq3)	0.9997	0.6471	0.9962	0.2144

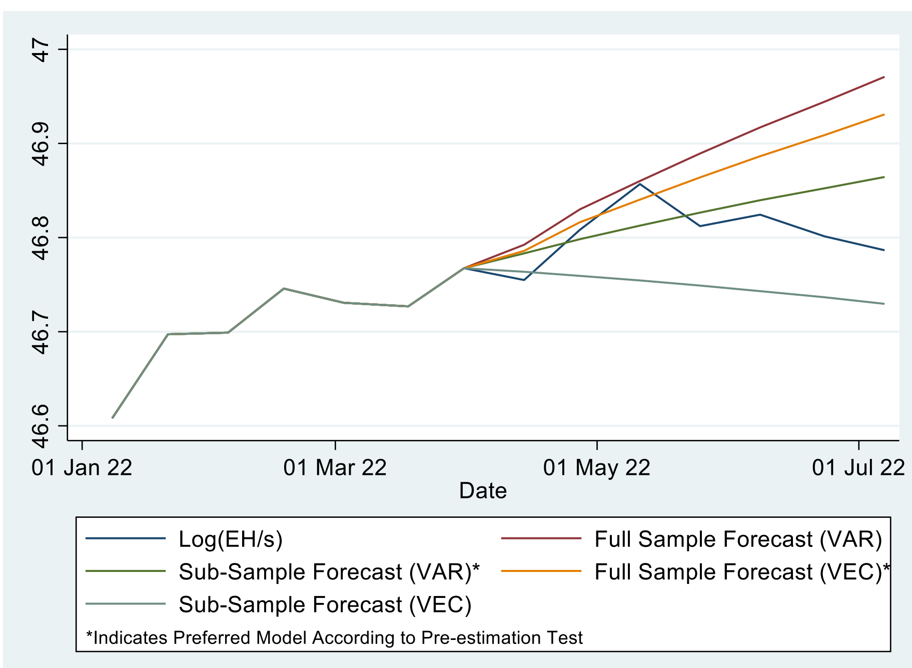
Figure Chapter 1-2: Hash Rate Price - Out-of-Sample Forecast

This figure shows out-of-sample forecasts for Log(EH/s) using VAR and VEC models as specified in Table 4 and adjusted for the data calibration period starting April 30, 2013 and ending January 8, 2022 for the full sample (Panel 1) and starting March 17, 2017 and ending March 13, 2022 for the subsample (Panel 2). Observations after the calibration period through July 7, 2022, are used to estimate forecast quality.

Panel 1:



Panel 2:



Note that our goal is not to forecast actual bitcoin prices, but to gain a fuller understanding of the expected bitcoin price trajectory distribution, including tails (see Kachnowski, 2020; Ruiz and Pascual, 2002; Trimono et al., 2021). Based on the sample of biweekly bitcoin returns during the subperiods beginning March 17, 2017, and July 7, 2022, we bootstrap 5,000 x 100 biweekly bitcoin returns (four-year period). The cumulative return path is converted into a bitcoin price trajectory. In total, we thereby simulate 5,000 possible bitcoin price trajectories over the subsequent four years. It also makes economical sense to use the aforementioned subperiod, because Bitcoin has matured greatly since its introduction. The course of its movement patterns and overall economic importance have shifted significantly.

Table Chapter 1-5: Forecast Quality

This table shows the root mean squared error (RMSE), mean absolute error (MAE), mean absolute percent error (MAPE), and Theil's U for our various models using the data covering April 30, 2013-January 8, 2022 for our full sample, and March 17, 2017-January 8, 2022 for our subsample to calibrate our models, and data from January 21, 2022-July 7, 2022 to estimate forecast quality. Bold indicates best forecasting model for the respective sample, and the cursive best model overall according to the different forecast quality measures.

	VAR (full sample)	**VEC (full sample)**	**VAR (subsample)**	**VEC (subsample)**
6-month (13-observation) forecast				
RMSE	0.0595	0.0548	0.0650	0.2401
MAE	0.0467	0.0493	0.0589	0.2255
MAPE	0.0010	0.0011	0.0013	0.0048
Theil's U	1.5032	1.3864	1.6433	6.0667
3-month (7-observation) forecast				
RMSE	0.1006	0.0758	0.0413	0.0665
MAE	0.0799	0.0602	0.0344	0.0609
MAPE	0.0017	0.0013	0.0007	0.0013
Theil's U	2.9282	2.2069	1.2026	1.9367

Figure Chapter 1-3: Cumulative BTC Log-Return Simulation and Resulting Log (BTC)

This figure illustrates the transformed-to-log (BTC) prices over 100 periods calculated from the first ten cumulative bitcoin log-return Monte Carlo simulations (1 period is equal to 2 weeks).

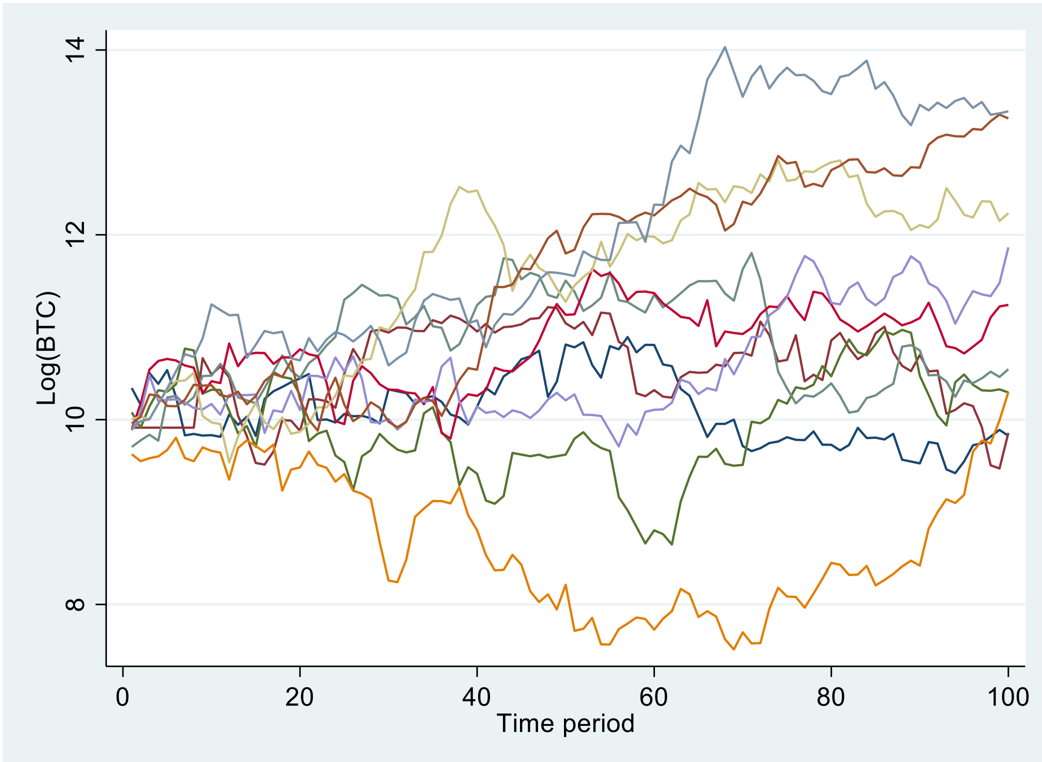


Figure Chapter 1-3 illustrates the first ten cumulative bitcoin log-return simulations transformed-to-log (BTC) prices. In the following analysis, we are interested in the median expected bitcoin price, as well as the 95% upper and 5% lower bounds for expected bitcoin prices over the next 100 observations (or four years for the 5,000 bitcoin price trajectories). To obtain a more robust estimate for the 95% upper and 5% lower bounds, then we take the average over 10% best- and (worst-) performing simulation paths for bitcoin price trajectories, based on the observed outcome in t = 100 (end of year 4). We calculate the median by taking the average of the 45% and 55% quintiles for bitcoin price trajectories. We can then use the forecasted bitcoin prices to obtain updated forecasts for the expected hash rate.

In sum, we conduct a dynamic forecast updating model parameters and bitcoin prices (based on our bootstrapping approach) for each subsequent biweekly period. In this way, we can obtain the hash rate over the subsequent four-year forecast period.

Figure Chapter 1-4: Hash Rate Price – Out-of-Sample Forecast

This figure displays the long-term dynamic out-of-sample forecasts (LT) for the Hash Rate - Log(EH/s) - using the VAR (*p*=1, *m*=1) model and bitcoin price simulations for the subsample period for calibration. It includes the 5% lower and 95% upper credible bounds with dynamic forecasting. UPD, demonstrates how dynamic forecasts evolve by predicting hash rate using updated outcome values from previous periods, spanning a total of 100 observations or four years.

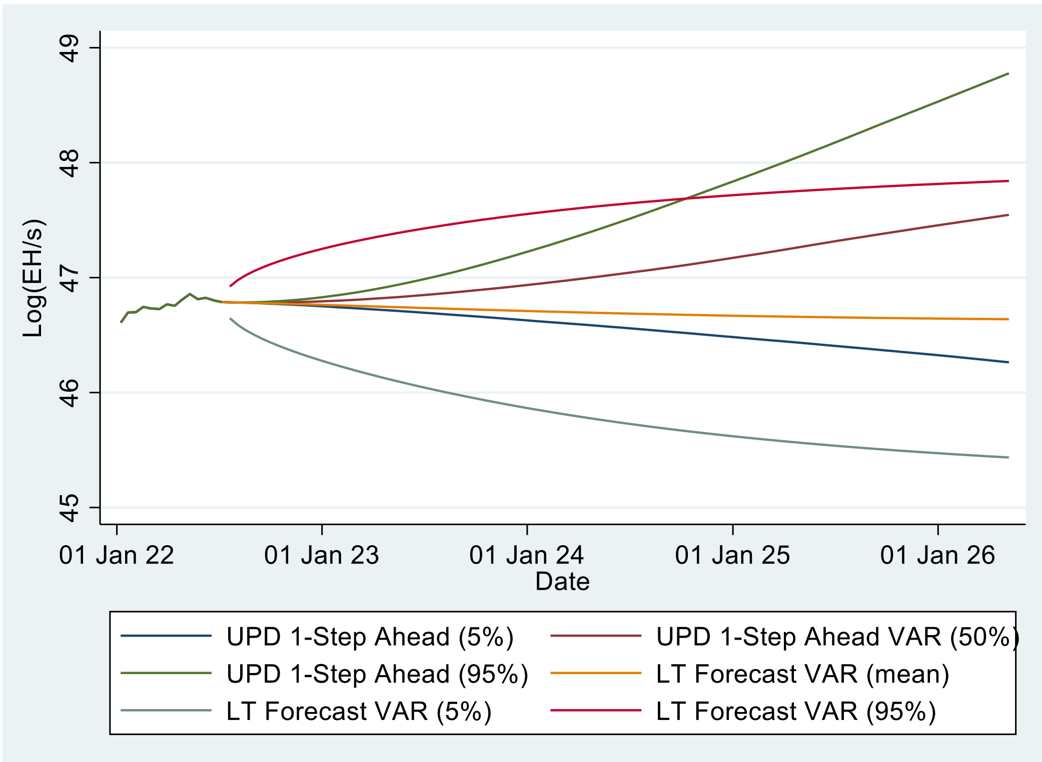


Figure Chapter 1-4 illustrates the long-term out-of-sample forecasts for our VAR ($p = 1, m = 1$) model specified in Table Chapter 1-4 (using the subsample period to calibrate the model). It includes 95% lower and upper credible bounds using dynamic forecasting (with and without bitcoin price simulations). For comparison purposes how dynamic forecasts change, Figure Chapter 1-4, UPD, predicts hash rate and bitcoin prices for the next period by using updated (predicted) outcome values at previous periods, for a total period of 100 observations (four years).

However, this prediction does not update bitcoin prices, and is thus rather static. We modify our dynamic forecast in two ways: 1) We replace the bitcoin price with our price simulations, and 2) we re-estimate the VAR model with the updated information for each new estimate. Figure 4, LT, shows our prediction results for the average hash rate using median expected bitcoin, as well as the 95% upper and lower bounds.

1.5.3. *Energy and Emissions*

To calculate Bitcoin's energy consumption, we convert our forecasted hash rate into Bitcoin's carbon footprint. We use forecasted computing power (hash rate) to draw conclusions about required power consumption. Table Chapter 1-9 in Appendix A provides an overview of Bitcoin miners, and reports average hash rate, power consumption (watts), and profitability (as of July 7, 2022), sorted by manufacturer and model.[3] Based on the observable average hash rate of the Bitcoin network, which was 208.52 EH/s (see Figure Chapter 1-1 on July 7, 2022), the mean hash rate (in TH/s) for the average profitable single Bitcoin miner is 90.3 TH/s. Average required energy consumption would be 3,254 watts (see Table Chapter 1-6).

Table Chapter 1-6: Average Profitable Bitcoin Miner's Hash Rate and Power Consumption

This table shows for various profitable Bitcoin miners the average Hash Rate and energy consumption based on the market share.

Manufacturer	Average Age (Oldest Profitable)	Hash Rate (in TH/s)	Power (in W)	Efficiency (in W/TH)	Revenue (in $/day)	Profit (in $/day)	Market Share
Bitmain (Antminer)	2.0 (3.7)	93.0	3,124	33.6	8.57	4.08	59%
Canaan (Avalonminer)	1.5 (2.0)	84.8	3,404	40.1	7.82	2.94	9%
MicroBT (Whatsminer)	1.8 (3.4)	92.3	3,600	39.0	8.51	3.30	27%
Others	2.9 (3.1)	57.6	2,655	46.1	5.30	1.48	5%
Mean (Profitable Miner)		90.3	3,254	36.3 ± 5%	8.32	3.64	

To provide computing power of 208,520,000 TH/s, we would need 2,309,191 (= 208,520,000 TH/s/90.3 TH/s) average miners. Given the average rate of power flow per miner of 3,254 watts, the total power of the Bitcoin network needed is calculated as 7,514 MW (= 3,254 watts x 2,309,191/1,000,000) to run the network for one hour, or 65.82 TW per year (= 7,514 MW x 24 x 365/1,000,000). To calculate total CO_2 emissions, we need to consider the energy source, e.g., whether renewable or coal. We therefore assess the percentage contributed by each country to the hash rate, the related energy consumed, and the related CO_2 emissions in the respective country to calculate total CO_2 needed to power the Bitcoin network for one year (see Table Chapter 1-7).

[3] See https://hashrateindex.com/rigs or https://miningstore.com/understanding-the-bitcoin-mining-rig-market/.

Table Chapter 1-7: Hash Rate, Energy Consumption, and CO2 Emissions per Country

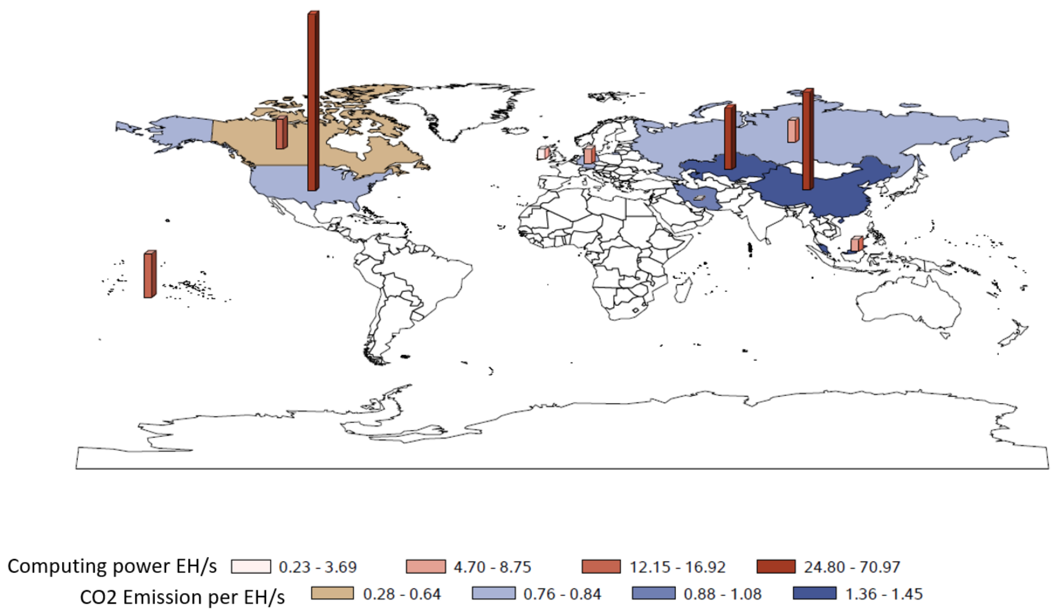
This table presents the computation of the total CO_2 emissions associated with powering the Bitcoin network for one year, taking into account the varying energy sources used, whether e.g. renewable or coal-based. It evaluates the percentage contribution of each country to the total Hash Rate, and by extension, the energy consumed and the related CO_2 emissions specific to each country. These figures are then aggregated to provide an estimation of the total annual CO_2 emissions necessary to sustain the Bitcoin network.

Country	% Total Computing Power	Total TW/ Year	kg CO2/MW	Tons CO_2	% Total	% Total CO_2 / % Total Hash Rate
Iran, Islamic Rep.	0.1%	0.1	492.2	32,397	0.1%	1.08
Malaysia	2.5%	1.6	662.1	1,089,507	3.6%	1.45
Russian Federation	4.7%	3.1	374	1,157,006	3.9%	0.82
Canada	6.5%	4.3	129.1	552,339	1.8%	0.28
Kazakhstan	13.2%	8.7	637.4	5,537,992	18.5%	1.40
Mainland China	21.1%	13.9	622.4	8,644,072	28.8%	1.37
United States	37.8%	24.9	382.4	9,514,282	31.7%	0.84
Germany *	3.1%	2.0	344.5	702,938	2.3%	0.76
Ireland *	2.0%	1.3	294.1	387,161	1.3%	0.65
Other	9.0%	5.9	403.4	2,389,767	8.0%	0.88
Total	100.00%	65.8	455.9	30,007,462	100.0%	

Figure Chapter 1-5 provides an overview of the countries that contribute significantly to the network's computing power and their respective CO_2 emissions (see Table Chapter 1-7 as well for details). In sum, our calculations show that, as of July 7, 2022, and assuming everything remains constant, the energy needed to power the Bitcoin network for one-year yields about thirty mTons of CO_2 per year.

Figure Chapter 1-5: Computing Power and CO2 Emissions by Country Related to Bitcoin Mining

This figure illustrates computing power by country and is based on CBECI data from January 2022 (https://ccaf.io/cbeci/mining_map). CO_2 emissions per EH/s by country are calculated based on data from the International Energy Agency.



To estimate the carbon footprint going forward, we use three scenarios: base case, upper bound, and lower bound. These are based on simulated bitcoin prices and implied hash rates (averaged over the 10% worst- (best-) performing, as well as median hash rate trajectories). The base case scenario in Table 8 can be viewed as the expected CO_2 emissions of the Bitcoin network. It reveals that they roughly double to about sixty-four mTons. The upper bound predicts a staggering emission level of about 220 mTons; the lower bound predicts about 18 mTons (see again Table Chapter 1-8). However, these scenarios do not consider the miners' increase in energy efficiency, or that many regions, such as the EU, are committed to increasing their percentage of renewable energy. Mining may therefore shift to countries like Canada, which already has the highest percentage of renewable energy as well as low energy costs. Moreover, any shift toward innovative forms of Bitcoin mining, as discussed in the previous sections, should also reduce the carbon footprint.

Table Chapter 1-8: Expected Bitcoin Network Energy Consumption and CO2 Emissions

This table presents the estimated future carbon footprint of the Bitcoin network under three distinct scenarios: base case, upper bound, and lower bound. These scenarios are derived from simulated bitcoin prices and their implied Hash Rates, taking into account the 5% and 95% quantile worst and best-performing trajectories, as well as the median Hash Rate trajectory. The base case scenario can be viewed as the expected CO_2 emissions from the Bitcoin network. However, the table does not factor in potential improvements in miners' energy efficiency or shifts in mining location to regions with higher renewable energy usage and lower energy costs, which would reduce the carbon footprint.

Year	Expected TW/Year (5% lower bound)	Expected TW/Year (95% upper bound)	Expected TW/Year (50% Median)	Expected average change	MTons CO_2 (5% lower bound)	MTons CO_2 (95% upper bound)	MTons CO_2 (50% Median)
0	65.82						30.01
1	60.52	78.38	69.37	5%	27.59	35.73	31.63
2	53.23	127.34	83.01	20%	24.27	58.05	37.84
3	46.08	237.60	106.93	29%	21.01	108.32	48.75
4	39.00	481.81	140.67	32%	17.78	219.65	64.13

1.5.3.1. Context of our Results

In this subsection, we provide an overview of our own forecasts and estimations, and compare it to previous work. We also outline recent research on Bitcoin energy consumption (estimations and predictions) that is scaled to measure energy consumption in TW per year. Note that past literature used different measures and scales for energy consumption and emissions. We normalize those measures here to TW per year (energy consumption) and mTons CO_2 per year (carbon emissions) in order to ensure a suitable comparison (see Figure Chapter 1-6 and Figure Chapter 1-7). If available, we show the lower and upper bounds, along with best predictions. Most past research (excluding Mora et al., 2018, and de Vries, 2018, 2021) follows a bottom-up approach based on miner power efficiency. It is similar to that of the Cambridge Bitcoin Electricity Consumption Index (CBECI) which was initially developed by Bevand (2017). It is based on a profitability assumption about the distribution of active Bitcoin miners. The lower (upper) bound assumes all miners always use the most (least) energy-efficient equipment, and the best guess assumes miners use an equally weighted basket of profitable hardware, rather than a single model assuming a constant electricity price of 5 c/kWh. Electricity consumption is then:

$$P_{el} = \frac{\sum_{i=1}^{N} \vartheta_i}{N} \bullet PUE \bullet H \bullet 60 \bullet 60 \bullet 24 \bullet 365.25 \tag{6}$$

with a power usage effectiveness of $PUE_{lower} = 1.01$, $PUE_{upper} = 1.20$, $PUE_{best\ guess} = 1.10$, average energy efficiency of profitable hardware of $\frac{\sum_{i=1}^{N} \vartheta_i}{N}$ in J/h, and hash rate H in h/s.

Our estimate follows a comparable approach. However, for $\frac{\sum_{i=1}^{N} \vartheta_i}{N} \bullet PUE$, we assume electricity costs of 6 c/kWh. This allows us to identify profitable miners, and account for recent energy cost increases due to the Russia-Ukraine conflict that began in February 2022. We also assume a market share-weighted basket of profitable miners, including other ASIC manufacturers, as follows: Bitmain (Antminers) 59%, Canaan (Avalon Miners) 9%, MicroBT (Whatsminers) 27%, and other ASIC manufacturers 5% (see also Table Chapter 1-9 in Appendix A). Moreover, we assume $\frac{\sum_{i=1}^{N} \vartheta_i}{N} \bullet PUE = 3{,}254\ W/\ 90.3\ TH/s = 36.03\ W/TH/s$. For our historical estimates, we assume hardware is profitable for three years in total and is then replaced. For our forecast, we assume constant miner efficiency. This is a rather conservative approach, because the energy efficiency of miners generally increases over time (see Figure Chapter 1-9 in Appendix A). Contrary to this approach, Digiconomist in comparison calculates mining revenues, and assumes 60% are spent on operating costs. For every 5 cents spent on operating costs, 1 kWh is consumed, which then provides an estimate for total Bitcoin energy consumption per year.

Figure Chapter 1-6: Bitcoin Mining Energy Consumption Estimates

This figure presents a side-by-side comparison of our energy consumption estimates (measured in TW/year) for Bitcoin mining with the estimates provided by other researchers, namely McCook (2018), de Vries (2018), Digiconomist, CBECI, and Zade et al. (2019). Our energy consumption forecasts show the expected (median), 5% and 95% forecasted bitcoin mining related energy consumption based on the VAR model (see equations (1) and (2)) for the period July 2022 to December 2025. The non-linear dynamics between bitcoin prices and energy consumption in our model are showcased as providing a more accurate projection during periods of elevated bitcoin prices. The comparison highlights variations in assumptions about miner profitability and differences in methodology. The figure also includes the broad range of minimum and maximum estimations given by certain studies, along with the forward-looking predictions from Zade et al. (2019).

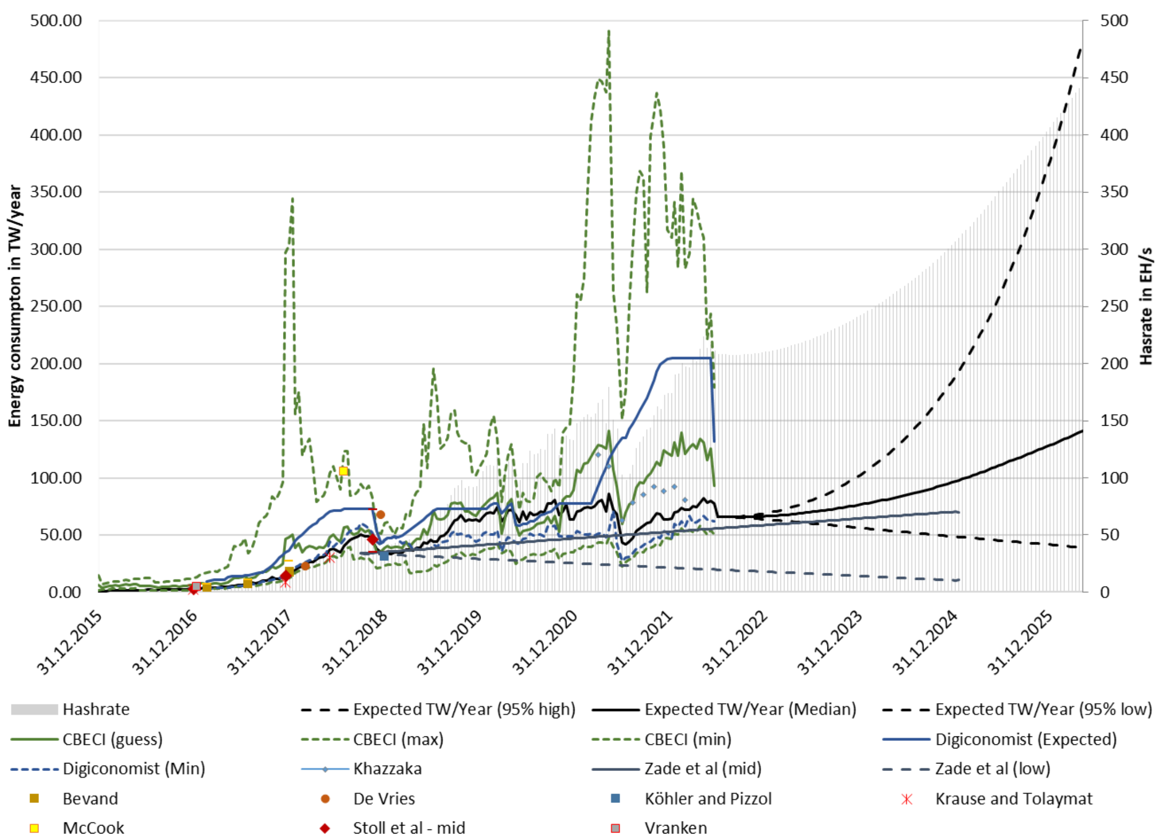


Figure Chapter 1-6 compares our historic estimate with past research. It shows our results are in line with the literature with a few key exceptions, such as McCook (2018) and de Vries (2018), who provide somewhat higher estimates. Compared to Digiconomist and CBECI, our results are also somewhat lower, which we posit is due to our stricter assumptions about miner profitability, and to using a market share-weighted approach for profitable miners. It is worth noting that the range between CBECI's max and min estimation is relatively wide, similarly to Digiconomist's min and expected energy consumption estimate. Zade et al. (2019) is the only paper that provides an estimate of future energy consumption, beginning in 2018 and predicting out to 2024. The estimates shown in Figure Chapter 1-6 assume a linear growth of the block difficulty and increasing hardware efficiency. The authors also considered an exponential growth in block difficulty but considered it unlikely and thus results are not plotted. The linear model however underestimates elevated Bitcoin mining activities when the price soars, because the energy costs and miner efficiency become less relevant. This explains why the predictions underestimate energy consumption when Bitcoin price levels are high. In comparison, our model allows for a non-linear relationship, and is more suitable for modeling the actual dynamics between bitcoin price and the related energy consumption.

Figure Chapter 1-7: Bitcoin Mining Carbon Footprint

This figure reports our estimates and predictions as well as recent findings on the environmental impact of Bitcoin mining, expressed in mTons CO_2 emissions annually. It underscores the intricacies involved in establishing an accurate environmental footprint, taking into account factors such as miners' energy efficiency and location, which in turn impact the energy type and cost. The figure utilizes data from both the CBECI mining map and the International Energy Agency's index of energy cleanliness to estimate the environmental ramifications of Bitcoin mining. Our estimates are largely consistent with past research, except in the cases of McCook (2018) and de Vries (2021). This figure also shows the expected (median), 5% and 95% forecasted bitcoin mining related carbon footprint based on the forecasted energy consumption using the VAR model (see equations (1) and (2)) in Figure 6 for the period July 2022 to December 2025.

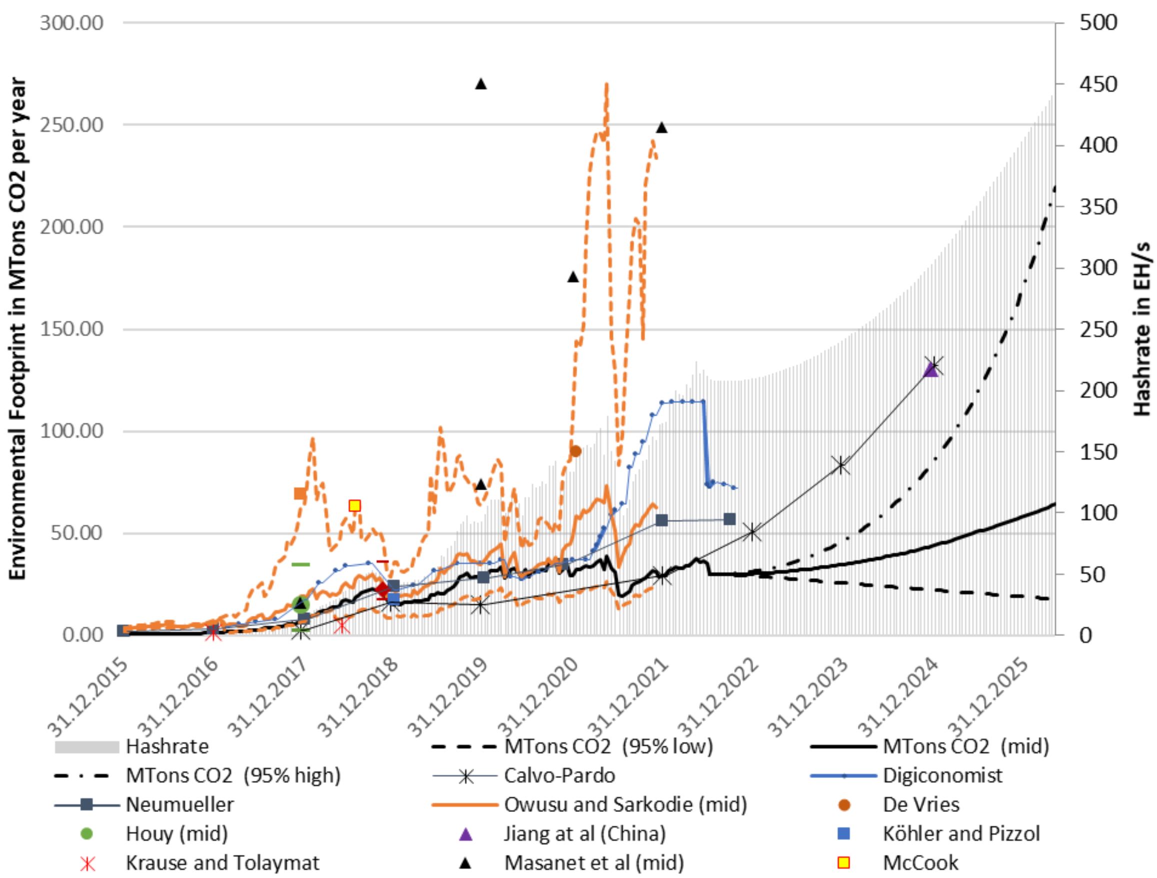


Figure Chapter 1-7 provides an overview of our estimations and predictions, and of recent research on the environmental footprint of Bitcoin mining measured in mTons CO_2 emissions per year. The main challenge in determining an accurate environmental footprint is not just knowledge of miners' energy efficiency, but also their location, which determines the type (coal, nuclear, hydro, oil, etc.) and cost of the energy used in the mining process. Since 2020, CBECI has published a useful mining map (see Figure Chapter 1-5). The International Energy Agency provides information about the "cleanness" of the energy produced in each country. Based on both of these sources, we can estimate the environmental impact of Bitcoin mining, as shown in Figure Chapter 1-7. Our historical estimates are generally in line with past research (except, as previously mentioned, with McCook, 2018, and de Vries, 2021).

Masanet et al. (2019) estimate a significantly higher CO_2 footprint than other research in this field. This is likely due to their hypothesis that Bitcoin technology will ultimately replace many traditional payment forms. We believe this notion is clearly beyond the scope and application of Bitcoin, and does not consider the scaling effect of the Lightning Network. In contrast, our estimates are somewhat lower than those of, e.g., Digiconomist, which is mainly because they posit higher energy consumption in their revenue approach. Our historical estimation is in line with that of Calvo-Pardo and Mancini's (2022) predictions during the period 2018 to 2021. But their CO_2 emissions predictions are somewhat higher than ours for 2022 to 2024 because of differences in their forecasting methodology, which is based on machine learning. Their predictions for 2022-2024 are closer to our upper bound estimation. Jiang et al. (2021) also predict higher CO_2 emission rates. Their model assumes 70% of mining operations based in China, with the use of coal-based energy. However, we consider this unrealistic, because China banned Bitcoin mining in 2021.[4]

To conclude, we examine the various approaches in the literature to calculating the Bitcoin mining-related carbon footprint. We find that our approach is generally in line with past calculations of CO_2 emissions. When focusing on predictions, however, we find that alternative approaches often forecast highly unrealistic CO_2 emissions. This is due to using inadequate assumptions or prediction models that are incapable of fully capturing the relationship between bitcoin price levels and the related energy consumption. We argue that our predicted CO_2 emissions are a more realistic image of the future carbon footprint, assuming that Bitcoin mining continues relatively unchanged. As previously discussed, it seems plausible that miner efficiency will increase in the future, and we will see a shift toward more innovative Bitcoin mining forms. Therefore, our Bitcoin mining-related carbon footprint forecasts should be viewed as an upper bound.

[4] China's Bitcoin mining ban should have ended all Bitcoin mining activities, but they apparently persist, as Figure 5 shows.

1.5.3.2. Innovative Mining

The solid economic incentives of Bitcoin mining have created a highly competitive, and, consequently, innovative environment. The network hash rate has been consolidating to increasingly larger mining operations and mining pools. This benefits miners with economies of scale, but can erode competitive edges. Arguably, one of the key differentiators of a mining operation is the energy source powering their pools. Energy costs comprise the majority of mining expenses. They are directly tied to a miner's ability to survive a "bear market," when bitcoin prices depreciate and revenue is reduced. Researchers expect mining to transition more to a low-margin business in the long term, but current crypto market dynamics continue to render margins highly elastic, ranging from extremely profitable to very tight.

Naturally, for profit maximization and the ability to navigate extended bear markets, mining operations should seek the lowest-cost energy. Although many factors influence electricity prices, they generally reflect the cost to build, finance, maintain, and operate power-generating plants and the electrical grid. In the U.S., the split is 56% generation, 31% distribution, and 13% transmission (see EIA, 2021, 2022a). Historically, gas and coal energy production has been the cheapest, due to low capital costs and inexpensive fuel. But renewable energy sources, such as wind and solar, are growing cheaper and more popular (see IEA, 2020). Renewable sources come with their own disadvantages, however, such as producing energy at inconsistent rates, which can lead to large amounts of curtailment. So, the search for the optimum equation persists.

Bitcoin mining is a "mobile" industry and can be located anywhere if miners have access to electricity and the Internet. But accessing the Bitcoin network in remote areas via satellites allows mining pools to operate directly at energy production sites in order to capitalize on cheap energy.[5] This permits miners to set up shop wherever energy prices are lowest, with operations that are increasingly flexible and creative. In the following subsection, we discuss some innovative forms of Bitcoin mining.

1.5.3.2.1. Flaring

Flaring is the process of burning off excess natural gas from an oil or gas well or refinery. The excess gas may result from, e.g., extracting oil from wells, which releases trapped natural gas. Many operations do not capture this gas, but instead release it into the atmosphere or simply burn it to reduce emissions. Some Bitcoin mining operations, such as Crusoe Energy, Giga Energy, and even Exxon, have begun utilizing the excess gas to power Bitcoin mining operations. To this end, mining operations set miners up close to

[5] See https://blockstream.com/satellite/.

wells or refineries, and reroute the excess natural gas into generators, which convert the otherwise wasted energy into Bitcoin.

According to a study by Crusoe Energy, flaring combusts approximately 93% of methane, releasing 7% directly into the atmosphere, while the generators combust 99.89% (see Cool, 2021). The process helps eliminate routine flaring and reduce methane, CO_2e, CO, VOC, and NO_X by 98%, 63%, 95%, 100%, and 89%, respectively, thereby reducing overall CO_2-equivalent emissions by about 63%. In sum, Bitcoin mining using flaring can facilitate the conversion of excess gas into a revenue-generating resource while significantly reducing its environmental impact.

1.5.3.2.2. Coal Refuse

Coal refuse, or coal waste, is the material left over from coal mining. Coal refuse piles are generally the result of mining during the last century, when processing techniques were less sophisticated. But they can cause severely negative environmental consequences even today. For example, Pennsylvania has 770 coal refuse piles, of which 92 are currently burning uncontrollably. This constitutes about 220 million tons, covering more than 8,500 acres of land (ARIPPA, 2015). Bitcoin miners, such as Stronghold Digital Mining, burn coal refuse in an emissions-controlled manner, thereby reducing the toxic emissions. This process also allows for the reclamation of previously toxic sites by using the energy to mine bitcoin.

1.5.3.2.3. Landfill Methane

Landfills generate methane as organic waste decomposes, and it can be captured and used to produce electricity. However, most landfills either freely release methane, or flare it to reduce emissions. According to EPA (2022), landfills represented 15% of anthropogenic methane emissions in the U.S. due to human activity in 2020, the third largest source. This is not only a significant portion of total greenhouse gas emissions, but also a lost opportunity for energy generation.

Bitcoin miners, such as Vespene Energy, capture methane and use it as an energy source by flaring it. This provides a low-cost source of energy for Bitcoin mining, while substantially reducing methane emissions. As with coal refuse, mining proceeds are usually shared, in this case with landfill operators. In the U.S., many states are beginning to require a reduction in methane emissions. But implementing appropriate infrastructure can be capital-intensive and requires ongoing maintenance expenses. Although some landfills currently use methane emissions to generate power locally, many cannot because of the remote location of the landfills and the high capital costs to connect to the power grid. These costs are not needed for Bitcoin mining.

1.5.3.2.4. Thermal "DeManufacturing" of Tires

Tires do not decompose. If disposed of whole or scrapped in landfills, they can lead to the damaging of landfill liners ultimately causing contamination of the local surface and groundwater.[6] In the U.S., about 300 million scrap tires are produced per year, and roughly 15% end up in landfills or junkyards (see USTMA, 2020). The most common way to dispose of scrap tires is burning, burying, or grinding, which are all environmentally damaging (see Chen et al., 2022). However, a new technology, called "Thermal DeManufacturing," has been developed, which is claimed to be almost zero waste, energy-positive, and uses carefully managed temperature and pressure to break rubber down into useful commodities, such as syngas, carbon, steel, and heat. The released energy can also be used for Bitcoin mining.

1.5.3.2.5. Mining Heat Waste

The process of Bitcoin mining also generates a large amount of heat. Unutilized heat is at best a waste byproduct of Bitcoin mining, but the more miners that are located in closer proximity, the more cooling is needed. This necessitates additional energy. However, instead of cooling the Bitcoin miners, the heat could be used to heat buildings during the winter or for water heating. Mintgreen is an example of a professional application of this technology. It heats a district of 100 residential and commercial buildings in the city of North Vancouver.[7] The company claims that their proprietary "Digital Boilers" recover more than 96% of the electricity used for mining in the form of heat energy, preventing more than 20,000 tons of greenhouse gases. By inserting the Bitcoin mining process as an intermediary between renewable energy generators and the end-user that requires heating, Mintgreen is providing access to low-cost energy while maintaining a low environmental footprint.

1.5.3.3. Energy Consumption per Transaction

An alternative approach to evaluating the energy intensity of Bitcoin and other cryptocurrencies is to consider consumption per transaction. Wanecek (2021) compares consumption of the two top PoW protocols, Bitcoin and Ethereum, with a popular PoS alternative, Stellar, and with Visa. The results show that Stellar's consumption is 0.00022 kWh/transaction, compared to Bitcoin's 814.95 kWh/transaction[8] and Visa's 0.00092 (see also Sori et al., 2020). The difference in consumption is staggering. However, there are important nuances to consider.

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[6] See https://archive.epa.gov/epawaste/conserve/materials/tires/web/html/basic.html.
[7] See https://mintgreen.co/#projects.
[8] See Digiconomist's Bitcoin Energy Consumption Index in January 2023 (https://bitcoinenergyconsumption.com).

For example, Digiconomist's consumption estimate for Bitcoin of 814.95 kWh/transaction assumes that total annual energy consumption is divided by the total number of blockchain transactions per year (about seven per second). The underlying assumption is that Bitcoin's base layer is not scalable. Thus, within an expanding network, consumption will grow exponentially, but without any added benefits. This assumption is somewhat misleading, though, especially considering the existing financial network. Technology tends to be built in layers, because more built-in functionalities can lead to more complications (e.g., Ethereum congestion and gas fees, Solana down time).

Visa as a payment processing enterprise exists multiple layers above the financial system's base settlement layer such as the Fedwire Funds Service which is more comparable to Bitcoin. Central to Bitcoin's philosophy is maintaining simplicity in its core code, for decentralization and security purposes. Therefore, transaction scalability is achieved with higher layers, such as through the Lightning Network, which can currently process up to 1 million transactions per second (TPS) (a number that is expected to rise in the future (see https://lightning.network). Note that a fully utilized Lightning Network with identical energy estimates would dramatically decrease Bitcoin's consumption per transaction, to 0.0057 kWh/transaction.

Although this would still exceed Visa's rate, the Bitcoin network offers a host of benefits that go far beyond payment processing. When considering PoS solutions, such as Stellar, the energy consumption per transaction may also be lower, but it comes at the cost of serious compromises, such as increasing centralization, reduced security and potential loss of transaction immutability. Thus, many of the core benefits are eliminated.

In other words, a comparison of energy consumption per transaction between Bitcoin's base layer and a pure payment processing solution is misleading. Scalability from higher layers, such as the Lightning Network, must be included for full comparability.

1.5.3.4. Full Node Energy Consumption

Being a peer-to-peer network, Bitcoin is built on an infrastructure of nodes of which there are three main types: Full nodes, mining nodes, and light nodes. The type of node is determined by the functionality it is supporting of which there are four: Wallet, Miner, Full Blockchain and Network Routing Node. All types of nodes must have the network routing function in order to communicate with the network and will then include other functions depending on its planned use. Miners will generally have two types of configurations which depends on their affiliation, if they solo mine they will have the Mining, Network Routing, and Full Blockchain functionalities, whereas mining pool miners will not hold a copy of the full blockchain. Light nodes usually refer to wallet applications which then only typically have the Wallet and Network Routing functions. Lastly, full nodes are the core of the network which maintain up-to-date copies of the blockchain, independently and authoritatively verify all transactions, which requires the Full Blockchain and Network Routing functions, and if desired, the Wallet function.

Thus far, we have only considered miners which represent the largest portion of the energy consumption of the Bitcoin network by design. However, it is important to consider its other key components. Although there are millions of light nodes acting as wallet applications for users, these are considered to have a negligible net impact as they exist as applications on phones and computers and are only used when needed on already operating machines, not unlike to accessing your banking account. Full nodes on the other hand maintain an up-to-date copy of the blockchain and are typically operated 24/7/365, and so their energy consumption and impact should be accounted for. Although many full nodes are operated on personal computers that may be always left on anyway or only used sporadically (the blockchain catches up in the background). For simplicity we assume all full nodes operate using a designated device. A large portion of nodes are known to operate using a Raspberry Pi and a Solid-State Drive (SSD) to store the blockchain, which we will assume is the universal setup. Based on technical specifications these require on average roughly 5.5W (average between 3.5W when idle and 7.5W under load) for the Raspberry Pi 4 and 4W for the SSD. Assuming the node operates at full capacity half the time (i.e. processing transactions at max capacity), this would equate to an 83.22 kWh[9] annual consumption, or roughly one 9W LED lightbulb. As of June 5, 2023 there are 45,452 global full nodes (reachable and unreachable).[10] The energy consumption of the full nodes assuming these values would remain constant for the year would be 3,782 MWh[11]. For comparison, the U.S. Energy Information Administration estimates banks or other financial institutional buildings consume on average 19.3 kWh[12] per square foot per year, with the average size at roughly 2,700 square feet a bank branch consumes roughly 52 MWh annually. Put differently, the Bitcoin's Network of global nodes consumes energy of an equivalent of about 73 commercial bank branches. Given the estimates of the International Monetary Fund (IMF) that a commercial banks reach on average about 9,000 adults, these 73 commercial bank branches could regionally service about 650,000 adults.[13] In comparison, the Bitcoin network has a global reach with currently about 47 million addresses (equivalent to a traditional bank account) with non-zero balance. Put differently, the Bitcoin network can increase the number of addresses without needing to increase the number of nodes or energy consumption, which is not possible for commercial banks.

[9] Annual power consumption can be calculated as follows: hourly consumption (9.5W = 5.5W + 4W) x hours per year (8.76 = 24hours x 365 days / 1,000) = 83.22 kWh.
[10] See https://bitnodes.io/nodes/all.
[11] Total consumption: 83.22 kWh x global full nodes (3,782) / 1,000 = 3,782 MWh.
[12] See https://www.eia.gov/consumption/commercial/data/2012/c&e/cfm/pba4.php.
[13] See https://data.worldbank.org/indicator/FB.CBK.BRCH.P5?end=2021&name_desc=true&start=2004&view=chart.

The Lightning Network is a second-layer scaling solution built on top of the Bitcoin blockchain. It aims to address scalability limitations by enabling faster and cheaper transactions off-chain. Similarly to the Bitcoin network, it is peer-to-peer. It is connected by Lightning nodes, which create payment channels. Using the Lightning Network requires a user to send on-chain bitcoin to a wallet address tied to the Lightning node, where it is then accounted for and moved using the Lightning Network. Unlike nodes for the Bitcoin network, those validating transactions on the Lightning Network need only confirm transactions in which they are directly involved. This reduced validation requirement allows nodes to process transactions much more quickly than on the Bitcoin blockchain.

However, it's worth noting that the energy consumption of the Lightning Network is relatively small compared to the energy-intensive process of Bitcoin mining. Since Lightning transactions are conducted off-chain, they significantly reduce the number of transactions that need to be processed on the Bitcoin blockchain. On-chain transactions associated with the Lightning network include entering or exiting the network, and so opening/closing and rebalancing channels require an on-chain transfer of bitcoin. Moreover, the Lightning Network's ability to enable micropayments and faster transactions can have indirect energy-saving benefits. By reducing the need for frequent on-chain transactions, which typically require more computational resources and energy, the Lightning Network is capable of positively contributing to the overall energy efficiency of the Bitcoin ecosystem.

The base requirement to operate a Lightning node is having a Bitcoin full node. As per available data, there are 20,516 Lightning nodes and 45,452 Bitcoin full nodes. This indicates that a substantial portion of Bitcoin full nodes also serve as Lightning nodes. A Lightning node is essentially a Bitcoin full node with additional software to participate in the Lightning Network. Therefore, considering the overlap between Lightning and Bitcoin nodes, the additional energy consumption contributed by the Lightning network to Bitcoin is relatively minimal.

In summary, the energy implications of operating the Lightning Network are primarily tied to the energy consumption of running Lightning nodes. While not entirely negligible, the energy usage of the Lightning Network itself needs only a fraction of the energy consumption of the Bitcoin network. Furthermore, the Lightning Network's scalability benefits can indirectly contribute to energy efficiency by reducing the need for frequent on-chain transactions.

1.5.4. Water

The Bitcoin mining process is energy intensive, and can have direct and indirect environmental impacts, including on water resources. Note that water resources can be used directly for cooling miners, but it is more common to use electricity consumption methods, such as air cooling. Another, less popular, method is immersion cooling,

Air cooling reduces the direct draw on water resources. However, cooling of electricity-producing fossil fuel power plants can nevertheless involve significant water usage, an indirect impact on water resources. For example, the reintroduction of warmed water waste into ecosystems potentially affects wildlife and overall water quality (Speight, 2019). Therefore, it is crucial to consider both the direct and indirect effects of water usage in the context of Bitcoin mining, and its reliance on various energy sources.

Air cooling involves installing large fans to ventilate a mining facility. But this is ultimately an inefficient cooling method, furthermore it draws significant power and generates noise pollution. In some instances, miners combine air cooling with a water curtain (panels with flowing water). This improves efficiency sixfold and does not require traditionally used air conditioning. Therefore, this method does require the direct and constant consumption of water resources, but it substantially reduces overall energy consumption.

Water cooling is gaining in popularity as a simple, scalable, and sustainable solution. It is a closed loop and involves circulating a water and glycol coolant through a water block or cooling plate (see, e.g., Bitmain's Antminer S19 XP Hyd). The advantages are a dramatic reduction in cooling energy expenses (by ~50%), and virtually no fluid expense.

The last method is immersion cooling, where ASIC miners are submerged in a dielectric (electrically non-conductive) liquid that efficiently dissipates heat and vibrations. Oil is then circulated outside the system to dissipate the heat through radiators and fans.

Consider an average data center, where the use of typical 10 kW racks lead to an estimated draw of 63,000 gallons of potable water when air cooled. In contrast, closed loop water cooling (or immersion cooling) leads to a substantial reduction in water requirements (Ebrahimi et al., 2014). We expect to see a shift away from air cooling as Bitcoin miners increasingly gain access to public capital. This should drastically reduce the negative impact of the cooling of Bitcoin miners on water supplies and improve the economics of immersion cooling.

In addition to electricity produced by hydropower, the draw on water is largely caused by fossil fuel-fired thermal power plants with traditional once-through cooling systems. These may lead to chemically and thermally polluted wastewater (The White House, 2022). However, as previously highlighted, the Bitcoin mining industry is shifting away from the use of fossil fuels, and toward renewable or waste energy sources. Thus, the strain on water resources should decrease even as the industry scales. In the case of hydropower, establishing the required infrastructure has a significantly negative environmental impact, but the resulting electricity generation is efficient and clean. Therefore, the added strain on hydro powered electrical grids caused by Bitcoin mining is not so easily resolved. In Québec, for example, Canada Hydro-Québec opted to freeze new mining projects to conserve power. However, less developed jurisdictions may opt instead to build new dams.

The United States Institute of Peace (2023) highlights the idea that Bitcoin miners target jurisdictions with weak governance and corruption to benefit from cheap energy and avoid regulation. Note further that any additional direct and indirect strains on water resources can be especially detrimental to areas such as Central Asia, which have a more limited water supply (Wang et al., 2022). Although certain actors in the industry have effectively gone this route, such as those that moved from China to Kazakhstan (a Central Asian country), most operators displaced due to the China ban relocated to the U.S. According to the Cambridge Bitcoin Electricity Consumption Index (CBECI), the average monthly hash rate share in December 2021 for the U.S. was the densest in the world, at about 40%. The shift suggests that miners favor stable jurisdictions with regulatory clarity, rather than those with cheap resources they can exploit.

In sum, water resources are affected indirectly during the mining process when fossil or nuclear energy resources are used. This is because they require water for cooling, which results in environmentally harmful thermal pollution. Furthermore, total energy consumption of Bitcoin miners is largely influenced by the cooling method they employ. The popular air-cooling method has the lowest energy efficiency. When the energy used is supplied by fossil or nuclear energy, it implicitly exerts the greatest impact on water resources.

With the shift to more renewable energy resources, the use of water in bitcoin mining should be greatly reduced. The industry's impact on water resources will be further diminished with the shift to alternative cooling systems. These will not only reduce energy costs, but, in the case of non-renewable energy resources, water usage as well.

1.5.5. Waste

Bitcoin's environmental impact, however, extends beyond just the energy consumption of the mining process and related water resources. It also requires specialized mining hardware and its production requires resources and energy (see De Vries and Stoll, 2021). As described in subsection 1.5.1 Bitcoin Mining is the process of bundling transactions and generating a single hash output ("hashing"). This process requires large amounts of hashing calculations, which are carried out using the SHA-256 algorithm. Mining was originally conducted using average CPUs but the process evolved to using the more computationally powerful GPUs found in graphic cards. The shift to GPUs caused a short-term surge in graphics card demand[14] until mining ultimately shifted to ASICs which are optimized solely to conduct SHA-256 hashing calculations.

This evolution has led to an exponential growth in the number of hashes per second that can be performed per chip. But the chips cannot perform any other computation; their use is limited to SHA-256 hashing (mainly for Bitcoin mining) (see Bitcoin miner efficiency evolution in Figure Chapter 1-9 in Appendix A).

Moreover, the underlying technology of the integrated circuits has been rapidly evolving. Packing transistors closer together leads to more computationally powerful silicon (e.g., 5nm vs. 12nm between transistors). Therefore, outside of reducing the cost of electricity, miners can most efficiently improve their economics by utilizing more computationally powerful equipment. Because miners are only used for Bitcoin mining, the decision to replace a miner depends on current bitcoin price, energy costs, difficulty rating (based on total network hash rate), and miner efficiency. But all these factors must be considered simultaneously, so the process is not straightforward.

The basic economics of miner replacement suggest that a miner is less likely to be replaced when bitcoin prices are high, energy costs and hash rates are low, and average miner hashing efficiency is relatively high. Bitcoin prices and hash rates can change quickly, so replacement decisions hinge on how they are expected to fluctuate in the (near) future. This adds a further layer of complexity to the decision-making process. Once a miner is permanently retired, it becomes e-waste, although it can be recycled. Thus, some portion of the resources used to produce it may be recoverable.

De Vries and Stoll (2021) find that the average miner operates for 1.29 years before becoming obsolete and replaced by a newer, more efficient miner. This assumption is the driver behind the estimate of 30.7 metric kilotons of e-waste annually from Bitcoin mining, which was projected to exceed 64.4 metric kilotons by the end of 2021.

However, when we fact check the actual lifetime use of various mining models, we observe that it is much longer. The most relevant example comes from the Antminer S9, which leaves specific patterns that can be identified via an analysis of "nonce" distribution on the blockchain (see Coin Metrics, 2020). In other words, with this signature, we can precisely identify Antminer S9 mining activity. The S9, which launched in May 2016, remained profitable until May 2022, when it was almost fully removed from the network

[14] The popular media has often attributed the price inflation of GPUs to the mining of proof-of-work cryptocurrencies, a category that lumps in Bitcoin. While GPUs were initially used for Bitcoin mining between 2010 and 2012, their role in mining was later replaced by more powerful ASICs. However, prices of GPUs continued to be driven upward by other proof-of-work blockchains, particularly Ethereum, which became the second most valuable crypto-asset after Bitcoin (The Economist, 2021). The transition of Ethereum to a proof-of-stake consensus mechanism in September 2022 has effectively ended the era of GPU mining and resulted in a significant drop in GPU prices.

(CryptoSlate, 2022). However, S9s may yet come back online depending on difficulty level, bitcoin price, and the cost of electricity available to the miner in question.

It is important to note that most of De Vries and Stoll's (2021) calculations center on a cost of electricity of $0.05/kWh. However, many miners are in lower energy cost zones because they are using inexpensive waste or stranded energy sources (see subsection 1.5.3.2 Innovative Mining). Furthermore, professional mining businesses may sell unprofitable miners to other operations with cheaper access to energy or may simply turn them off until favorable conditions return. Since professional mining businesses usually access public capital via IPOs or SPACs, they appear to grow their infrastructure by increasing capacity, rather than by replacing less profitable miners.

Although the efficiency of ASICs has grown exponentially since their introduction in 2012, there remain physical limitations to how much more they may attain. It has become extremely difficult to design and manufacture chips with transistors packed at or closer than 3nm. Thus, overall growth in the hashing capacity of newer rigs has diminished in recent years. We expect this phenomenon to further extend the profitability of the existing fleets of miners.

In sum, there is no doubt that Bitcoin mining is a net contributor to e-waste, and its effects on pollution and resource consumption must be considered. However, based on the abovementioned arguments, especially the very short assumed useful life of a miner in the study by de Vries and Stoll (2021), the amount of e-waste has been greatly overestimated. The slowdown in chip development should further extend miners' useful lives and lower the amounts of future e-waste, even when networks and the total numbers of miners are growing.

1.6. Social, "S"

Under the Social factor of ESG, we identify four primary elements of Bitcoin that impact people: 1. User Satisfaction, 2. Data Protection and Privacy, 3. Human Rights, and 4. Criminal Activity.

1.6.1. User Satisfaction

User satisfaction refers to the level of satisfaction and fulfillment experienced by Bitcoin users. Bitcoin, both as a crypto-asset and a network, offers features and benefits that positively contribute to user satisfaction, enhancing its social impact.

Bitcoin provides protection against the devaluation of traditional currencies caused by inflation. This characteristic offers users value that can resist the erosion of purchasing power over time, leading to increased satisfaction. In a response to the U.S. Congress, human rights advocates highlighted specific situations where Bitcoin was critical in providing a haven from failing currencies for, e.g., Argentinians, Turks, Russians, and Lebanese (see Aderinokun et al., 2022). Moreover, certain Bitcoin network characteristics, such as transactional transparency and pseudonymity, offer enhanced levels of privacy and security in financial transactions. These also contribute positively to user satisfaction.

One of the key value propositions of Bitcoin is the trustlessness of its peer-to-peer network, which allows users to safeguard their bitcoin themselves. Through self-custody, users do not rely on traditional financial intermediaries, so they maintain full control of their funds and eliminate counterparty risk. Although there are challenges to self-custody, and best practices must be followed to maximize security, Bitcoin reduces the risk of theft or loss due to vulnerabilities associated with third-party involvement.

When compared to traditional banking systems and practices, Bitcoin offers users a greatly enhanced transactional experience. With its 24/7/365 network availability, users can transact at any time, from anywhere in the world, and for any desired amount. Transactions on the Bitcoin blockchain are settled rapidly (~10 minutes vs. 24+ hours), and the finality eliminates any need for intermediaries to confirm or validate them. This provides users with certainty and efficiency.

However, for smaller transactions, from a consumer perspective, full settlement in ~10 minutes may be viewed as an inconvenience. To enable instant payments, Bitcoin uses the Lightning Network, a second layer that allows individuals to transact in satoshis, Bitcoin's smallest denomination, with near zero transaction fees. When compared to fees in the traditional financial system, Bitcoin and the Lightning Network offer a more cost-effective alternative.

Overall, Bitcoin's features, including protection against devaluation, transactional transparency, pseudonymity, elimination of counterparty risk, improved transactional experience, and low fees, collectively contribute to user satisfaction. These aspects enhance the social impact by providing individuals and businesses with alternative financial options. This empowers them to retain greater control over their finances, while fulfilling their needs for security, privacy, and cost-effective transactions.

1.6.1.1. Challenges

The Bitcoin network offers clear advantages for society. Its potential will likely far exceed what we have highlighted here. However, there are certain caveats, such as price volatility, and security in the context of transaction irreversibility and coin custody. At its essence, Bitcoin provides three key uses: medium of exchange, store of value, and value of transfer infrastructure. However, it is subject to speculation, and at times high volatility levels. It has occasionally experienced price changes of more than 15% within minutes, with price shifts of more than 80% and price gains exceeding 1,000% during a cycle.

Although this volatility does not influence the ability to use the Bitcoin network as the underlying infrastructure to transfer and settle value, it can be problematic when using bitcoin as a store of value or medium of exchange (Cermak, 2017). Bitcoin's volatility may also lead to steep losses in (short-term) purchasing power, which makes it a risky medium for store of value, especially in times of crisis (See Stulz, 2023). Supporters argue that, over a four-year investment horizon, Bitcoin's price history is clearly upward-trending, irrespective of purchase date. However, this may not necessarily be the case going forward.

The objective of an efficient medium of exchange is to facilitate the purchase, sale, or exchange of goods or services between parties by avoiding barter and using a commonly accepted unit of account. To this end, it is important for a medium of exchange to maintain stable purchasing power. Economies with volatile currencies, such as Venezuela, Turkey, Argentina, and Zimbabwe, for example, have experienced weakening purchasing power and seen a flight to safer currencies, such as USD. El Salvador went a step further, and officially declared bitcoin legal tender in September 2021, making it an official medium of exchange along with USD. However, one year later, bitcoin's price has halved, and the experiment has proven disastrous. The full implications are not yet known, but the short-term pain may signal that Bitcoin was not quite ready as an asset class.

1.6.2. Data Protection and Privacy

From the perspective of data protection and privacy, Bitcoin offers several key features that contribute to its social impact and align with the social pillar of ESG. One crucial aspect is the ability for users to maintain control over their assets, ensuring individual autonomy. Bitcoin cannot be readily confiscated, and ownership can only be transferred if the current owner authorizes it by providing access to private keys. These keys, commonly represented as mnemonic phrases, ensure that only the rightful owner can initiate transactions.

Bitcoin addresses consist of 256-bit numbers, so there are 2^{56} key pairs (public and private) mapped to 2^{160}, or ~1.4615 x 10^{48}, possible valid wallet addresses. Therefore, it is highly improbable that anyone could gain unauthorized access to a wallet on their own. However, we recognize there are certain risks inherent with data protection in the Bitcoin ecosystem. For example, losing or forgetting the private keys can render Bitcoin stored in a wallet irretrievable. Moreover, Bitcoin transactions are irreversible in nature. Thus, individuals have no recourse if they make a mistake transferring funds. The use of Bitcoin comes with significant personal responsibility. Users must fully comprehend the risks involved, and take appropriate precautions.

Another important consideration is the pseudonymous nature of the Bitcoin network. The full suite of transaction details is immutably recorded on the public blockchain, but the participants' real-world identities are not directly linked to their Bitcoin wallet addresses.

This provides users with tremendous privacy, allowing for transactions without revealing personal information. However, it is important to note that the privacy is not foolproof. Indeed, with sufficient effort and analysis, transactions may potentially be linked to individuals, no matter how long ago the transaction settled.

For users seeking to enhance privacy, various technologies are available, with more in development. One example is CoinJoin, which is known as a mixer. It allows multiple users to combine their transactions, obfuscating the flow of funds and ultimately improving privacy. Along with mixers, technologies like ring signatures and zero-knowledge proofs are being developed to further augment privacy within the Bitcoin ecosystem.

As previously noted, despite Bitcoin's pseudonymity, failing to follow privacy best practices, even one time, can lead to the identification of the user. For example, reusing the same Bitcoin address for multiple transactions may compromise privacy. Therefore, Bitcoin recommends using a new address for each transaction.

Although users highly value privacy, regulators need a certain level of identification for reporting purposes and to combat illicit activities. The cryptocurrency industry has historically been very lightly regulated, but most developed countries have now implemented Know Your Client (KYC), Anti-Money Laundering (AML), and Anti-Terrorist Financing (ATF) regulations. These requirements may affect user privacy, but some balance is necessary to curb criminal activities.

As the technology surrounding Bitcoin continues to develop, there is an expectation of new interfaces and strategies to protect users from accidental loss of funds and heighten privacy. One example is the use of multi-signature (multisig) wallets, which involve multiple parties authorizing transactions. These provide an added layer of security and reduce the risk of unauthorized access (Dietz et al., 2021).

In sum, by providing users with control over their assets, emphasizing privacy through pseudonymity and privacy-enhancing technologies, and promoting best practices, Bitcoin fully addresses data protection and privacy concerns. The decentralized nature of the network and the cryptographic principles underlying it contribute to the social impact of Bitcoin. It offers individuals increased autonomy, consent, and privacy in their financial transactions, which align well with the principles of ESG.

1.6.3. Human Rights

Bitcoin's impact on human rights, particularly in developing and underprivileged countries, deserves careful consideration from an Environmental, Social, and Governance (ESG) perspective. In this sub-section, we delve into the ways in which Bitcoin's characteristics and applications have positively contributed to human rights, with a focus on economic empowerment, financial inclusion, and resistance against authoritarian regimes. As highlighted by human rights advocates from twenty different countries in a letter to the U.S. Congress, Bitcoin has particularly contributed to the human rights of people living under authoritarian regimes and in unstable economies (Aderinokun et al., 2022). The signatories highlight many specific situations where Bitcoin proved helpful, such as: providing a haven from failing currencies to, e.g., Argentinians, Turks, Russians, and Lebanese; helping Afghans survive after the Taliban takeover and subsequent U.S. sanctions; helping the Ukrainian government rapidly raise funds to help defend themselves against the Russian invasion; and helping finance anti-government protests in Nigeria and Hong Kong.

Furthermore, as mentioned briefly earlier, many of Bitcoin's qualities align neatly with the U.N.'s Sustainability Development Goals (U.N. SDGs).[15] The SDGs are an urgent call to end poverty and other deprivations, improve health and education, reduce inequality, and spur economic growth, while reducing climate change and preserving oceans and forests. In this section, we discuss how Bitcoin positively impacts various SDGs.

SDG #1: End Poverty in All Its Forms Everywhere

The 2021 World Bank report on financial inclusion underlines the ongoing unbanked crisis in many developing countries. Despite global bank account ownership having increased from 51% to 76% between 2011 and 2021, nearly 1.7 billion people worldwide remain without access to sufficient banking services (Andrews et al., 2021). According to the United Nations' Financing for Sustainable Development Report 2021, 94% of adults in developed countries hold a bank account, while, in developing countries, the total is only 63% (United Nations, 2021). These statistics are a stark reminder that a large segment of the population remains excluded from the financial services industry. A 2017 study of the Philippines Central Bank found that as much as 60% of their unbanked population cited "not having enough money" as their main reason, while 21% felt they did not need one, and 18% lacked proper documentation (Bangko Sentral ng Pilipinas, 2017). Other important factors were the cost of accounts, and simple access to the nearest bank.

Therefore, the first U.N. SDG that Bitcoin explicitly supports is "*#1: End poverty in all its forms everywhere*." It directly contributes to SDG #1's underlying Target 1.4: "*By 2030, ensure that all men and women, in particular the poor and the vulnerable, have equal rights to economic resources, as well as access to basic services, ownership and control over land and other forms of property, inheritance, natural resources, appropriate new technology and financial services, including microfinance*."

Bitcoin software is open-sourced, and requires only a network connection, through, e.g., a direct Internet connection, satellite phone, ham radio, or even SMS texting. This makes it

[15] United Nations Department of Economic and Social Affairs Sustainable Development, The 17 Goals (https://sdgs.un.org/goals).

readily available to most of the world. To participate in the Bitcoin network, users must have a bitcoin “wallet” to receive and send funds. Obtaining a wallet is straightforward and accessible, and non-custodial smartphone wallet applications are available that provide the private keys (a twelve- or twenty-four-word mnemonic phrase used to send wallet funds) and public keys (the associated address given out to receive funds) needed.[16] Individuals can store wealth in their wallets, maintaining full custody without counterparty risk, and can send and receive funds internationally with final settlement within minutes. Although the most common way to purchase bitcoin is via an exchange using funds deposited in a bank, unbanked individuals can still readily acquire bitcoin through ATMs or peer-to-peer transactions.

Because physical access to financial services in many countries remains a hurdle and can be cost-prohibitive, crypto has begun to fill that gap. For example, about one-third of Nigerian adults invest in crypto assets (KuCoin, 2022). Although the Bitcoin network has no passive or maintenance fees, transaction fees are imposed when sending funds. The transaction fees are driven by network congestion but are the same regardless of transaction size (value). As of August 2022, average fees per transaction were about $1 USD, with a range of $1 to $5 USD the previous year, and an all-time high of about $60 USD in April 2021.[17]

With the expected increase in adoption, the concurrent increase in the number of transactions may clog Bitcoin’s blockchain, which currently processes approximately seven transactions per second. To resolve scalability issues and transaction costs, the Lightning Network protocol was developed as a second layer on top of Bitcoin. The Lightning Network allows users to transfer funds as small as one “satoshi” (0.000000001 BTC) for 0.000026 satoshis. At the bitcoin price of $21,194 USD, that represents $0.000000005482 USD per $0.000021 USD, or a 0.0026% fee (see Divakaruni and Zimmerman, 2022). Unlike “on-chain” Bitcoin transactions, Lightning Network transactions settle instantly and for nearly zero fees, making it a very viable means of payment.

SDG #7: Affordable and Clean Energy

Overwhelming evidence indicates that the world is undergoing severe climate changes caused by, e.g., carbon dioxide emissions. This has led to an increase in more frequent and more extreme weather events, such as heat waves, droughts, and storms. Such events strain the reliability of electrical grids and increase power interruptions (see Sanstad et al., 2020). The problem is aggravated by more extreme temperatures, which, among other factors, have caused the growth in global electricity demand to outpace the growth in supply. The

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[16] Even without access to smartphones or computers, one can manually generate the keys with pen and paper. However, it is a more mathematically challenging process.
[17] See https://studio.glassnode.com/metrics?a=BTC&category=Fees&m=fees.VolumeMean.

resulting increases in energy price volatility have led to further hardship and unsafe situations for many households (EIA, 2020a; IEA, 2022).

Obviously, significant investment in energy infrastructure is needed. The focus should ideally be on low-carbon-emitting and renewable energy sources, such as solar and wind energy, to avoid worsening the cycle. However, renewable energy sources can be unreliable and involve high initial capital investments. To offset these disadvantages, an "overbuilding" of renewable energies is necessary, along with adequate incentives such as subsidies or tax credits (Perez et al., 2019; EIA, 2022b).

Although it may seem counterintuitive due to its high energy use, Bitcoin mining can actually help accelerate the rollout of renewable energy, and also help balance energy supply and demand. The unreliable nature of renewable energies, as well as the overbuilding, may result in excess energy at times. This could be used for Bitcoin mining because of the technology's proverbial "*flip of a switch*" feature. Therefore, Bitcoin mining can stabilize grids while generating proceeds to, e.g., invest in further expanding renewable energy infrastructure (Niaz, Liu, and You, 2022). The state of Texas provides solid evidence that this symbiosis is working. In 2022, the Electric Reliability Council of Texas used Bitcoin mining flexibility to relieve strain on the power grid during extreme weather events. This improved the robustness of the grid and helped stabilize energy costs during extreme events.

Many countries have committed to using renewable energy, including the U.S., which aims for an increase from 24% to 44% of the energy supply coming from renewable sources (Linga, 2022). Leveraging the relationship between utilities and Bitcoin miners could help accelerate the transition to renewables, and help meet SDG's Target 7.1: By 2030, ensure universal access to affordable, reliable, and modern energy services, and Target 7.2: By 2030, substantially increase the share of renewable energy in the global energy mix.

SDG #10: Reduce Inequality Within and Among Countries

Developing countries have seen rapid growth in remittance payments, where migrants send funds or goods back home to support their families. As such, these payments have become an important part of the GDP of developing countries, representing nearly 6% for low-income countries, and 2% for medium-income countries (Gupta, Pattillo, and Wagh, 2009). The cost of sending remittance payments is usually a percentage of the principal amount. The World Bank estimates it is about 6%, but the amount can reach as high as 20% if funds are sent in smaller remittance corridors (Ratha, 2022). In its Target 10.c, the U.N. has established an important goal of lowering remittance costs by 2030: "*By 2030, reduce to less than 3 percent the transaction costs of migrant remittances and eliminate remittance corridors with costs higher than 5 percent.*"

Strike presents a possible solution to this challenge by using Bitcoin's global and peer-to-peer network to eliminate such remittance corridors. As noted earlier, the Lightning Network allows users to make remittance payments with virtually no fees.[18] Funds sent are converted to bitcoin, delivered instantly, and converted back to whatever currency the receiver desires. The process simply uses the Bitcoin network on the back end to transfer value more efficiently than traditional financial infrastructure. This ensures the receiver is not exposed to bitcoin's price volatility.

1.6.4. Criminal Activity

Bitcoin was created as a trustless, independent financial system, with control outside of government hands. However, the pseudonymity can lead to criminal activity. The most infamous case to date is the Silk Road online marketplace. It operated on the dark web from February 2011 to October 2013, when the entire marketplace was seized by the FBI. The platform gained notoriety for facilitating illegal transactions, using bitcoin as the primary form of payment. It was accessible only through the Tor network, which provided anonymity to both buyers and sellers.

Silk Road aimed to create a platform for free trade and privacy, but it quickly became a known hub for illegal activities. Although users' locations and identities were efficiently masked by the Tor network, all bitcoin transactions are publicly visible. So, the flow of funds could still be tracked pseudonymously.

Silk Road's popularity was presumably a result of insufficient regulation of Bitcoin and crypto-assets. Such early exchanges and platforms allowed users to operate anonymously, without any form of KYC, AML, or ATF procedures. However, as each Bitcoin halving cycle led to explosive increases in the network's market capitalization, regulators and governments began to pay more attention. Currently, most crypto-asset exchanges are required to implement KYC and AML procedures to operate in developed jurisdictions. In some countries, like Canada, recent regulations prohibit residents from trading crypto-derivative products and require operating exchanges to register as restricted dealers.

Thus, it has become increasingly difficult for individuals to on-ramp, and, more specifically, to off-ramp funds from the Bitcoin network anonymously (non-KYC). With the flow of funds permanently and openly available on the blockchain, it has become more possible to determine the identity of wallet addresses ex post. Therefore, conducting criminal activities through the Bitcoin network is much riskier than through other means, such as cash.

Even with these improvements in the Bitcoin and crypto-asset industry, there remain significant regulatory gaps and ambiguity. These permit cybercriminals to operate

[18] See https://strike.me.

efficiently, and at lower cost than traditional money laundering methods (van Wegberg et al., 2018). For example, in 2021, criminals were found to have laundered $8.6 billion USD of cryptocurrency (including $2.8 billion in Bitcoin) (Chainalysis, 2022). However, since Bitcoin processed roughly $3 trillion USD of payments in 2021, laundered funds represented only a small fraction of transactions.

To illustrate the contrast between the Bitcoin network and the traditional financial system, as well as the tractability of transactions on the Bitcoin network, we consider the case of Ilya Lichtenstein and Heather Morgan. The couple are tied to the 2016 hack of the cryptocurrency exchange Bitfinex, which became the largest crypto heist in history. They were arrested on February 8, 2022, for the theft of 119,754 bitcoins, estimated to be worth about USD $4.5 billion at the time (see Department of Justice, 2022). Of those, the couple had approximately 90,000 in their possession.

Over a period of five years, the alleged thieves were able to transfer a portion of the bitcoin (~20%) into financial accounts under their control. This required an extremely complex money laundering scheme, including fake identification. To withdraw funds in USD, while keeping their real identities private, the couple also needed to exploit the traditional financial system. This highlights the fact that, even when using elaborate money laundering schemes, transactions on the Bitcoin network could be traced back, even more than five years after the hack. Moreover, accessing the funds was only possible through the traditional financial system, due to certain security flaws, such as, in this case, KYC using fake IDs.

Companies such as Chainalysis conduct in-depth analyses of blockchains to track the flow of funds, and identify, tag, and monitor wallet IDs. They assist governments and regulatory agencies to enforce compliance and investigate crypto crime. Although crypto users can access so-called coin mixing services to obfuscate their activities, Chainalysis claims they can even disentangle their effects now (Shin, 2022).

Naturally, criminals always find new ways to leverage the pseudonymity of Bitcoin and blockchains to, e.g., launder funds. However, such dangers are not exclusive to crypto. Reflecting on Bitcoin’s history, we observe a clear trend of an improving regulatory environment and compliance by key industry players. Thus, overall crypto crime may be trending upward in dollar value, but the illicit share of all cryptocurrency transactions is decreasing. In 2022, it was reported to be about 0.24% (Chainalysis, 2023).

Chainalysis (2023) also finds that, in 2022, the majority (about 89%) of crypto-related illicit activities were tied to theft (18%), scams (29%), and interactions with sanctioned entities (42%) (e.g., Garant X, a Russian exchange sanctioned by the Office of Foreign Assets Control (OFAC), and Tornado Cash, a mixer sanctioned by the U.S. Treasury).

Although the social impact of sanctioned transactions may be difficult to evaluate, the toll of thefts and scams on (retail) investors is high.

In 2022, USD $3.8B in crypto-assets were stolen, primarily from DeFi protocols and by North Korean-linked hackers. These thefts occurred by exploiting smart contracts, which only exist on blockchains other than Bitcoin. And retail investors lost an even higher amount (USD $5.9B) to scams. Chainalysis categorizes these scams as Giveaways, Impersonations, Investments, NFTs, and Romance Scams, which largely prey on investors' lack of experience and/or technical blockchain knowledge. Although some scams are crypto-specific, many exist outside of crypto. Furthermore, although scammers historically favored payments in bitcoin, since 2021, they are increasingly requesting stablecoins.

In sum, a certain amount of illicit activity may be facilitated by the pseudonymity and borderless nature of crypto markets (mainly theft and sanctions). However, a large portion of the criminal activity is unavoidable, and would occur anyway due to flaws in the traditional financial system. It is important to note that most of the criminal activity occurs on, and is facilitated by, blockchains other than Bitcoin. With improved regulation through KYC/AML requirements, industry surveillance (e.g., Chainalysis), and the permanent and transparent transactional history of blockchains, using the Bitcoin network for illicit activities is increasingly risky. However, because of the technical barriers associated with safely transacting on the Bitcoin network, it remains a much higher risk environment for the inexperienced. As the industry matures, and jurisdictions continue to develop targeted regulations, we expect retail investors will benefit more easily from the unique advantages this technology offers.

1.7. Governance, "G"

Under the Governance element of ESG, we identify three primary elements of Bitcoin that impact governance: 1. Accounting Integrity and Transparency, 2. Compensation, and 3. Principles of Governance

1.7.1. Accounting Integrity and Transparency

Within the governance pillar of ESG, accounting integrity and transparency are vital factors. They play a significant role in assessing the credibility and trustworthiness of Bitcoin's ecosystem. Accounting integrity refers to the quality and reliability of financial information within an accounting system. It encompasses principles and practices that ensure accuracy, completeness, and consistency in recording financial transactions. In the context of Bitcoin, we find it fully embodies the aforementioned underlying principles.

a. **Accuracy:** The mechanisms behind Bitcoin's blockchain ensure a high degree of accuracy when recording and verifying transactions. Each transaction is digitally signed and time-stamped, which provides cryptographic proof of authenticity. The decentralized nature of the blockchain, its validation, and its mining process prevent the risk of fraudulent (double-spent) transactions.

b. **Completeness:** The blockchain maintains a complete and immutable record of all transactions on the Bitcoin network since its inception. This permanently available, complete transactional history allows for a comprehensive audit at any time.

c. **Consistency:** Bitcoin is governed by a code that establishes a consistent set of rules for validating transactions. This allows for greater consensus and ensures the integrity of the ledger.

Transparency is a fundamental aspect of governance. It is essential to fostering trust, accountability, and responsible decision-making. In the case of Bitcoin, we find an unparalleled level of transparency in accounting integrity, and on the governance structure and decision-making process for the protocol itself. As we noted earlier, Bitcoin's blockchain is a public and distributed ledger. Anyone can install the protocol, download the blockchain, and independently and authoritatively audit every transaction since inception.

As for Bitcoin's governance, it operates in a decentralized manner, with decisions made by consensus among network participants. They can propose and vote on changes to the protocol, thereby influencing the direction and evolution of the system.

Accounting integrity and transparency are key to Bitcoin's governance. They ensure accuracy and trustworthiness, which in turn influences decision-making within the ecosystem. The transparent nature of the ledger provides stakeholders with the ability to independently verify and audit financial transactions. This mitigates the risk of fraud, manipulation, or misrepresentation. Transparency also fosters accountability among participants. And eliminating reliance on centralized intermediaries aligns with the decentralized ethos of Bitcoin.

In sum, accounting integrity and transparency are vital factors in evaluating Bitcoin from an ESG perspective, particularly within the governance pillar.

1.7.2. Compensation

Bitcoin is a decentralized protocol that continues to operate as long as more than two people run full nodes. The protocol ensures that those who work toward processing transactions and documenting them into blocks (miners) are rewarded. Miners are compensated with new bitcoins entering circulation (Coinbase reward), where the amount is predetermined and dependent on the current halving cycle. Total rewards are then supplemented with transaction fees, which can vary greatly.

Placing a bitcoin transaction requires payment of a minimum fee based on the units of data required for the transaction (this is abbreviated as sats/vByte). However, miners will always prioritize the transactions that offer the highest transaction fees in the "mempool." Naturally, as transaction volumes increase, users compete to ensure their transactions are settled more rapidly, thereby inflating fees.

To participate in Bitcoin mining, one needs only to download the core protocol and set up the node as a mining node. The mining process is stochastic in nature, so each hashed output is equally able to mine a block. Therefore, almost anyone can attempt to earn the coinbase reward and the transaction fees by successfully mining a block.

Although the mining process is fair, the bitcoin mining industry has significantly evolved since its early days. Initially, individuals could only meaningfully contribute to mining via personal computers. Nowadays, successful mining has become a professional endeavor, requiring hefty capital investments to own enough hashing power to efficiently operate them and mine independently (solo mining) (see also subsection 1.5.1 Bitcoin Mining). This is by design, because the best way to generate revenue is to successfully mine a block. Otherwise, no bitcoin(s) are earned, regardless of effort (hashing power) contributed.

To address the increasing difficulty of successful solo mining, the first cooperative (mining pool) was launched in 2010. Named Bitcoin.cz, it is now known as Braiins. The idea behind a mining pool is to combine the resources of multiple miners to create one collaborative mining entity with greater hashing power. This is generally achieved by using a mining software that is compatible with the mining pool, and simply registering an account. Large mining pools represent an important percentage of the total hash rate of the bitcoin network, and consistently produce blocks. They thus provide miners with a steady stream of revenue.[19]

The profit-sharing models of Bitcoin mining pools can vary, with several important differences to keep in mind. The underlying concept of distributing mining rewards among

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[19] See https://explorer.btc.com/en/btc for mining pools and related hash rate.

contributors is common, but the specific mechanisms and parameters differ. There are four main models:

1. **Proportional Distribution:** Some mining pools distribute rewards proportionally, based on the individual miner's contribution. Miners thus receive a share of the rewards that is equivalent to the proportion of their contributed computational power. This model ensures a fair distribution of rewards. The Braiins pool operates under this model.

2. **Pay-per-Share (PPS):** In a pay-per-share model, miners receive a fixed payout for each share they contribute, regardless of whether the pool successfully mines a block. This model offers predictable and steady income for miners. They are compensated for their work based on the number of shares they contribute. F2Pool operates under this model.

3. **Score-Based Systems:** Some pools use score-based systems, such as the "Double Geometric Method" (DGM), or the "Geometric Method" (GM), to distribute rewards. These models consider factors like the number of shares submitted by a miner over a certain period, and the difficulty of those shares. Miners are then rewarded proportionally, based on their score relative to other participants. Antpool operates under this model.

4. **PPLNS (Pay-per-Last-N-Shares):** PPLNS is a profit-sharing model where miners are paid based on the number of shares, they contributed during a specific time window. However, payouts are calculated based on the "last N shares," instead of all submitted shares. "N" represents a certain number of shares, and the model aims to reward miners who stay with the pool for a longer duration. BTC.com operates under this model.

5. **Fee Structures:** Mining pools often charge for their services, which can affect the profitability and actual rewards received by miners. Fee structures can vary and may include flat fees or percentage-based fees on rewards. Miners need to consider the fee structure when choosing a mining pool, because higher fees can impact overall profitability. ViaBTC offers various profit-sharing models, such as PPS and PPLNS, as well as different fee levels.

Besides mining pools, there are other ways to structure profit-sharing arrangements, such as cloud mining contracts and hosted mining. In cloud mining contracts, individuals purchase a portion of the hashing power from a larger mining facility. The buyer then receives a percentage of the mined bitcoin from the purchased hash rate, minus a service fee. Similarly, hosted mining occurs when an individual purchases mining hardware from a manufacturer, and subsequently rents hosting in their facilities. Unlike cloud mining, the individual owns the mining hardware, and can request it be shipped if they no longer want to pay the rental fees.

In sum, profit-sharing in Bitcoin mining exemplifies good governance. Models such as proportional distribution, pay-per-share, score-based systems, and PPLNS ensure fair allocations based on contributions. Transparency, choice, and absence of corruption foster accountability and participation. This inclusive and equitable approach aligns with the principles of good governance, including transparency, accountability, participation, and fairness.

1.7.3. Principles of Governance

In the broadest sense, the "G" (Governance) of ESG is the process of overseeing control and direction. Good governance is necessary to optimize outcomes and protect stakeholders in any type of organization or system. The more people an institution impacts, the greater the need for good governance of an institution's actions. In Bitcoin's case, the technology is being adopted as a monetary form, while acting as a value transfer, or payment, network. It aims to replace some aspects of central banking and various portions of the financial industry. In other words, adopting Bitcoin beyond a speculative asset will directly affect the underpinnings of our economy and how we transact. Therefore, it is critical to understand how the technology is controlled.

Central to Bitcoin's philosophy, and directly integrated into its design, is the creation of an independent money source that is separate from that of the state. To accomplish this disintermediation, Bitcoin's design aims to maximize trustlessness, which is the removal of the need to trust a third party (such as a bank). Bitcoin was created as an open-source software, and the fully decentralized network was bootstrapped by users. Thus, there is no centralized governing body, in contrast to current fiat monies and other cryptocurrencies. Bitcoin governance is the process by which transaction and block verification rules are decided upon, implemented, and enforced. The users that adopt the same validation rules to verify payments and transactions form an intersubjective social consensus of how Bitcoin is defined.

Bitcoin has evolved since its initial release. It has received updates to its protocol that have patched security flaws and added functionality, such as the most recent Taproot update. There are three general ways to propose protocol changes: e-mailing the bitcoin-dev mailing list directly; publishing a formal white paper; and/or submitting a Bitcoin Improvement Proposal on the Bitcoin Github repository. However, since 2013, changes have been published as BIPs (Bitcoin Improvement Proposals), which act as a standardized means of communicating ideas.

Before any proposed changes can be implemented, consent from the community, in the form of consensus from the economic majority of Bitcoin users, is required. Submitted BIPs are screened by editors to ensure formatting follows the community's agreed upon structure. Each BIP must also constitute a single key proposal or idea. BIPs can then be accepted or rejected. However, the BIP authors are responsible for building consensus by addressing concerns and questions about the change. The review process is fully transparent, so anyone can view and follow the progress.

To achieve acceptance, a BIP must meet three criteria: 1) It must follow the agreed upon format specified in BIP-001; 2) it must include the necessary code to implement the proposed changes to the Bitcoin Core protocol; and 3) it must attract 95% support from the last 2,016 miners. Signaling, which is accomplished by setting the version field of the block to a specific value, is mandatory, because of certain implications for miners. It is typically done once the new code is incorporated. Miners must vote to include the agreed upon data in their hashed blocks. Final approval of a BIP takes place when users update their nodes to the version that reflects the proposed change.

It is important to note that changes to the Bitcoin protocol are usually backward compatible (this is often referred to as a "Soft Fork"), so users are not forced to update their nodes. Changes that are not backward compatible, and force an update, are known as Hard Forks. They remain a highly contentious issue in the Bitcoin community because of the danger they may pose to the protocol. The process Bitcoin follows is extremely conservative, deliberate, and democratic. Historically, it has also been quite lengthy. For example, the latest Taproot update was proposed on January 23, 2018, and was finally activated on November 16, 2021, nearly four years later.

The United Nations defines governance as "*the process of decision-making and the process by which decisions are implemented (or not implemented)*" (Sheng, 2009). The U.N. Human Rights Council identifies five key attributes of good governance: transparency, responsibility, accountability, participation, and responsiveness (OHCHR, 2022). Reflecting on Bitcoin's governance process, we find high degrees of alignment with the U.N.'s attributes of good governance:

- The Bitcoin protocol simply enforces a set of validation rules agreed upon by the entirety of its participants.
- The network itself performs a self-audit of its transactional history roughly every ten minutes, which can be performed by anyone.
- Its entire transactional history is always visible to anyone.
- The Bitcoin protocol is open-source, with fully transparent and auditable source code.

- The ability to propose (and actively participate in all phases of) changes to the source code is available to anyone.
- The network adopts changes only when a consensus of the economic majority is reached.
- The Bitcoin network is inclusive and non-discriminatory. No personal information needs to be disclosed to create a wallet or use the network.

Although no system is perfect, Bitcoin is undeniably fairer, more transparent, more inclusive, and more corruption-resistant than most existing monetary systems and networks. As such, the governance model adopted by Bitcoin also supports the U.N.'s SDG #16: "*Peace, Justice and Strong Institutions,*" by directly contributing to Targets 16.5: "*Substantially reduce corruption and bribery in all their forms*"; 16.6: "*Develop effective, accountable and transparent institutions at all levels*"; 16.7: "*Ensure responsive, inclusive, participatory and representative decision-making at all levels*"; and 16.8: "*Broaden and strengthen the participation of developed countries in the institutions of global governance.*"

1.8. Discussion and Conclusion

After Bitcoin was invented in 2008, and came into use in 2009, only a few individuals mined Bitcoin using CPU-based personal computers. This number grew to a few hundred in 2010, so related energy consumption was still negligible. In 2012, however, this changed dramatically with the specifically designed application-specific integrated circuits (ASICs). Thus began the true start of professional Bitcoin mining.

Within that year, bitcoin surpassed $100 for the first time, and then quickly overtook the $1,000 mark. The steep increase in bitcoin's price kickstarted the professional Bitcoin mining business by creating Bitcoin mining pools or farms. The former are groups of miners who share computational power; the latter are centralized collections of miners in, e.g., a warehouse, with the sole purpose of mining Bitcoin. With the increase in professionalism, however, mining competition intensified, resulting in a concurrent sharp increase in Bitcoin miners. This increased the hash rate, and energy consumption.

As long as the bitcoin price exceeded the administrative, hardware, and energy costs of the mining process, it was lucrative to invest in more miners, thereby setting in motion a spiral of increasing hash rate and energy consumption. The spiral breaks as soon as the bitcoin price falls below the levels needed to mine profitably, as seen during the crypto winter in 2022. This resulted in insolvencies of numerous professional crypto mining operations, such as Core Scientific Inc., one of the largest publicly traded crypto mining companies in the U.S. to file for Chapter 11 bankruptcy. It underlines the risk to traditional Bitcoin mining of relying on sufficiently high bitcoin prices, which are not only highly volatile, but can remain depressed for extended periods of times (uncertain revenue). It also highlights the importance of fixed energy costs.

In contrast, more innovative methods of Bitcoin mining, such as flaring or coal refuse, do not rely on conventional energy sources like gas or coal-fired power plants and instead consume waste or stranded energy which may ultimately reduce emissions. Therefore, the innovative forms of Bitcoin mining are a better fit for bitcoin's price volatility and cost structure, making them generally more sustainable. Ultimately, they still consume energy, but with a much lower (and perhaps negative in the future) carbon footprint. However, it is uncertain how quickly the industry can fully transition to these alternate methods. Elevated bitcoin price levels will presumably continue to favor conventional Bitcoin mining in the short term.

The discussion of Bitcoin's energy consumption, however, ignores the many benefits of its value transfer network. As an open-source protocol with no overarching governing body, the Bitcoin network has had a positive impact on human rights, particularly in oppressed and developing jurisdictions. Furthermore, we show that many of Bitcoin's qualities align with some of the U.N.'s Sustainability Development Goals and can thus help achieve their targets. Easy access to the Bitcoin network, and the ability to manage one's own wealth, is helping ensure that everyone has equal access to vital financial services. This supports the U.N.'s goal of ending poverty in all its forms everywhere.

The strong economic incentives, mobility, and stochastic nature of Bitcoin mining also provides utilities with unique opportunities to build out renewable energy infrastructure and stabilize their grids. Bitcoin miners can consume any excess energy generated from, e.g., renewable energy sources like solar and wind. This should improve the economic viability of those projects, and, consequently, hasten the transition to clean energy. Furthermore, the ability to provide an instant demand response at any scale significantly improves grid stability. As such, Bitcoin miners can leverage their relationships with utilities and increase their share of renewable energy production (SDG 7, Target 7.2). This will improve access to affordable and reliable energy services (SDG Target 7.1).

Last, Bitcoin's peer-to-peer network eliminates expats' reliance on costly network corridors to make remittance payments (SDG Target 10). Leveraging the Lightning Network, Bitcoin's second layer, allows for more efficient payment transmissions at little to no cost, and without exposure to bitcoin's price volatility (SDG Target 10.c). Thus, Bitcoin is clearly more than a speculative asset; its network and infrastructure can improve quality of life worldwide.

When evaluating Bitcoin's ESG performance, the most pronounced criticism focuses on energy consumption during the mining process, as well as on the related emissions and carbon footprint. Regardless of Bitcoin’s numerous benefits (discussed in-depth in the “S” and “G” sections), and the fact that current estimates are largely overstated, it remains that the absolute energy consumption is not negligible. Increases in the bitcoin price will improve the economics of mining and will arguably also increase fuel energy consumption.

However, given the current turmoil in the professional Bitcoin mining business, investors will likely be more careful and more diligent in the future about their decisions to finance traditional mining operations. This should create more opportunities for the innovative Bitcoin mining alternatives to attract investors and substantially increase their market share. Their business models can smooth the effects of bitcoin’s inherent price volatility, and they also feature lower mining costs.

It is probably overly optimistic to expect this shift to occur soon, especially if the bitcoin price soars again. But the economic advantages make a move to newer methods virtually inevitable. Therefore, we conclude that all Bitcoin mining-related carbon emission forecasts (excluding the newer, innovative forms) are overstating their emissions footprints. We are likely to see dramatically reduced net emissions, or even net negative emissions, in the future.

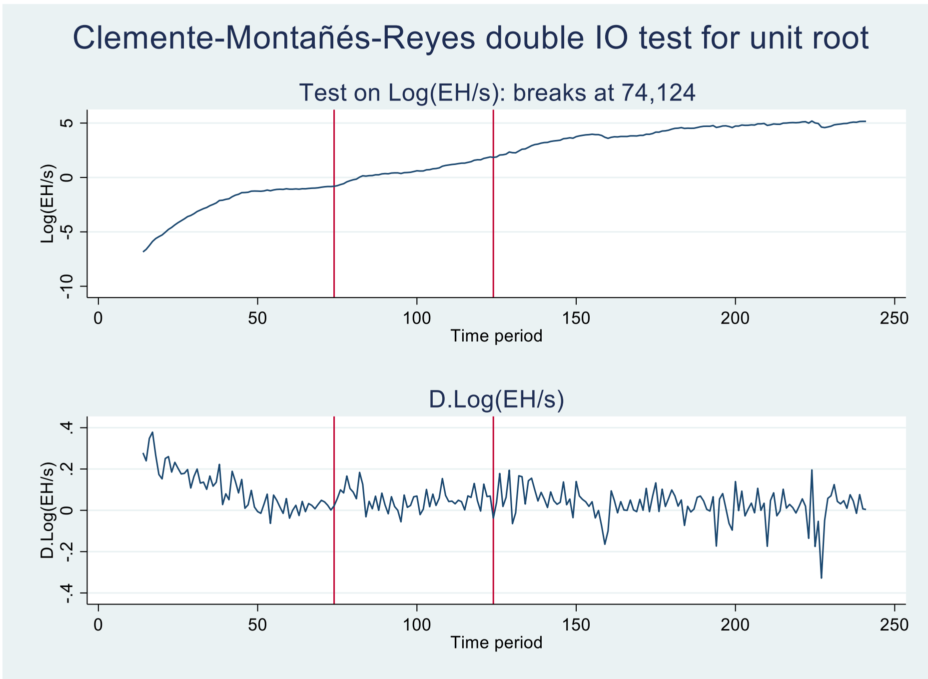
As the industry adapts and evolves, it is crucial to move beyond a narrow focus on the absolute contribution to the environmental aspect “E” and evaluate Bitcoin's overall impact through a holistic lens. By considering the net contribution, the utilization of curtailed or waste energy, and the significant social “S” and governance “G” benefits enabled by the Bitcoin network, we can recognize the industry's potential to advance global sustainability goals.

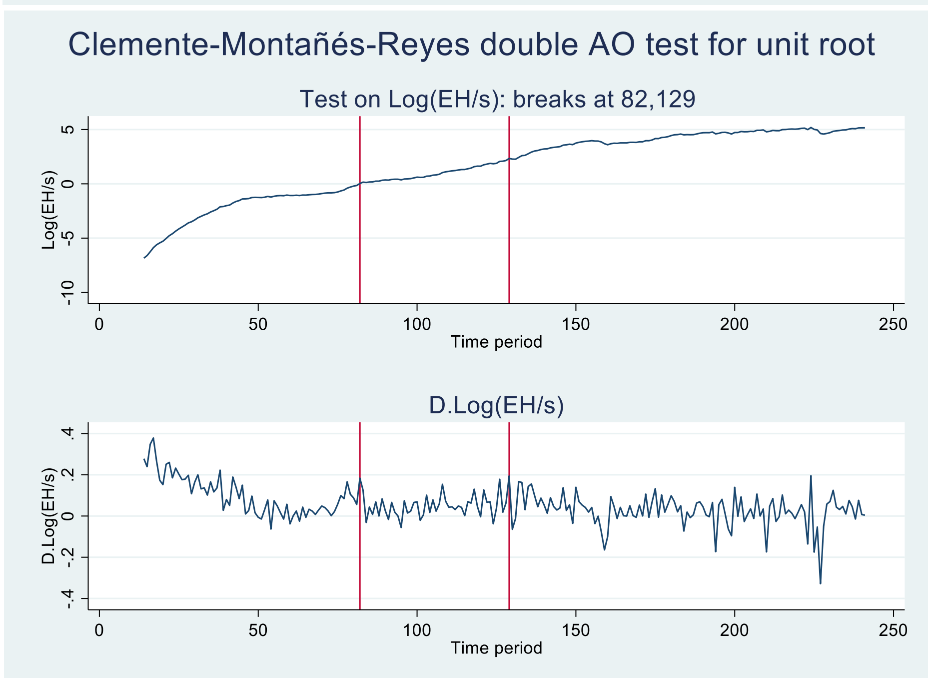
In conclusion, we firmly assert that a grounded, holistic approach is essential for the future progress of the Bitcoin mining industry. By addressing energy consumption concerns, embracing innovative methods, and accounting for the wider positive contributions, we can pave the way for a more sustainable and inclusive future. It is through this approach that we can unlock the full potential of Bitcoin's network and infrastructure to improve the quality of life worldwide, while concurrently striving towards a greener, more equitable global economy.

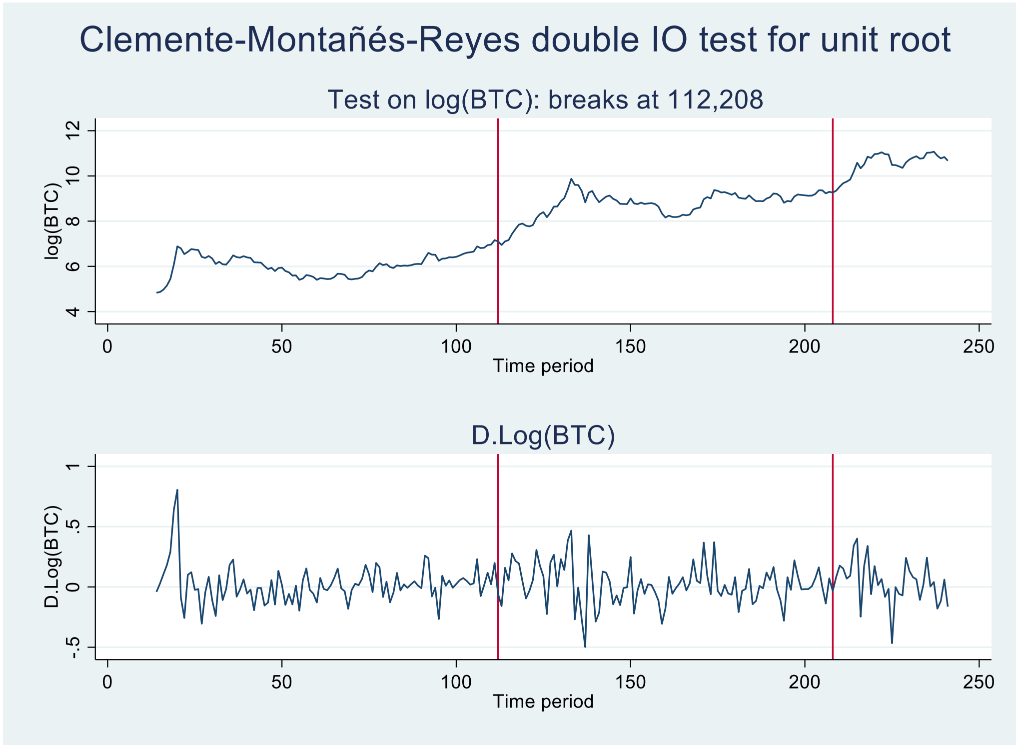
Appendix A. Supplemental Information for Chapter 1

Figure Chapter 1-8: Visualization of CMR test for unit root with two breakpoints

This figure shows the results of the Clemente-Montañés-Reyes (CMR) test for innovational outliers (IO) for gradual shift in the mean and additive outliers (AO) for a single mean shift with two structural breaks (see Clemente, Montañés, and Reyes, 1998) for the log-transformed hash rate (EH/s) and bitcoin price (BTC) as well as the differences.






Clemente-Montañés-Reyes double IO test for unit root
Test on log(BTC): breaks at 112,208
log(BTC)
Time period
D.Log(BTC)
D.Log(BTC)
Time period

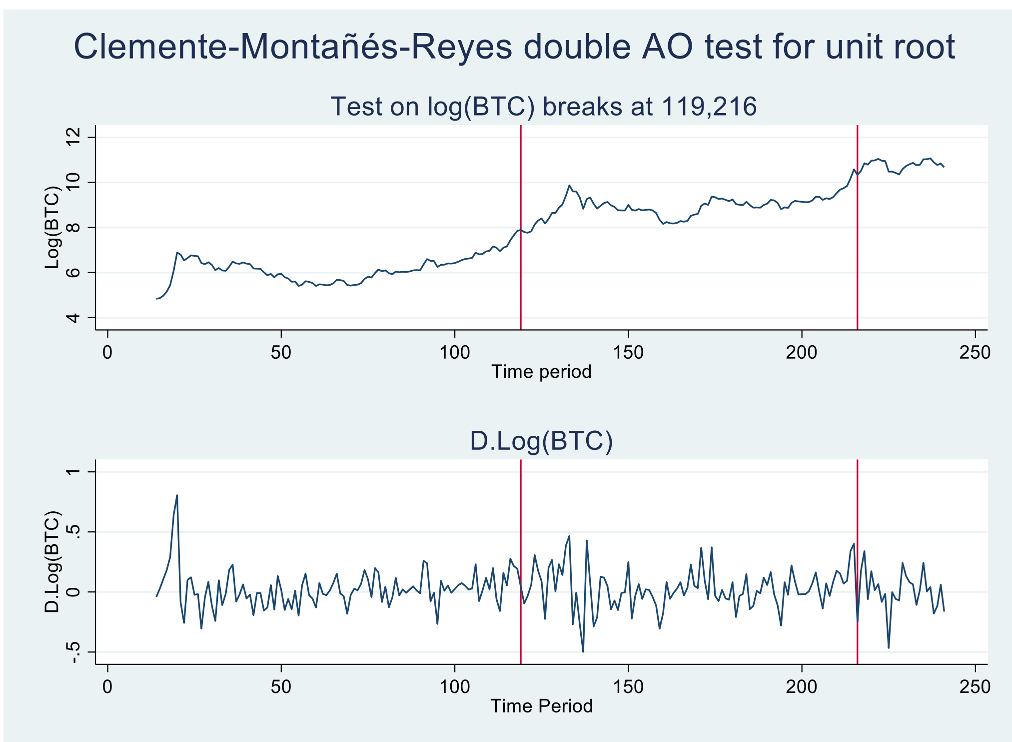

Clemente-Montañés-Reyes double AO test for unit root
Test on log(BTC) breaks at 119,216
Log(BTC)
Time period
D.Log(BTC)
D.Log(BTC)
Time Period

Figure Chapter 1-9: Bitcoin Miner Efficiency

This figure shows the miner energy efficiency in W/Th for different miner models over time.

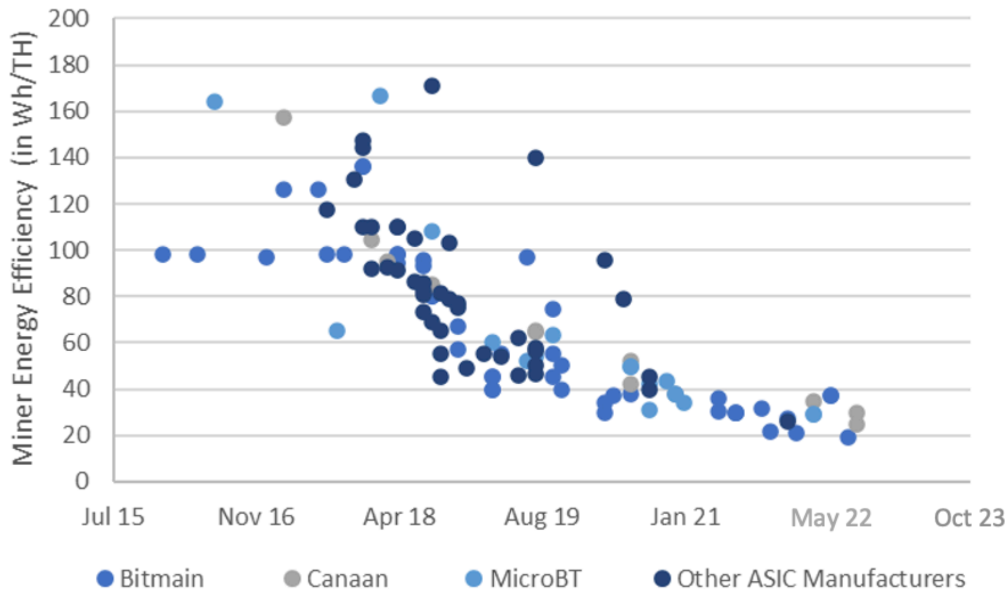


Table Chapter 1-9: Hash Rate, Watts, and Profits of Bitcoin Miners (July 7, 2022)

This tables shows for different miner models (Name) and for each manufacturer the release date, its hash rate (in TH/s), Watts (in W), efficiency (in W/TH), revenue (in $/day) and profits (in $/day) assuming energy costs of 0.06 $/kW.

Manufacturer	Name	Release	Hash rate	Watts	Efficiency	Revenue	Profit
Bitmain	Antminer S7	Aug 15	4	1093.6	273.4	0.4	-1.4
Bitmain	Antminer V9	Mar 17	4	1027.2	256.8	0.4	-1.1
Bitmain	Antminer T9	Jul 17	12	1513.2	126.1	1.2	-1.1
Bitmain	Antminer T9	Dec 17	10	1364	136.4	1	-1.1
Bitmain	Antminer T9+	Dec 17	10	1364	136.4	1	-1.1
Bitmain	Antminer T9	Mar 17	11	1387.1	126.1	1.1	-1
Bitmain	Antminer S7-ln	May 16	2	516.2	258.1	0.2	-0.8
Bitmain	Antminer S9 hydro	Jul 18	18	1728	96	1.7	-0.8
Bitmain	Antminer S5	Nov 14	1	508.6	508.6	0.1	-0.7
Bitmain	Antminer S9	Aug 17	13	1274	98	1.2	-0.7
Bitmain	Antminer S9	Oct 17	14	1372	98	1.3	-0.7
Bitmain	Antminer S9	Jan 16	12	1176	98	1.2	-0.6
Bitmain	Antminer S9	May 16	11	1078	98	1.1	-0.6
Bitmain	Antminer S9	Apr 18	13	1280.5	98.5	1.2	-0.6
Bitmain	Antminer S9i	Apr 18	13	1280.5	98.5	1.2	-0.6
Bitmain	Antminer S9i	Apr 18	14	1320.2	94.3	1.3	-0.6
Bitmain	Antminer S9j	Jul 18	14	1303.4	93.1	1.3	-0.6
Bitmain	Antminer S9k	Jul 19	13	1261	97	1.2	-0.6
Bitmain	Antminer S3	Jun 14	0	0	762.5	0	-0.5
Bitmain	Antminer R4	Jan 17	8	776.8	97.1	0.8	-0.4
Bitmain	Antminer S9se	Aug 18	16	1280	80	1.5	-0.4
Bitmain	Antminer S9se	Aug 18	16	1280	80	1.5	-0.4
Bitmain	Antminer S11	Oct 19	20	1492	74.6	1.9	-0.3

(continued)

Table Chapter 1-10: Hash Rate, Watts, and Profits of Bitcoin Miners (July 7, 2022)—*continued*

Bitmain	Antminer T15	Nov 18	23	1541	67	2.1	-0.1
Bitmain	Antminer S15	Nov 18	28	1596	57	2.6	0.3
Bitmain	Antminer T17	Apr 19	40	2200	55	3.7	0.5
Bitmain	Antminer T17e	Oct 19	53	2915	55	4.9	0.7
Bitmain	Antminer T17+	Nov 19	64	3200	50	5.9	1.3
Bitmain	Antminer S17	Mar 19	53	2385	45	4.9	1.4
Bitmain	Antminer S17	Mar 19	56	2520	45	5.2	1.5
Bitmain	Antminer S17 pro	Mar 19	50	1975	39.5	4.6	1.8
Bitmain	Antminer S17e	Oct 19	64	2880	45	5.9	1.8
Bitmain	Antminer S17 pro	Mar 19	53	2093.5	39.5	4.9	1.9
Bitmain	Antminer S17+	Nov 19	73	2920	40	6.7	2.5
Bitmain	Antminer T19	May 20	84	3150	37.5	7.7	3.2
Bitmain	Antminer T19	Jul 20	88	3344	38	8.1	3.3
Bitmain	Antminer S19j	May 21	90	3249	36.1	8.3	3.6
Bitmain	Antminer S19i	unknown	90	3051	33.9	8.3	3.9
Bitmain	Antminer S19	Apr 20	95	3249	34.2	8.8	4.1
Bitmain	Antminer S19j Pro	Jul 21	92	2714	29.5	8.5	4.6
Bitmain	Antminer S19j Pro	May 21	100	3050	30.5	9.2	4.8
Bitmain	Antminer S19j Pro	Jul 21	96	2832	29.5	8.8	4.8
Bitmain	Antminer S19a Pro	Oct 21	104	3255.2	31.3	9.6	4.9
Bitmain	Antminer S19j Pro	Jul 21	104	3068	29.5	9.6	5.2
Bitmain	Antminer S19 Pro	Apr 20	110	3245	29.5	10.1	5.5
Bitmain	Antminer T19 Hydro	Jun 22	145	5437.5	37.5	13.4	5.5
Bitmain	Antminer S19 XP	Nov 21	140	3010	21.5	12.9	8.6
Bitmain	Antminer S19 Pro Hydro	Jan 22	198	5445	27.5	18.2	10.4

Bitmain	Antminer S19 XP Hydro	Feb 22	255	5304	20.8	23.5	15.9

(continued)

Table Chapter 1-11: Hash Rate, Watts, and Profits of Bitcoin Miners (July 7, 2022)—*continued*

Canaan	Avalonminer 741	Mar 17	7	1102.5	157.5	0.7	-1
Canaan	Avalonminer 821	Jan 18	11	1147.3	104.3	1.1	-0.7
Canaan	Avalonminer 841	Mar 18	13	1233.7	94.9	1.3	-0.6
Canaan	Avalonminer 921	Aug 18	20	1700	85	1.8	-0.6
Canaan	Avalonminer 1066	Aug 19	50	3250	65	4.6	-0.1
Canaan	Avalonminer 1047	Aug 19	37	2379.1	64.3	3.4	0
Canaan	Avalonminer A1046	unknown	36	2318.4	64.4	3.3	0
Canaan	Avalonminer 1146 pro	Jul 20	63	3276	52	5.8	1.1
Canaan	Avalonminer 1166 pro	Jul 20	81	3402	42	7.5	2.6
Canaan	Avalonminer 1246	Dec 20	90	3420	38	8.3	3.4
Canaan	Avalonminer 1247	unknown	90	3420	38	8.3	3.4
Canaan	Avalonminer 1266	Apr 22	100	3500	35	9.2	4.2
MicroBT	Whatsminer M21	Aug 18	31	3360.4	108.4	2.9	-2
MicroBT	Whatsminer M3x	Jul 16	12	1968	164	1.2	-1.8
MicroBT	Whatsminer M3	Feb 18	12	2000.4	166.7	1.1	-1.8
MicroBT	Whatsminer M10	Sep 17	33	2145	65	3	0
MicroBT	Whatsminer M10s	Oct 19	55	3498	63.6	5.1	0
MicroBT	Whatsminer M21s	Mar 19	56	3360	60	5.2	0.3
MicroBT	Whatsminer M32	Aug 19	62	3348	54	5.7	0.9
MicroBT	Whatsminer M32s	Jul 19	66	3432	52	6.1	1.1
MicroBT	Whatsminer M20	Jul 20	68	3359.2	49.4	6.3	1.4
MicroBT	Whatsminer M20s	Jul 20	68	3359.2	49.4	6.3	1.4
MicroBT	Whatsminer M31s	Nov 20	76	3313.6	43.6	7	2.2
MicroBT	Whatsminer M31s+	Sep 20	80	3360	42	7.4	2.5

MicroBT	Whatsminer M30	Dec 20	86	3268	38	7.9	3.2
MicroBT	Whatsminer M30s	Dec 20	86	3268	38	7.9	3.2

(continued)

Table Chapter 1-12: Hash Rate, Watts, and Profits of Bitcoin Miners (July 7, 2022)—*continued*

MicroBT	Whatsminer M30s+	Jan 21	100	3400	34	9.2	4.3
MicroBT	Whatsminer M30s++	Sep 20	112	3472	31	10.3	5.3
MicroBT	Whatsminer M50	Apr 22	114	3306	29	10.5	5.7
MicroBT	Whatsminer M53	Apr 22	226	6554	29	20.8	11.4
Other	Bitfury B8	Nov 17	49	6399.4	130.6	4.5	-4.7
Other	Pantech Wx6	Dec 17	34	5001.4	147.1	3.1	-4.1
Other	Snow Panthera1	Dec 17	49	5399.8	110.2	4.5	-3.3
Other	Ebit E10d	Aug 19	25	3500	140	2.3	-2.7
Other	Gmo B3	Oct 18	33	3415.5	103.5	3	-1.9
Other	Bitfury Tardis	Oct 18	80	6304	78.8	7.4	-1.7
Other	A1	unknown	25	2800	112	2.3	-1.7
Other	Ebit E10.3	Jan 18	24	2640	110	2.2	-1.6
Other	T1	unknown	32	3100.8	96.9	2.9	-1.5
Other	Default	unknown	10	1500	150	0.9	-1.2
Other	Ebit E9.3	Apr 18	16	1760	110	1.5	-1.1
Other	V9	unknown	4	1000	250	0.4	-1.1
Other	Ebit E9+	Dec 17	9	1299.6	144.4	0.8	-1
Other	Ebit E9	Aug 18	6	1026	171	0.6	-1
Other	Aisen A1 pro	Apr 20	23	2201.1	95.7	2.1	-1
Other	S5	unknown	25	2200	88	2.3	-0.9
Other	Ebit E9.2	Apr 18	12	1320	110	1.1	-0.8
Other	Ebit E9i	Jun 18	13	1367.6	105.2	1.2	-0.8
Other	Snow Pantherb1+	Jul 18	24	2056.8	85.7	2.3	-0.8

Other	A1	unknown	24	2100	87.5	2.2	-0.8
Other	B1+	unknown	24	2056.8	85.7	2.3	-0.8
Other	F1	unknown	24	2100	87.5	2.2	-0.8

(continued)

Table Chapter 1-13: Hash Rate, Watts, and Profits of Bitcoin Miners (July 7, 2022)—*continued*

Other	Pantech Sx6	Aug 17	8	940.8	117.6	0.8	-0.7
Other	Ebit E10	Jan 18	18	1650.6	91.7	1.7	-0.7
Other	Dragonmint T1	Mar 18	16	1480	92.5	1.5	-0.7
Other	Innosilicon T2 terminator	Apr 18	17	1552.1	91.3	1.6	-0.7
Other	Innosilicon Turbo hf+	Jun 20	33	2600.4	78.8	3	-0.7
Other	Innosilicon T2	Jul 18	26	2100.8	80.8	2.4	-0.6
Other	Innosilicon T2 turbo	Jul 18	24	1980	82.5	2.2	-0.6
Other	Gmo B2	Sep 18	24	1951.2	81.3	2.2	-0.6
Other	Snow Pantherb1	Jun 18	16	1380.8	86.3	1.5	-0.5
Other	Innosilicon T2t	Jul 18	30	2199	73.3	2.8	-0.4
Other	Holic H22	Nov 18	22	1700.6	77.3	2	-0.4
Other	Holic H28	Nov 18	28	2100	75	2.6	-0.4
Other	F3	unknown	30	2199	73.3	2.8	-0.4
Other	F5	unknown	40	2852	71.3	3.7	-0.4
Other	Innosilicon T2 turbo+	Aug 18	32	2201.6	68.8	2.9	-0.2
Other	Ebit E11	Sep 18	30	1950	65	2.8	0
Other	Innosilicon T3	Jun 19	50	3100	62	4.6	0.1
Other	Ebit E11+	Sep 18	37	2035	55	3.4	0.5
Other	Innosilicon T3	Feb 19	39	2148.9	55.1	3.6	0.5
Other	Ebit E12	Aug 19	44	2499.2	56.8	4.1	0.5
Other	Innosilicon T3+	Aug 19	57	3300.3	57.9	5.3	0.5
Other	Innosilicon T3+	Apr 19	52	2797.6	53.8	4.8	0.8

Other	Innosilicon T3	Dec 18	43	2098.4	48.8	4	0.9
Other	Ebit E12+	Aug 19	50	2500	50	4.6	1
Other	Ebit E11++	Sep 18	44	1980	45	4.1	1.2
Other	Stu-u8	Jun 19	46	2102.2	45.7	4.2	1.2

(continued)

Table Chapter 1-14: Hash Rate, Watts, and Profits of Bitcoin Miners (July 7, 2022)—*continued*

Other	U8	unknown	46	2102.2	45.7	4.2	1.2
Other	Strongu Pro	Aug 19	60	2802	46.7	5.5	1.5
Other	F5i	unknown	60	2820	47	5.5	1.5
Other	Hornbill H8	Sep 20	74	3330	45	6.8	2
Other	Hornbill H8 pro	Sep 20	84	3360	40	7.7	2.9
Other	Bonanza Mine 2 (BZM2)	Jan 22	135	3510	26	12.4	7.4

Table Chapter 1-15: Expected Bitcoin Network Energy Consumption and CO2 Emissions

This table shows the expected forecasted energy consumption in TW/Year for the different forecast models including the 5% lower and 95% upper bound, including the expected change in energy consumption as well as the implied CO_2 release from the network.

Year	Expected TW/Year (5% lower bound)	Expected TW/Year (95% upper bound)	Expected TW/Year (50% Median)	Expected average change	MTons CO_2 (5% lower bound)	MTons CO_2 (95% upper bound)	MTons CO_2 (50% Median)
Subsample VAR Forecast							
0	65.82						30.01
1	60.52	78.38	69.37	5%	27.59	35.73	31.63
2	53.23	127.34	83.01	20%	24.27	58.05	37.84
3	46.08	237.60	106.93	29%	21.01	108.32	48.75
4	39.00	481.81	140.67	32%	17.78	219.65	64.13
Full Sample VEC Forecast							
1	42.87	72.19	54.58	-17%	19.54	32.91	24.88
2	25.34	153.06	57.86	6%	11.55	69.78	26.38
3	13.93	463.05	70.29	21%	6.35	211.10	32.04
4	6.99	1763.87	89.49	27%	3.19	804.14	40.780
Full Sample VAR Forecast							
1	63.79	98.80	78.58	19%	29.08	45.04	35.82
2	57.74	236.15	113.37	44%	26.32	107.66	51.68
3	49.28	689.07	176.67	56%	22.48	314.14	80.54
4	39.94	2315.70	282.51	60%	18.22	1,055.71	128.80

Chapter 2: GameFi: The perfect symbiosis of blockchain, tokens, DeFi, and NFTs?

2.1. Citation

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2.2. Abstract

GameFi is a portmanteau of "game" and "finance." The concept involves blockchain games that offer economic incentives to play, otherwise known as play-to-earn (P2E) games. We explain in detail how GameFi differs from traditional games, and carve out its unique value proposition. We also explore how the mechanics of blockchain games influence the social facet of P2E games, where guilds and clans essentially function as profit-sharing organizations. GameFi leverages disparate elements of the crypto space: tokens, DeFi, and NFTs. Lastly, we discuss in detail some of the challenges of GameFi.

2.3. Introduction

As a response to the global financial crisis, Satoshi Nakamoto's (2009) white paper introduced Bitcoin, a digital peer-to-peer monetary system. This innovation brought true digital scarcity with the invention of blockchain technology: a shared, decentralized ledger, without a central governing entity, that allows for immutable trustless transactions (Corbet et al., 2019). Decentralized blockchains provide users with bona fide ownership of their native digital assets, as well as the ability to transact with them freely and with finality.

The functionality of blockchains expanded with the invention of *smart contracts*, which allow programming of blockchain native currencies (see Buterin, 2014). Smart contracts are addresses on the blockchain, with programmed conditions imposed on those who choose to interact with them. These contracts are fully transparent and can be freely audited, so individuals can conduct complex transactions without the need for trusted intermediaries (see Clack, 2018). Using smart contracts, traditional financial (TradFi) activities can be replicated online and without a central authority. This is known as decentralized finance (DeFi) (see Harvey et al., 2021). DeFi transactions occur on Web 3.0 decentralized applications (dApps). They include such activities as asset swaps (e.g., Ethereum to a U.S. dollar stablecoin (ETH/USDT)), liquidity providing (depositing a \$1-to-\$1 value of two pairs, such as ETH/USDT, known as liquidity mining), and lending and borrowing services (see Schär, 2021; Jensen et al., 2021; Harvey et al., 2021; Chiu et al., 2022; Treleaven et al., 2022; Corbet et al., 2023).

Within these activities, the majority of fees generated are distributed to peers that facilitate the transaction (e.g., liquidity providers). The balance is kept by the platform that provides the interface. The most commonly used assets in DeFi are fungible tokens, which represent a form of currency. However, since 2021, non-fungible tokens (NFTs) have also been gaining wide acceptance. Note that each token equals a digital unit of value that represents an asset or utility. Unlike coins, tokens do not have their own blockchains. They are issued on top of existing networks. Furthermore, they are not mined in the process of transaction validation, but are instead minted.

NFTs can represent ownership (see Fairfield, 2021; Yousaf and Yarovaya, 2022b) of any type of item, ranging from digital art or images (such as the popular Bored Ape Yacht Club collection), to concert tickets, to real estate in the metaverse (see Chohan, 2021). The novelty is that digital assets with fully unique characteristics and value are tokenized. But each NFT is unique, and tied to a specific digital asset that is non-fungible in nature (unlike Bitcoin or USD).

NFTs originated in 2013, when Meni Rosenfeld (currently Chairman of the Israeli Bitcoin Association) introduced the concept of colored coins. The idea was to tie real world assets to Bitcoin as a way to authenticate ownership (see Rosenfeld, 2013). Although colored coins were not ultimately implemented, they led to the release of the Rare Pepes memes in 2016 on the Ethereum blockchain (see www.rarepepes.com).

In 2017, Larva Labs created CryptoPunks, the first of many series of randomly generated unique character images (see http://cryptopunks.app). Series like CryptoPunks use randomly selected defining characteristics, such as background, face, hair, hats, and accessories, to create a collection of unique characters (there are 10,000 CryptoPunks). This collection inspired the ERC-721 data standard that now powers most digital art and collectibles on the Ethereum network. Owning these types of NFTs offers access to events, physical items, and various DeFi utilities.

Also in 2017, by leveraging NFT technology, Dapper Labs released the first official blockchain game on Ethereum, CryptoKitties. It took the world of crypto by storm (see Jiang and Liu, 2021, and www.cryptokitties.co). In this game, players purchase, breed, and trade virtual cats that, like CryptoPunks, have unique defining visual characteristics of varying rarity. The game's popularity exploded, clogging the Ethereum network and accounting for about 25% of all traffic. Regular transactions were delayed for days. Since then, multiple blockchain-based games of various genres have been developed, such as Gods Unchained (see https://godsunchained.com), which is comparable to Activision's Hearthstone, and Axie Infinity (see https://axieinfinity.com), inspired by Pokémon.

Blockchain-based games typically use crypto-assets in two ways. They tokenize in-game items as NFTs, and they use fungible tokens as in-game currency. Traditional online games are considered "walled gardens," where the in-game items, characters, and currencies exist on developers' servers. Consequently, users have no ownership rights to their accounts or content, and items and in-game currencies are limited to that specific game. As such, players trade their time and effort to grow their accounts, but gain nothing of lasting economic value. And, if they switch games, or if the developer shuts down the servers, all is lost.

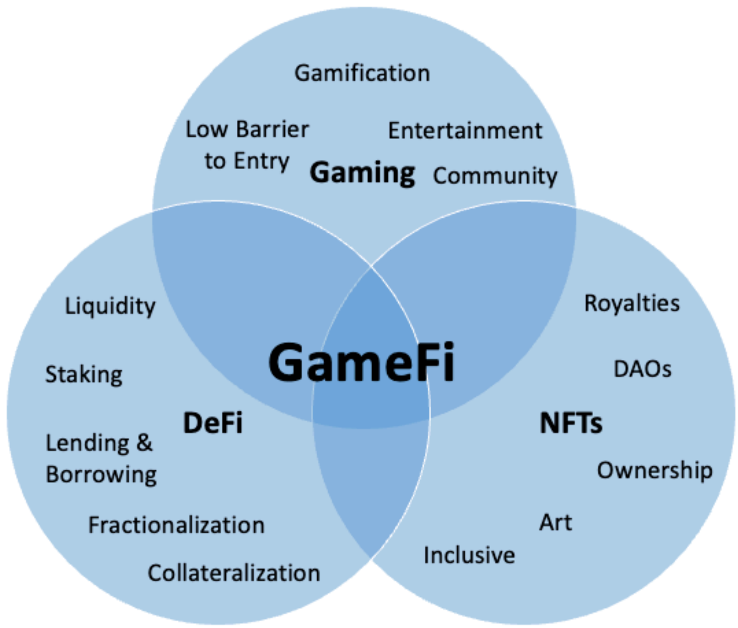
In blockchain-based games, the digital assets exist outside the game, and can be sold, transferred into another game, or used in certain DeFi transactions. Thus, building a game around blockchain technology redefines the incentive models for both players and developers. This has the potential to revolutionize what is already one of the fastest growing industries.

The term GameFi merges the concepts of "gaming" and "finance," and is generally defined as the convergence of three markets: gaming, DeFi, and NFTs (see Figure Chapter 2-1). Each component is significant, and growing rapidly. The gaming industry at large, including PC games, console games, social/casual gaming, and video games, generated approximately $200 billion in revenue in 2022. And the number of players increased during the COVID-19 lockdowns from about 2.6 billion to 3.1 billion (see World Economic Forum, 2022). Astonishing growth was also seen in the DeFi segment, which grew from about a $1 billion market capitalization[20] before the pandemic, to an all-time high of nearly $200 billion in November 2021, before dropping significantly to $60 billion by the end of 2022 (see Inside Bitcoins, 2022).

[20] Market capitalization represents the sum of all market capitalizations for all DeFi projects. We calculate the market capitalization of a DeFi project by multiplying the native DeFi token price, which is related to the respective DeFi project, by the number of tokens in circulation.

Figure Chapter 2-1: Illustration of GameFi

This figure shows how GameFi is positioned at the intersection of Gaming, DeFi, and NFTs.



We observe a similar pattern in the NFT market, which grew from almost no daily volume to a peak monthly volume of about $5 billion in January 2022. However, the NFT market had also declined by the end of the year, to about $600 million in December 2022, according to CryptoSlam's NFT Global Sales Volume Index.[21]

GameFi refers to play-to-earn (or P2E) games, where players can earn crypto-asset tokens (fungible or non-fungible) through gameplay. Players can sell the fungible tokens, or NFTs, via exchanges or marketplaces for fiat currencies (such as USD), or use them on DeFi protocols to, e.g., rent NFTs. Therefore, tokenizing in-game assets into NFTs serves as a way to bridge games and DeFi, allowing for unique opportunities (such as creating yield-generating in-game assets). This type of structure maximizes value for players, rather than extracting value from players (see Hays et al., 2022). Unlike traditional gaming, effort and time is exchanged for entertainment, as well as ownership of digital assets, which is a new P2E model.

The unique benefits and opportunities of GameFi, however, are only made possible by the synergistic nature of its elements. The gaming aspect has a low barrier to entry and provides entertainment, which drives new players and creates a marketplace while acting as a gateway to crypto-assets. NFTs act as securities that facilitate the monetization of certain

[21] The CryptoSlam NFT Global Sales Volume Index is available at https://www.cryptoslam.io/nftglobal.

game mechanics, while creating new revenue streams for developers via royalties from NFT transactions.

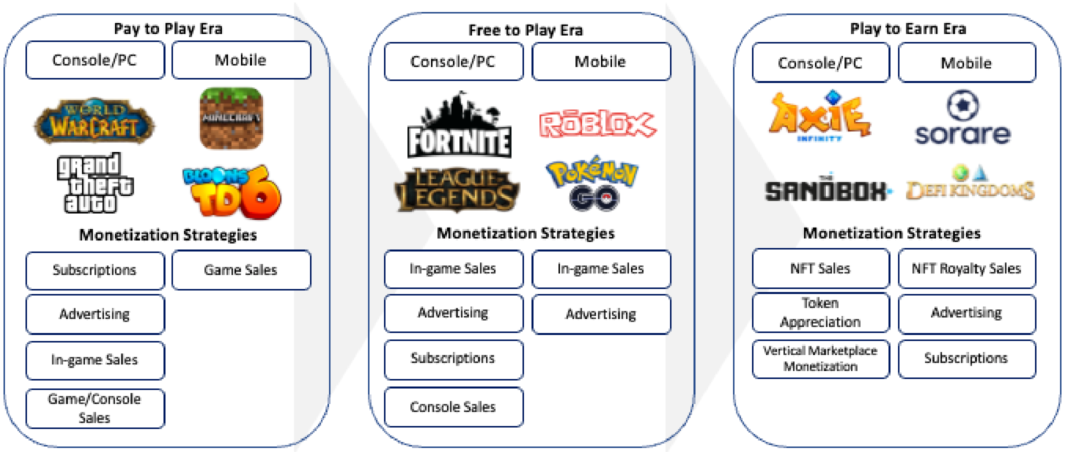
The DeFi protocols also act as a decentralized gamification of financial services, providing GameFi players with an entirely new dimension to monetize their in-game assets. Besides simply selling in-game currency fungible tokens, the key to P2E are the NFTs. They connect the game and its community with decentralized financial services such as "staking" and lending/borrowing.

As we mentioned, the integration of these technologies into games permits many unique monetization strategies (see Figure Chapter 2-2). Traditionally, games generated revenue from pay-to-play (P2P) or free-to-play (F2P) models. They used advertisements, in-game purchases, subscriptions, and data monetization with the F2P, or the newer and rapidly growing "freemium" model. For example, in 2021, of the $200 billion generated in revenue, mobile F2P contributed about 38% ($75.6 billion). Under the freemium model, players access the game for free, but can accelerate their progress, purchase more powerful items, or customize their look by paying for items like avatars and hard in-game currencies. Steady revenue is generated from average players, but most "freemium" games depend on players known as "whales," who are big spenders. Whales take gaming to the next level, seeking completion, optimization/ranking, and/or recognition from the community.

For example, in Diablo Immortal, a recent mobile game, players have spent up to $100,000 to optimize avatars (see Forbes, 2022). The P2E model, in contrast, provides developers with new avenues for fundraising and monetization. Investors may speculate on a game's success and popularity. They can inject capital into the gaming environment without playing the game, by purchasing in-game currency tokens or NFTs. This raises the market capitalization of the in-game currency, and can lead to steady revenues via royalties from NFT transactions. We note that developers have raised enormous sums of capital with the initial issuance of in-game currency tokens, as well as by the sales of virtual plots of land, such as in Sandbox, where one plot alone sold for $4.3 million USD (see Wall Street Journal, 2021).

Figure Chapter 2-2: Evolution of Gaming Monetization

This figure illustrates monetization strategies for the gaming categories Pay to Play, Free to Play, and Play to Earn, as well as examples for games in the respective categories.



Integrating crypto-assets into video games comes quite naturally, because they are already digital in nature. Moreover, crypto-assets also usually feature some form of in-game currency and an economic model. Integrating blockchain technology permits the further monetization of various elements, such as converting an in-game item into a tradable NFT. From a player perspective, interest is heightened from the actual ownership of items or progress earned for time and effort invested, which can also be brought to market. Previously, selling in-game items was overly complex, and not always possible. Therefore, the rise of tokenized items and currencies allows for a smoother, safer, and more liquid secondary market.

Some research has noted the benefits to players in developing countries, who have been able to earn a living via non-professional gaming with P2E games (see De Jesus et al., 2022). Game developers are incentivized by the monetization mechanics. Not only do they draw adoption and engagement, but developers earn a percentage of every in-game transaction. From a community perspective, innovative DeFi products are being created for further monetization and profit making.

Interestingly, in addition to the potential for financial compensation and gameplay, GameFi may eventually provide innovative new medical solutions. The metaverse, which is compatible with GameFi, is expected to combine with various medical technologies, such as telemedicine, virtual care, and holoportation (see Johannes et al., 2021). In 2020, the FDA granted marketing authorization to “EndeavorRx,” a video game treatment for children diagnosed with ADHD. Initial results show improvements in ADHD-related behaviors after two months of treatment, without supplementary medication.

Although still in its infancy, GameFi, as the nexus of three rapidly growing technologies, has experienced exponential growth since its introduction. Even during the depths of the 2022 crypto bear market, venture capital activity in this sector increased, from $874 million in 2021 to $2.4 billion in 2022 (including investment in the metaverse and other gaming projects). Therefore, as an important emerging sector in the crypto space, with the potential to disrupt large industries, it is essential to better understand GameFi's history, underlying mechanisms, and expected trajectory.

Our paper contributes to the literature by introducing and defining GameFi as the intersection of DeFi, NFTs, and gaming. We aim to provide future researchers with a solid foundation of the underlying literature, as well as a sense of the challenges underpinning this rapidly growing multibillion dollar industry. Our work is both descriptive and exploratory. For the descriptive part, our primary contribution lies in introducing and explaining the economics of blockchain gaming, especially GameFi. We clarify how it is related to other crypto sectors, such as DeFi and NFTs. We also discuss GameFi's economics using a case study of Axie Infinity, one of the leading games, and the related gaming guild, Yield Guild Games. We provide a comprehensive DeFi and NFT literature review in order to clearly position our paper. For the exploratory part, our contribution lies in empirically investigating how GameFi is related to the leading coins (Bitcoin, Ethereum), the impact of transaction costs (measured by gas fees), and the related crypto-asset sectors (DeFi, NFTs, and P2E). We also analyze return spillovers during various subperiods. Our results contribute to the DeFi and NFT literature by illustrating how NFTs can be embedded in the gaming ecosystem and intersect with DeFi applications. Furthermore, we find that NFTs are a key component for the new P2E functionality of gaming.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive literature review of DeFi and NFTs. Section 3 describes the evolution of GameFi, and presents a case study of one of the most successful games (Axie Infinity), outlines the concept of guilds, and provides an overview of its related gaming guild (Yield Guild Games). The section also contains a discussion of the industry's challenges. GameFi's role in the crypto ecosystem is explored in-depth in Section 4. Section 5 concludes.

2.4. Literature Review

The crypto-asset market is fast moving, dynamic, and innovative, which has inspired a rapidly growing stream of research on the two GameFi-related sectors, DeFi and NFTs. In this section, we present a systematic literature review on both topics. We aim to provide a comprehensive understanding of the current literature, and identify possible future research directions.

Table Chapter 2-1: Literature Overview

This table summarizes the current literature in decentralized finance (DeFi) (Panel A) and non-fungible tokens (NFTs) (Panel B). See Appendix Table Chapter 2-5 for more details including the article title, journal name and research type.

Panel A: Decentralized Finance (DeFi)	
1. Micro-level	
1.1. Smart Contracts	
1	Clack (2018)
1.2. Tokens	
2-8	Klages-Mundt et al. (2020), Clements (2021), Saengchote (2021), van der Merwe (2021), Kim et al. (2022), Corbet et al. (2023), Fan et al. (2023),
1.3. DeFi Apps	
9-18	Angeris et al. (2019), Foundation, L. X. L., Legal Counsel at Interstellar and Stellar Development (2019), Gudgeon et al. (2020), Bartoletti et al. (2021), Kim (2021), Reno et al. (2021), Stepanova and Erins (2021), Han et al. (2022), Metelski and Sobieraj (2022), Makridis et al. (2023)
2. Meso-level	
2.1. Multichain Scaling	
19	Shekhawat et al. (2021)
3. Macro-level	
20-58	Larios-Hernández (2017), Chen and Bellavitis (2020), Ellul et al. (2020), Guseva (2020), Popescu (2020), Tien et al. (2020), Zetzsche et al. (2020), Abdulhakeem and Hu (2021), Clements (2021), Duran and Griffin (2021), Jensen et al. (2021), Johnson (2021), Schär (2021), Smith (2021), Al-Tawil (2022), Allen et al. (2022), Chiu et al. (2022), Garon (2022), Koster and Lapidus (2022), Meyer et al. (2022), Makarov and Schoar (2022), Momtaz (2022), Park et al. (2022), Popescu (2020), Sauce (2022), Treleaven et al. (2022), Umar et al. (2022), Yousaf and Yarovaya (2022a,b), Allen (2023), Barbereau et al. (2023), Bennett et al. (2023), Brummer (2023), Chu et al. (2023), Kaur et al. (2023), Kirimhan (2023), Piñeiro-Chousa et al. (2023), Qiao et al. (2023), Wronka (2023)

(continued)

Table Chapter 2 1: Literature Overview—*continued*

Panel B: Non-fungible Tokens (NFTs)	
1. Review	
59-60	Nobanee and Ellili (2023). Vidal-Tomás (2023)
2. NFT Market	
61-76	Chohan (2021), Nadini et al. (2021), Borri, Liu and Tsyvinski (2022), Kräussl, and Tugnetti (2022), Ko et al. (2022), Mazur and Polyzos (2022), Oh et al. (2022), Sharma et al. (2022), Urom et al. (2022), White et al. (2022), Zhang et al. (2022), Chowdhury et al. (2023), Ghosh et al. (2023), Jiang and Xia (2023), Ko and Lee (2023), Umar et al. (2023), Wilkoff and Yildiz (2023)
3. Asset Pricing	
4. Tokens	
87-88	Nakavachara and Saengchote (2022), Wang et al. (2023)
5. Behavioral Finance	
89-103	Aharon and Demir (2022), Dowling (2022), Gunay and Kaskaloglu (2022), Umar et al. (2022a,b,c,d), Wang (2022), Xia et al. (2022), Yousaf and Yarovaya (2022a,b,c), Boido and Aliano (2023), Bani-Khalaf and Taspinar (2023), Qiao et al. (2023),
6. Regulatory & Societal Factors	
104-114	Guadamuz (2021), Fairfield (2021), Chalmers et al. (2022), Chandra (2022), van Haaften-Schick and Whitaker (2022), Al Shamsi et al. (2023), Bonifazi et al. (2023), Kraizberg (2023), Serneels (2023), Weking et al. (2023), Zhong et al. (2023)

2.4.1. Decentralized Finance (DeFi)

Since its inception in 2017, the DeFi sector has grown dramatically, reaching a peak market capitalization of nearly $200 billion (see https://coinmarketcap.com/view/defi/). Assets locked into DeFi smart contracts totaled approximately $175 billion as of November 2021 (see https://DeFiLlama.com/). However, as of May 17, 2023, the sector had declined in value to about $50 billion in market capitalization and total assets locked into DeFi smart contracts.

The majority of DeFi activity occurs on decentralized exchange ("DEX") platforms such as Uniswap, Curve, Balancer, Bancor, etc. (see Foundation, L. X. L., Legal Counsel at Interstellar and Stellar Development, 2019; Han et al., 2022; Metelski and Sobieraj, 2022; Makridis et al., 2023). DEX platforms offer lending (yield farming or liquidity mining), borrowing, token swapping, and derivatives trading (see Gudgeon et al., 2020; Kim, 2021; Reno et al., 2021; Stepanova and Erins, 2021). Most DEXs, such as Uniswap, are liquidity pool-based, and function using an automated market maker (AMM) model to determine asset prices algorithmically (see Angeris et al., 2019; Bartoletti et al., 2021). They thus depend on DeFi participants to provide liquidity for their asset pairs, compensating liquidity miners with an algorithmically determined yield and the majority of the generated swapping fees (weighted average contribution). AMMs also depend on arbitrageurs (see Fan et al., 2023) to normalize prices across the ecosystem.

The emergence of dollar stablecoins, such as Tether's USDT, Circle's USDC, Binance's BUSD, and MakerDAO's DAI, have contributed greatly to the growth of DeFi. They reduce friction for users, allowing for better risk management (see Klages-Mundt et al., 2020; Clements, 2021; Saengchote, 2021). Stablecoins have effectively become the bedrock of DeFi ecosystems. The most commonly used assets in DeFi are fungible tokens (stablecoins and other crypto-assets). But, since 2021, non-fungible tokens (NFTs) have also gained wide acceptance as collateralizable assets (see van der Merwe, 2021). Note that each token equals 1 digital unit of value that represents an asset or utility. NFTs can represent ownership (see Fairfield, 2021; Yousaf and Yarovaya, 2022b) of any type of item, ranging from digital art or images (such as the popular Bored Apes Yacht Club), to real estate in the metaverse (see Chohan, 2021), perpetual contract positions (Kim et al., 2022), or in-game equipment.

The financial activities available within the DeFi ecosystem are constantly evolving, and the possibilities are limited only by the community's imagination. This has attracted attention from regulators and researchers, giving host to a multitude of literature strands on DeFi. A framework developed by Meyer et al. (2022) categorizes the DeFi literature as follows: *Micro*, which groups strands of research on individual components of DeFi, *Meso*, which groups research on single DeFi blockchain systems and scaling beyond single-chain systems, and *Macro*, which groups research on the DeFi ecosystem as a whole and its broader implications. See Table Chapter 2-1 (Panel A) for a detailed overview.

Most of DeFi's activities reside on the Ethereum blockchain, and the rapid growth in a short time has caused severe congestion. Such congestion translates into increased delays in transactional treatments and very high transaction costs, measured in gas fees.

Shekhawat et al. (2021) discuss the challenges of DeFi on Ethereum, and the possibility of scaling by using cross-chain solutions. In this context, Smith (2021), Momtaz (2022), Chiu et al. (2022), and Makarov and Schoar (2022) provide an overview of the broader DeFi ecosystem. They examine the potential benefits and challenges of DeFi compared to traditional markets, while Kaur et al. (2023) identify and prioritize the risks.

Tien et al. (2020) propose maximizing the time value of cryptocurrencies by leveraging decentralized money market DeFi protocols, such as Compound. Zhang et al. (2022) investigate the market efficiency of the DeFi market through the lens of the adaptive market hypothesis, while Momtaz (2022) evaluates whether institutional investors improve DeFi market efficiency.

Furthermore, Chu et al. (2023) examine the dynamic volume-return relationship of the top five DeFi tokens, and the implications for trading strategies and market efficiency. Bennett et al. (2023) analyze the impact of behavioral finance factors on the pricing of assets in DeFi markets. From a broader perspective, Allen et al. (2022) explore how DeFi, crypto-assets, and fintech have transformed China's financial system.

There has been growing interest in the drivers of the DeFi market and its relation to other subsectors of the crypto-asset market. Piñeiro-Chousa et al. (2023) evaluate the impact of social metrics, such as tweets and social sentiment indicators, on returns. Park et al. (2022) study price comovements between DEX and CEX tokens in the DeFi market. Umar et al. (2022a) examine how COVID-19 impacted the connectedness among NFTs, DeFi tokens, TradFi assets, and other cryptocurrencies, as well as the spillover effects.

Qiao et al. (2023) take a slightly different tack by examining the time frequency extreme risk spillover network among these asset classes. Yousaf and Yarovaya (2022b) explore the portfolio implications of static and dynamic connectedness among NFTs, DeFi, and other assets. Yousaf and Yarovaya (2022a) also examine herding behavior in the DeFi market.

With the novel technology introduced by crypto-assets, and the existence of DeFi technically outside the traditional financial system, how to regulate the industry has become a hotly debated topic. This strand of the literature has also been rapidly growing. For example, Wronka (2023) investigates financial crime compliance in the rapidly evolving DeFi ecosystem, where regulatory oversight has thus far been minimal. Clements

(2021) and Johnson (2021) highlight the need to regulate exchanges, while Al-Tawil (2022) and Kirimhan (2023) emphasize the importance of anti-money laundering (AML) regulations. In contrast, Ellul et al. (2020) provide a regulator's perspective on regulating blockchain, distributed ledger technology (DLT), and smart contracts.

Duran and Griffin (2021) and Allen (2023) discuss the potential risks DeFi presents, as well as its potential to cause a financial crisis if left unchecked. Zetzsche et al. (2020), Guseva (2020), Koster and Lapidus (2022), and Sauce (2022) explore the current and upcoming regulatory landscape for DeFi in the U.S. and how it may affect the growing industry. Brummer (2023) considers how the industry and regulators must adapt dated disclosure frameworks to match the novel policy questions of DeFi. In addition, Garon (2022) highlights the potential shift in legal doctrine needed to properly approach regulation of this industry.

Another unique characteristic of decentralized protocols and networks is the governance mechanisms. Barbereau et al. (2023) analyze the distribution and exercise of tokenized voting rights in DeFi governance.

Beyond consumer protection, governance, and regulation of the industry, several authors debate the societal benefits of DeFi. For example, Larios-Hernández (2017), Chen and Bellavitis (2020), Popescu (2020), and Abdulhakeem and Hu (2021) highlight the technology's potential to provide open, borderless, and transparent alternatives to traditional services while increasing financial inclusion.

2.4.2. Non-fungible Tokens (NFTs)

Similarly to DeFi, the NFT market has grown exponentially in terms of number of NFTs, total value, media attention, and possible applications. Since 2021, the NFT literature has also been fast-moving. Nobanee and Ellili (2023) and Vidal-Tomás (2023) were the first to systematically summarize the literature on NFTs. They also conducted as a literature review on the concept of the metaverse, and an empirical assessment of the current state of the Web3 meta-economy. See Table 1 (Panel B) for a detailed overview. Mazur and Polyzos (2022) also provide a detailed overview of the infrastructure surrounding NFTs as an investment class. They examine the performance of various NFT categories over short- and long-term periods.

The first set of papers on NFTs identified token price dynamics in the market, as well as the appropriate financial and econometric models. Kireyev and Lin (2021), Kong and Lin (2021), and Wang et al. (2023) develop valuation models for two of the most successful and popular NFT collections, CryptoKitties and CryptoPunks. Goldberg et al. (2021), Nakavachara and Saengchote (2022), and Dowling (2022) explore the pricing factors for digital land in Decentraland (a cryptocurrency and metaverse that lives on the Ethereum platform). Yencha (2023) extends that work to investigating the digital land's spatial heterogeneity.

Horky et al. (2022) focus on the price determinants of NFTs in the digital art market, while Ante (2022), and Anselmi and Petrella (2023) explore the relationship between NFT digital artwork and traditional real-world art. Kräussl and Tugnetti (2022) provide an overview of the models used for pricing NFTs. Ghosh et al. (2023) attempt to predict and interpret the daily dynamics of NFT and DeFi prices using machine learning.

Nadini et al. (2021) expand the literature beyond token-specific studies and pricing research. They shift the focus from single NFT collections to NFT transactions on OpenSea, the world's first and largest Web3 marketplace for NFTs and crypto collectibles. The NFT universe is diverse. Thus, Borri et al. (2022) analyze various categories independently by creating indices. Along these lines, Oh et al. (2022) assess NFT investment returns, while Sharma et al. (2022), Jiang and Xia (2023), and Ghosh et al. (2023) explore the return and volatility properties and drivers of NFTs.

White et al. (2022) show how NFT returns react to NFT-related news. Later work by Wilkoff and Yıldız (2023) examines the behavior and determinants of illiquidity in the NFT market. Chowdhury et al. (2023) examine the efficiency and asymmetric multi-fractal features of various assets, including NFTs, DeFi, crypto-assets, and traditional assets. Moreover, to integrate NFTs into traditional investment portfolios, Umar et al. (2023), Zhang et al. (2022), Ko et al. (2022), and Ko and Lee (2023) examine their diversification, hedging, and safe haven properties.

Lastly, Urom et al. (2022) explore the roles market factors and geopolitical risks play in the dependence and predictability between the volume and return of NFTs in three submarkets: CryptoKitties, CryptoPunks, and Decentraland.

There is an extensive strand of literature on the spillover effects between NFTs and other assets or crypto-asset sectors. For example, Aharon and Demir (2022) and Umar et al. (2022c) investigate the relationship between NFT returns and major asset classes, specifically during the COVID-19 pandemic. Umar et al. (2022a) also explore spillover effects during the COVID-19 pandemic, but they focus on the relation between NFT segments and media coverage. Meanwhile, Wang (2022) examines volatility spillovers between NFT news coverage and broader financial markets.

Xia et al. (2022) also investigate the relationship between NFTs and broader markets, while Bani-Khalaf and Taspinar (2023) study the relationship among BTC, NFTs, and oil. Dowling (2022), Gunay and Kaskaloglu (2022), Qiao et al. (2023), Umar et al. (2022d), and Boido and Aliano (2023) focus more specifically on the relationship between NFTs and other crypto-assets. Relatedly, Umar et al. (2022b) and Yousaf and Yarovaya (2022c) consider the relationship among trading volume, volatility, and NFT returns. Other work by Yousaf and Yarovaya (2022a) examines herding behavior in the NFT, DeFi, and conventional crypto-asset markets.

As a new asset class, NFTs and their value proposition have generally perplexed the uninitiated. However, Kraizberg (2023), van Haaften-Schick and Whitaker (2022), Weking et al. (2023), Chalmers et al. (2022), and Chandra (2022) provide insights into NFTs by examining their potential value-generating mechanisms. This stream of work also explores how NFTs affect entrepreneurship, art, and intellectual property rights.

Garon (2022) examines the legal implications of the metaverse and Web3. Guadamuz (2021) specifically analyzes the relationship between NFTs and copyright laws from a U.K. legal perspective. Furthermore, there have been studies on the vulnerability of the NFT market to financial crimes, such as money laundering, fraud (Al Shamsi et al., 2023) and wash trading (Bonifazi et al., 2023; Serneels, 2023). Lastly, Zhong and Hamilton (2023) survey gender and race biases in the NFT market.

2.5. Emergence of GameFi

GameFi made its debut with CryptoKitties, which was released on November 23, 2017, and largely flew under the radar. On December 2, 2017, the "genesis" kitty, with identifier #1, sold for 247 ETH, which at the time exceeded $100,000 USD. This transaction was publicized and drew large crowds of speculators hoping to breed and flip kitties. According to Jiang and Liu's (2021) analysis of addresses tied to CryptoKitties transactions, activity peaked only eight days later on December 10, 2017. Since then, it has steadily declined. The authors attribute the sharp decline to four specific reasons: Imbalance in the supply and demand of kitties; loss of profit in kitty trading; increase in the gap between rich and poor players; and limitations of the blockchain infrastructure.

Thus, until 2021, when a variety of blockchain-based games were released, they saw only limited success. The highly anticipated Gods Unchained, a digital trading card game not unlike Magic: The Gathering and Hearthstone, was released in March 2021. In January 2022, the developer Immutable X reported having created over 13 million Gods Unchained NFTs, which generated $25 million worth of NFT trading volume over 65,000 unique user accounts.

Although that growth was impressive compared to that of CryptoKitties, Gods Unchained was ultimately dwarfed by Axie Infinity. Released in 2018, Axie Infinity experienced explosive growth in 2021, from a market cap of $29.6 million on January 1, to a peak of $10.5 billion on November 7. In February 2021, to help combat the prohibitively high gas fees (transaction costs) of the Ethereum blockchain, Axie Infinity released its own side chain, Ronin. The reduced transaction costs greatly improved the game's economics and value proposition, which led to a boom in volume and deposited balances that have far exceeded expectations.[22]

This period coincided with COVID-19-related lockdowns, which caused unprecedented disruptions and hardship among workers and employers, especially in the ASEAN region (Brunei, Burma (Myanmar), Cambodia, Timor-Leste, Indonesia, Laos, Malaysia, the Philippines, Singapore, Thailand, and Vietnam). As a result, millions of workers in the region, especially women and young people, were laid off in 2020. Furthermore, many families were dependent on overseas migrant family members sending remittances, which the pandemic halted.

GameFi therefore attracted the attention of unemployed workers seeking income in the virtual world. The opportunity was especially appealing to teenagers and young adults in the ASEAN region, because they are tech-savvy, and about 90% have access to mobile Internet. For these reasons, GameFi quickly gained popularity, at first in the ASEAN region by late 2020. Axie Infinity ultimately created an employment model that could help players generate additional revenue streams while playing the game. Motivated gamers found they could earn approximately $1,200 USD per month.

However, with an increase in in-game token prices, many aspiring players could not afford to buy the necessary items to start playing, e.g., monsters for Axie Infinity. This drove the community to adopt concepts of social gaming that date back to the days of Atari, but have evolved dramatically with the advent of digitization and the Internet. With the emergence of online gaming in the early 2000s, and massively multiplayer online role-playing games (MMORPGs), such as World of Warcraft (WoW), players not only assume the role of a character, but can team up within communities called guilds or clans. This quickly built social and democratic structures within the early virtual worlds, allowing players to coordinate around shared goals or quests, and to share in the spoils of victory.

Note that guilds in traditional gaming environments play a central role in games' longevity. The social environment created in a guild, as well as end-game content targeted to large groups (e.g., ten to twenty-five collaborating players), have become what players aspire to and what keeps them returning.

The same underlying social principles can be observed in blockchain gaming and P2E ecosystems. Gaming communities worldwide come together to complete tasks or quests and earn rewards in the form of tokens or NFTs. However, because resources hold real monetary value, players gain more than an entertainment value, they have an economic incentive as well. As such, P2E gaming guilds will likely continue to play important roles and will probably be operated much more professionally. One benefit of guilds is they help reduce or eliminate the high minimum capital barrier to entry of crypto games for new

[22] See https://explorer.roninchain.com.

users. Guild members, or managers, give scholarships to new members. In other words, they essentially rent out their NFTs, in the form of, e.g., units like Axies, or items like weapons.

Technically, we can define a blockchain gaming guild as a collection, or group of gamers, formed around playing, progressing in, sharing resources, and monetizing blockchain-based games. They are typically structured as so-called decentralized autonomous organizations (DAOs) that collaborate to acquire, manage, use, and monetize assets from blockchain games. Operated outside specific games, guilds gravitate toward the games with the most attractive incentive models. In this genre, as noted earlier, that is currently Axie Infinity, because it developed and popularized P2E GameFi and guild economies.

Axie Infinity's key innovation in building this new genre was focusing on the infrastructure necessary for gamers to enjoy the benefits of advanced blockchain-powered gameplay, while also profiting economically. The idea and infrastructure to implement scholarships (smart contracts, which allow the lending of Axies in exchange for a percentage of earnings) led to the development of the blockchain gaming guilds. This was because many new players could not afford the minimum purchase needed to be successful at the games.[23]

Traditional gaming is usually free-to-play (F2P), but can be enhanced through microtransactions that improve the gaming experience and success rate (commonly referred to as pay-to-win). In contrast to traditional gaming communities, blockchain gaming guilds democratize the process of generating revenue via gameplay. They have successfully monetized the concept of online entertainment.

However, it is not only the players who benefit from blockchain gaming guilds. The *Managers* can also maximize the utility and revenue generation of their NFT portfolios by securely lending them to *Scholars*. For example, in-game avatars like Axies can serve as yield-generating speculative assets. Blockchain gaming guilds provide both *Managers* and *Scholars* with a variety of unique opportunities in the P2E ecosystem, such as exposure to the latest gaming projects (e.g., parcels of land). This helps diversify income streams, and can increase expected revenues. Furthermore, many blockchain gaming guilds can influence game design by using their collective voting power. This helps ensure the longevity and profitability of the games.

There are many existing blockchain games. Each is somewhat unique in gameplay and mechanics, but have some core similarities. Thus, to better understand the mechanisms tying GameFi's elements together (gaming, DeFi, and NFTs), the economic incentives driving the P2E model, and the challenges facing the industry, we conduct an in-depth case study of a specific blockchain game. We choose Axie Infinity, which is the most successful

[23] The most expensive Axie NFT sold was named "Crypto-Kitty." It garnered 1,500 ETH (equal to $170,000 at the time).

project to date from both a financial and a player activity perspective, and the related blockchain gaming guild, Yield Guild Games.

2.5.1. Case Study: Axie Infinity

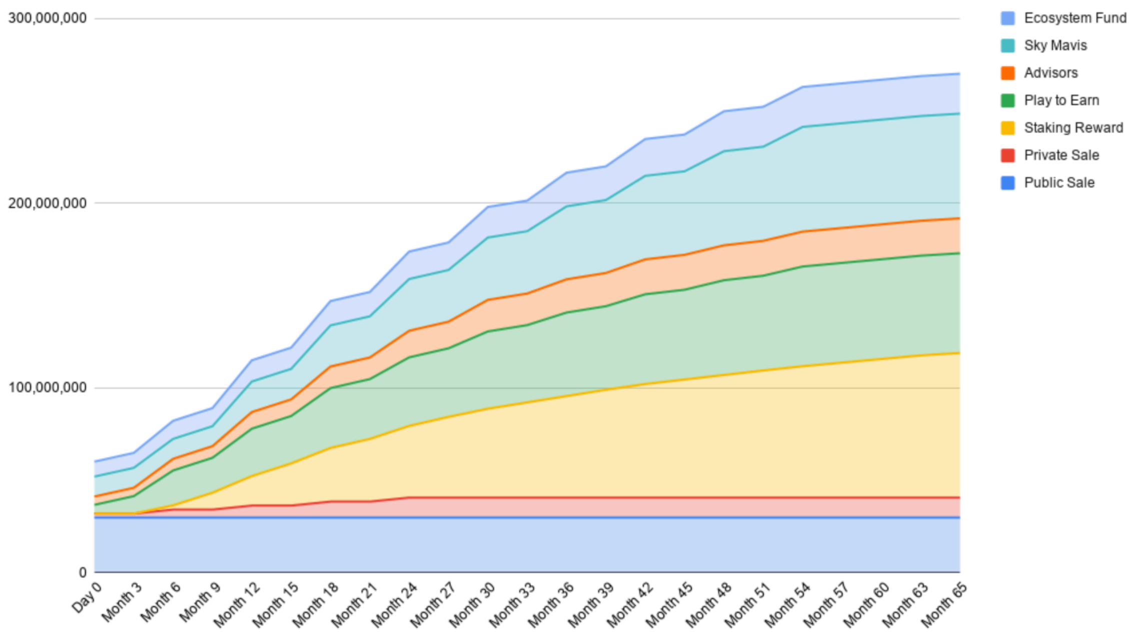
Launched in 2018, Axie Infinity's developers sought to expose people to crypto and Web3 through gameplay. To this end, they built a game where players and developers would collaborate through aligned financial incentives. Originally on the Ethereum blockchain, Axie Infinity switched to its own dedicated Ronin blockchain in order to eliminate gas fees. At its peak in 2021, Axie Infinity had 2.8 million daily active players (10 million total) and $3.6 billion USD of NFTs trading on their in-house marketplace, with an Axie (a playable digital pet NFT) selling for up to $820,000.

The game features a two-currency model: the in-game currency, known as Smooth Love Potion (SLP), and governance tokens known as Axie Infinity Shards (AXS). The game is a digital pet universe, where players use fantasy creatures known as Axies, similarly to the popular game Pokémon. Axies have four main attributes, determined by a combination of six body parts and the class of the Axie, making each one unique. With these creatures, players can 1) play solo in adventure mode, to earn items and experiences used to upgrade their Axies, 2) play in PvP (player versus player) arena battles to win SLP, or 3) engage in breeding to make new Axies by reinvesting SLP and AXS.

Following private investments, Axie Infinity raised capital in 2020 like any other non-Bitcoin crypto project. It used an initial private and public sale of a portion of the total supply of 270 million (see Figure Chapter 2-3). Axie Infinity retained key portions of the total supply in order to finance certain aspects, such as the Community Treasury and the P2E portion.

Figure Chapter 2-3: Axie Infinity Shards (AXS) Release Schedule

This figure shows the release schedule for the AXS token over time, as well as the related parties to which the tokens will be released.



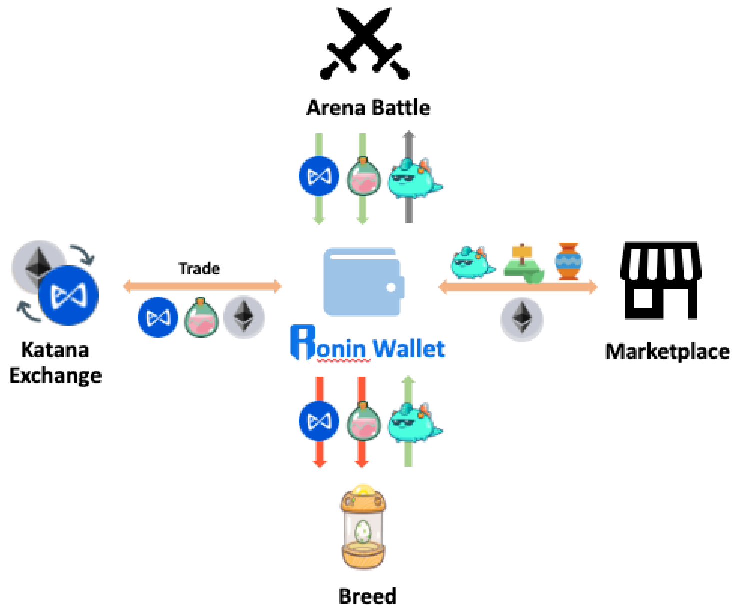
The Community Treasury is used to finance future game development. Although initially under the control of Sky Mavis (the parent company of Axie Infinity), it has shifted to AXS holders as more supply is issued. Treasury funds are replenished with spent AXS tokens and a flat 4.25% commission from all marketplace transactions. The P2E tokens are awarded to players for various activities within the Axie Infinity ecosystem, such as participating and winning in arena, winning tournaments, interacting and tending to plots of land, using the Axie Infinity marketplace, breeding Axies, and future, currently unannounced, features. Therefore, by playing, players can earn items, Axies, in-game currency (SLP), and AXS governance tokens.

The in-game mechanics combine to create a fully functioning in-game P2E economy (see Figure Chapter 2-4). First, individuals who wish to play must inject capital into their Ronin wallets using either a Binance integration or the Ethereum bridge. From there, they visit the marketplace on the Axie Infinity website (Web3), and acquire at least three Axies (the minimum for gameplay). They can then play the game to win rewards. They can choose to cash out, by selling the reward tokens on an exchange called Katana, or they can reinvest by performing in-game activities, such as breeding.

The simplified model in Figure Chapter 2-4 provides a general summary of the economic options.

Figure Chapter 2-4: In-Game Economic Model (Simplified)

This figure summarizes the economic options for gamers, from beginning the game by acquiring at least three Axies from the *Marketplace*, to participating in *Arena Battles*, cashing out tokens through the *Katana Exchange*, deciding to *Breed* new Axies, or trading Axies on the marketplace.



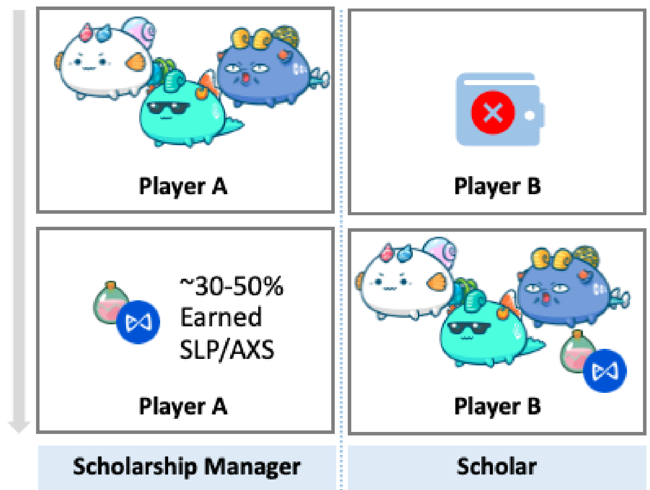
Similarly to many mobile games, players' daily activity is limited by energy points, which are generated based on the amount of Axies owned (e.g., 60 energy max with twenty Axies). Participation in arena battles costs players one energy point. Also, depending on their matchmaking rating (MMR), or in-game skill level, players earn between one and fourteen SLP per win. Thus, players can theoretically earn up to 840 SLP per day, which in May 2021 was approximately $180 USD.

With this earning potential, Axie Infinity attracted a large player base from developing countries, with a particularly large concentration from the Philippines. But in 2021, the cryptocurrency market experienced sharp price increases, leaving players suddenly facing a much higher barrier to entry. The cost to acquire the minimum of three Axies to play (or twenty to maximize earning potential) skyrocketed to hundreds of thousands of dollars. Because players own their NFTs, however, and could engage with smart contracts via DeFi protocols, a multitude of interesting solutions developed.

One is the Scholarship Program, which is an agreement between two parties, the Scholarship Manager (Player A) and the Scholar (Player B) (see Figure Chapter 2-5). Scholarship managers have accumulated a team of Axies, and seek to monetize idle Axies; scholars are individuals who lack the resources to acquire the initial three Axies. By using smart contracts, managers can lend out teams to scholars in exchange for a percentage of earned tokens, with a minimum quota per period (monthly or weekly). Through these programs and DeFi, NFT owners can generate a yield on their assets, while players (who are disproportionately in developing countries) can earn a living wage by playing. Because of the earning potential, the demand for scholarships became so high that managers developed selection processes.

Figure Chapter 2-5: Scholarship Program

This figure visualizes how players who do not own Axies (*Scholars*) can participate in the game by borrowing Axies from *Scholarship Managers* in exchange for a share of future profits.



In sum, Axie Infinity provides an excellent example of the mechanics of GameFi. Players can earn in-game currency (SLP), governance currency (AXS), and Axie NFTs via gameplay (P2E). These can be sold at popular cryptocurrency exchanges such as Binance, and ultimately exchanged for fiat currencies. Besides monetizing their efforts via the sale of fungible tokens, players can further monetize their gameplay activities by leveraging their NFTs and DeFi protocols. Using smart contracts from DeFi, players that own Axies can begin to earn a yield on their NFT assets via scholarships. In this way, players can benefit from an environment that maximizes their value, while developers benefit from new, steady income streams.

2.5.2. Case Study: Axie Infinity and Yield Guild Games

Yield Guild Games (YGG) was one of the earliest and largest guilds by market capitalization ($150 million), discord members (~80,000), and partnered games (#38 as of August 2022). The majority of other blockchain gaming guilds are organized similarly. YYG's initial proof of concept dates to 2018, when gaming industry veteran Gabby Dizon began lending out his Axie NFTs to other players who did not have the means to purchase them. By late 2020, it became clear that Axie Infinity had created an employment model that could help players in the Philippines generate additional revenue streams while enjoying gameplay. YYG was formally cofounded by Gabby Dizon and Beryl Li in

October 2020, with the primary objective of introducing as many people as possible to the P2E revolution spearheaded by Axie Infinity.

YGG's White Paper, along with Splinterlands' SubDAO Litepaper, outline the initial project roadmap and goals driving the guild: as follows 1) maximize the value of NFTs used in virtual worlds and blockchain-based games, 2) build a global community of P2E gamers who play competitively to collect in-game rewards, 3) produce revenue through the rental or sale of YGG's NFT assets at a markup, 4) allow the community to participate in the DAO by establishing proposals and voting, and 5) coordinate research and development for gamers in the DAO to arbitrage yield generation by being competitive in metaverse-related games (see YGG, 2021a, 2021b).

Thus, the goal of the guild is to implement a business model aimed at generating real world monetary value by supporting the emerging digital economy through earning, buying, selling, and renting NFTs to players. To achieve these goals, YGG is organized as a DAO, which is subdivided into *Treasury*, *Vaults*, and *SubDAOs*.

The main role of YGG's *Treasury* is to oversee the management of assets in order to maximize the value returned to the YGG DAO over time (see YGG, 2021a). The *Treasury* conducts multiple economic activities, including 1) purchasing assets in the form of cryptocurrencies, virtual assets in the metaverse, simple agreements for future tokens (SAFT), in-game tokens, and NFTs to contribute to the development of metaverse economies, 2) arbitraging farms to maximize yields, providing guidance on debt and interest payments, acquisition of assets, including any buybacks and future fundraising rounds, and 3) performing financial operations, such as accounting, audits, reporting, and taxes.

Vaults are connected to the *Treasury*, and consist of various guild functions and investments that aim to provide dividends to the *Treasury*. These include lending and borrowing, yield farming tokens, staking tokens, NFT and other asset loan-outs, purchases and sales (see YGG, 2021a).

In sum, each *Vault* represents a token rewards program for specific activities. To claim dividends or rewards for a specific activity, investors need to stake (lock up) YGG's native token in the respective *Vault* from which they would like to gain rewards. Each *Vault* has specific rules, such as lock-in periods, rewards escrows, or vesting periods. This methodology differs from traditional DeFi protocols. These allow token holders to stake their tokens and accrue yield at the interest rate, which varies depending on supply and demand or tokens allocated to a liquidity pool.

In contrast, the rewards paid to stakers in YGG's *Vaults* depend on the respective *Vaults'* economic success, which is ex ante unknown. For example, one *Vault* is dedicated to generating revenue from breeding and selling Axie NFTs. Another distributes revenue acquired from NFT rentals. The token rewards generated from gameplay (breeding and selling Axie NFTs) or NFT lending are distributed to guild members according to the portion staked by each individual guild member and the amount of revenue generated by the source assigned to the respective *Vault*. This means that guild members have the option to actively invest in different revenue streams according to their gauge of the best financial opportunity. Or they can invest in a diversified basket of all its yield-generating activities ("super index vault"), instead of just receiving a fixed rate.

The guilds' *SubDAOs* can be considered miniature economies that interact with the larger all-inclusive economy, which is the DAO itself. *SubDAOs* are thus similar to subsidiaries of a parent company. *SubDAO*s are specialized portions of a guild's main DAO. They are in turn dedicated to a specific game or activity, for example, one may be exclusively dedicated to players of League of Kingdoms, and another to players of Axie Infinity, etc. Members of the *SubDAO*, dedicated to, e.g., Axie Infinity, play and work together, with the aim of generating and increasing income from various activities. The more successful the members of a *SubDAO*, the more financial resources they accrue to better equip and strengthen their in-game characteristics. This further increases their likelihood of generating additional income. This structure of a DAO and subordinate *SubDAOs* facilitates the specialization of the respective *SubDAOs*.

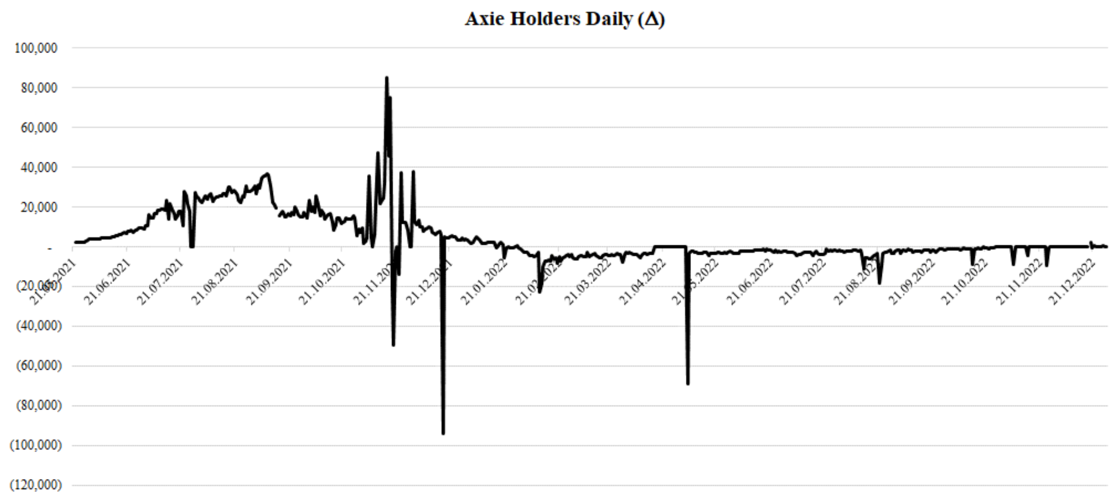
2.5.3. Challenges

P2E games have led to many intriguing developments, and offer both players and developers unique opportunities. But they are not without challenges. In their current state, most are not economically sustainable. We next illustrate some of these challenges, again using the example of Axie Infinity.

In order for players to sustainably generate income via gameplay, positive net cash inflows are required. This occurs naturally during periods of price appreciation in the cryptocurrency market, when speculators inject capital by acquiring tokens. Otherwise, and similarly to multi-level marketing businesses, the game is dependent on new players purchasing in-game creatures (Axies) from older players. When the influx of new players slows or decreases, the game's balanced economic model is endangered, and the likelihood of failing increases (see Figure Chapter 2-6).

Figure Chapter 2-6: Net Change in Axie Holders (Daily)

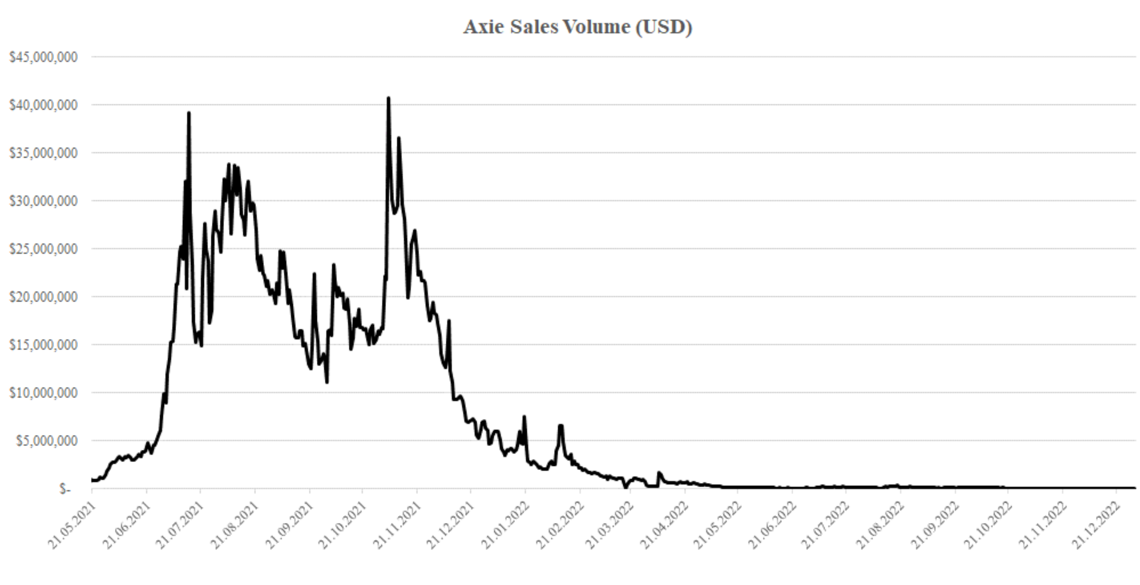
This graph shows the daily change of in-game Axie creature holders. It is produced by using on-chain data compiled from the Ronin network, an Ethereum-linked sidechain.



An early warning sign is a decline in trading volume in in-game Axies, because of a decline in new players who must acquire at least three Axies in order to begin play (see Figure Chapter 2-7). This can lead to a decline in Axie prices due to oversupply. The situation is exacerbated by the fact that there is no alternative for removing Axies from circulation, other than not putting them up for sale. However, if players exit the game, it is in their interest to try to sell their Axie NFTs.

Figure Chapter 2-7: Axie Sales Volume

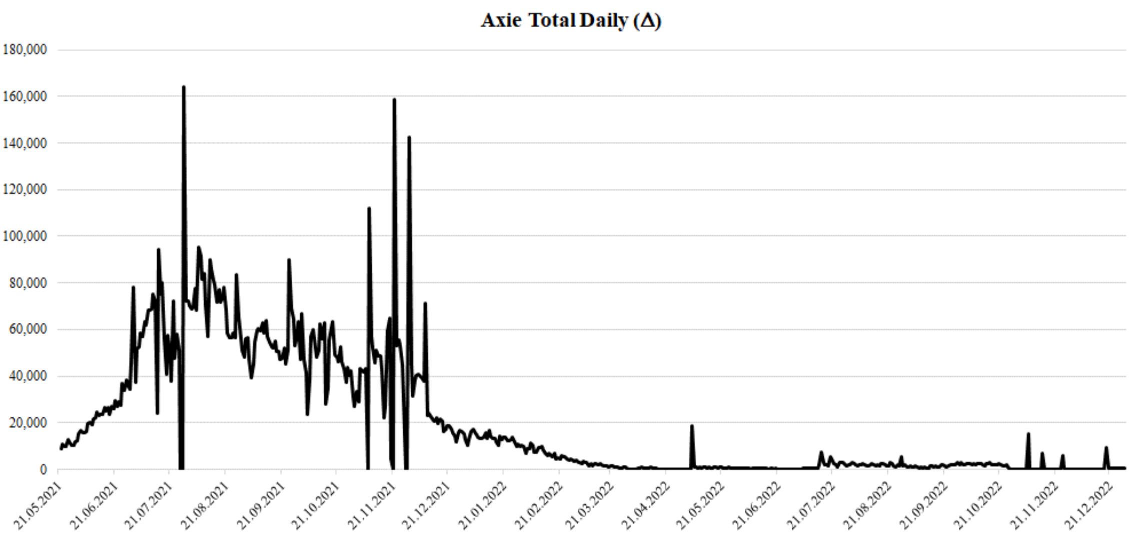
This graph shows daily sales volume in USD of in-game Axie creatures from May 21, 2021 to December 21, 2022. Data come from the Axie Infinity Marketplace (https://app.axieinfinity.com/marketplace/).



This has led to another imbalance in the economic model, where the incentives to breed new Axies are severely diminished (see Figure Chapter 2-8). Since breeding is the mechanism by which players can burn or reinvest SLP, and remove them from circulation, players are instead incentivized to cash out their SLP. The resulting downward price pressure imbalances SLP inflation further.

Figure Chapter 2-8: New Daily Axies

This graph shows the number of newly created in-game Axie creatures on a daily basis from May 21, 2021 to December 21, 2022. It is produced by using on-chain data compiled from the Ronin network, an Ethereum-linked sidechain.

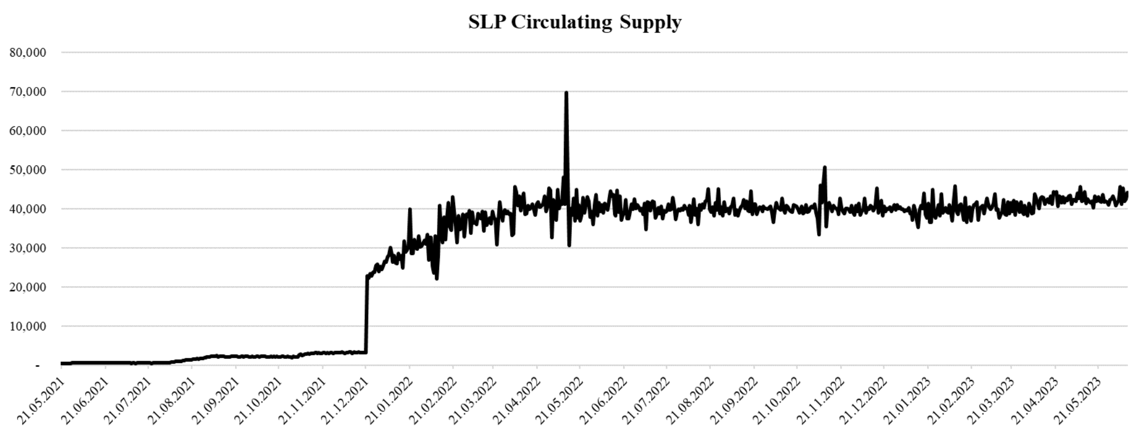


A second major challenge for Axie Infinity, as well as for other P2E games, is inflation of in-game currency (see Figure Chapter 2-9)[24]. For Axie, SLP is key to the game's economic model. A change in player behavior can throw off the token supply balance, and lead to substantial inflation of its circulating supply. There are three ways to earn SLP in-game, but only one way to burn it, which is breeding new Axies. If interest in breeding diminishes, the currency supply will naturally inflate. Because SLP has no supply cap, this can lead to drastic drops in price, and further exacerbate the problem.

[24] The game aims to maintain a stable supply via a careful equilibrium between SLP minting and burning in-game mechanics. Season 19, which lasted from November 10, 2021 to January 4, 2022 experienced a particularly high inflation of SLP supply due to an imbalance between these mechanics.

Figure Chapter 2-9: Circulating SLP Supply

This graph shows the number of SLP tokens in circulation for the period May 21, 2021 to June 10, 2023. It is produced by using data from Messari (https://messari.io/asset/smooth-love-potion/historical).



In addition to the above-mentioned in-game dynamics, the crypto markets have been in a downturn since November 2021. According to CoinGecko, SLP saw a 99% decline to \$0.00256 USD as of December 18, 2022, from its peak of \$0.3645 USD (on May 1, 2021). Axie has also seen a drastic crash in floor price, which once fetched \$340 USD per NFT, but is now at \$6 USD (see Blockworks, 2022). As a result, many players who are motivated to play for economic reasons would earn less than the hourly minimum wage, and this makes it economically unattractive to continue playing (TIME, 2022).

To increase player engagement, Axie Infinity has recently introduced land plots, and expanded the playable universe. This adds utility and new ways for players to interact and earn. The addition of digital land has had a particularly strong reception, with one plot of land selling for \$2.3 million. In total, the collection has generated \$4 billion in sales (see Cointelegraph, 2022).

The challenge now for P2E games, such as Axie Infinity, is their dependence on attracting new users. Player incentives and activity are overly dependent on economic conditions. As they deteriorate, those of the game do as well. This is an important finding: Players are there to earn, and not solely for entertainment. This finding stands in contrast to traditional games, where players are eager to pay to play because they enjoy the entertainment and intensity of the game, as well as the social interactions.

Furthermore, many P2E games are considered rather elementary, and lacking in entertainment value when compared to regular games. This is reflected in the steady decline of active players since the beginning of the 2021 decline in cryptocurrency prices (see Figure Chapter 2-6).

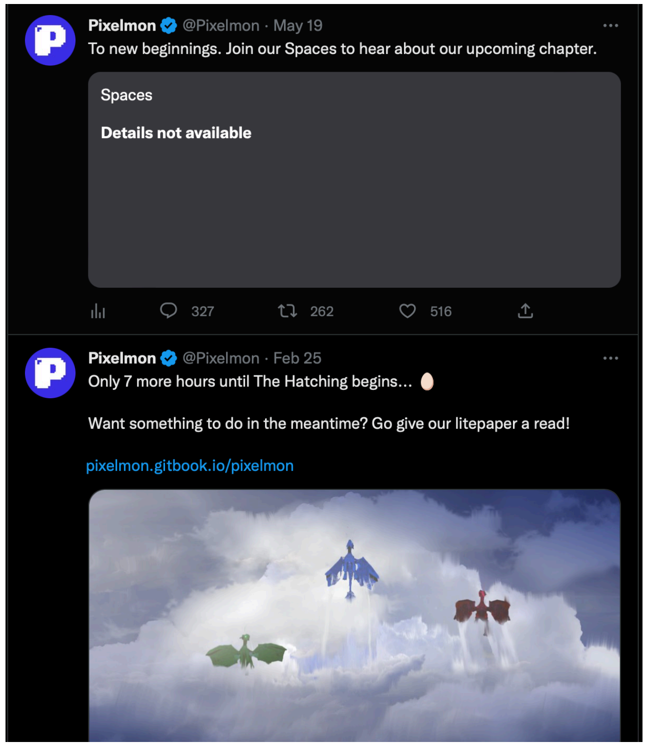
Relatedly, there are increasing occurrences of blockchain game projects that overpromise in trailers, demos, and general communications about quality, while subsequently underdelivering. One example is Pixelmon, a project that raised $70 million from its NFT sale (up to 3 ETH per mint, or ~$9,200 USD at the time), and subsequently revealed in-game art that fell far short of expectations (see Figure Chapter 2-10). The user backlash was so severe that the project expunged all traces of the original reveal from its website and Twitter account (see Figure Chapter 2-11, as well as CoinDesk (2022) and CNET (2022)). This kind of hype can foment disappointment and frustration, which negatively impacts the credibility of GameFi and its mainstream adoption.

Figure Chapter 2-10: Underdelivered Artwork Release

This figure shows the contrast between Pixelmon's originally promoted art during the fundraising process, and the finally delivered art.

Figure Chapter 2-11: Deleted Posts

This figure shows the removal of the promoted art during the fundraising process.

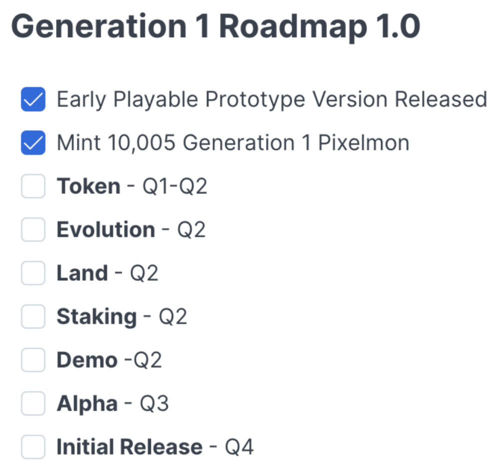


However, when comparing developers' roadmaps and timelines against those of recent gaming projects, it is obvious why GameFi projects sometimes underdeliver. For example, Pixelmon followed a standard development and release schedule, first by publishing a litepaper detailing the project and its ambitions, and a subsequent roadmap (see Figure Chapter 2-12). Similarly to other crypto-asset projects, Pixelmon's team followed the common formula of releasing a whitepaper, creating excitement through a highly ambitious teaser trailer, raising funds for development with an NFT sale, and then beginning development. Promising "the largest and highest quality game the NFT space has ever seen,"[25] before raising the necessary capital, and then expecting to complete the entire project within the same year, was ultimately unrealistic. Contrast this timeline with that of a top-tier game, Genshin Impact. It required two years of development, with a team of 700, and a budget of $100 million USD (see IGN, 2022). In the GameFi space, which is still in its infancy, it is important for projects to set realistic, achievable expectations.

[25] See Pixelmon's website at https://pixelmon.club/adventure.

Figure Chapter 2-12: Pixelmon's Roadmap 1.0

This figure shows Pixelmon's initially released roadmap.



In sum, current blockchain games are overly focused on economic incentive models, and underfocused on actual game design. The game tokenomics also need to avoid self-reinforcing cycles that can lead to high volatility. Such volatility can result in a death spiral. Expanding on gameplay and creating multiple burn mechanisms that have actual utility for players should help break these cycles, and even render tokens deflationary. Although GameFi does present exciting opportunities, and the space is evolving rapidly, it is critical for long-term success that it mature thoughtfully and learn to set realistic expectations.

2.6. GameFi's Role in the Crypto Ecosystem

GameFi is one of the most recent innovations in the crypto space, and its landscape is changing rapidly. In this section, we aim to identify how GameFi is embedded in the crypto ecosystem by determining spillover effects from the major coins (Bitcoin and Ethereum), gas fees, and related crypto-asset sectors (DeFi, NFT, and Play-to-Earn).

To measure spillovers, we estimate a Vector Autoregression (VAR) model, which can process several variables over time. Estimation results are then used to investigate relationships between those variables. We include Bitcoin as the most dominant digital asset (Kyriazis, 2019), and Ethereum because a significant amount of NFT trading volume rests on the Ethereum blockchain and GameFi-related games.[26] The bulk of GameFi-related transactions are on the Ethereum blockchain, so we also include gas in our analysis. It measures the amount of computational effort and costs required to operate on the Ethereum network.

[26] Despite the emergence of other blockchains that support NFT trading and P2E, tokens are often linked to or use the Ethereum blockchain directly. These include popular tokens such as ApeCoin, Sandbox, Immutable, Axie Infinity, and Decentraland.

The majority of scientific papers studying spillover in the crypto space focus on Bitcoin, Ethereum, and Litecoin, as well as Ripple or Stellar (see, for example, Katsiampa et al., 2019; Koutmos, 2018; and Luu Duc Huynh, 2019). Ohers research the impact on crypto-assets with relatively low market capitalizations (e.g., Koutmos, 2018; Omane-Adjepong and Alagidede, 2019; Zieba et al., 2019). Past research has been inconclusive, with results ranging from 1) bidirectional return spillover effects between Bitcoin and Ethereum, to 2) Bitcoin being the dominant return contributor to a range of other larger crypto-assets, including Ethereum, and 3) Bitcoin being the receiver of spillovers from large cryptocurrencies, while Ethereum remains unaffected.

Diebold and Yilmaz (2012) introduce a spillover index model based on a generalized VAR model to measure volatility spillover. It has been applied by Gillaizeau et al. (2019) and Trabelsi (2018) to investigate return and volatility spillover. It is also useful to explore the predictive power between crypto-assets and currencies, or crypto-assets at large and other markets, such as commodities and stocks, to gain insights into investment strategies. Dowling (2022) investigates volatility spillover among certain NFTs, such as CryptoPunks, Decentraland LAND tokens as a proxy for NFTs, and Ethereum and Bitcoin, using wavelet coherence. The results indicate that the NFT proxies are not only quite distinct, but exhibit only limited spillover.

However, those papers find mixed results for a multitude of reasons, including varying proxies, time frames, and applied methodologies.

In contrast, our aim is to carve out how GameFi is incorporated into the crypto space during different periods, because the dynamics are rapidly changing. We choose the general VAR model without restrictions, such as in a structured VAR, because we do not want to impose ex ante rules on potential relationships ex ante. That would only be required if we needed to isolate exogenous independent movements, such as the interference of a central bank. We are mainly interested in identifying and explaining the intertwined dynamics of the crypto sector and cryptocurrency returns during subperiods only. Furthermore, we do not forecast returns based on the model or aim to minimize forecast errors. Therefore, a general model is most suitable.

2.6.1. Methodology

Following past research, such as Lütkepohl (2005) and Greene (2008), we estimate a $VAR(p)$ model that allows for multiple independent variables without enforcing a distinct causal relationship:

$$\mathbf{Y}_t = \mathbf{A}_1\mathbf{Y}_{t-1} + \mathbf{A}_2\mathbf{Y}_{t-2} + \cdots + \mathbf{A}_p\mathbf{Y}_{t-p} + \boldsymbol{c} + \mathbf{u}_t \quad (1)$$

where $\mathbf{Y}_t$ is the $K \times 1$ vector of our seven endogenous return variables (BTC, ETH, Gas, DeFi, GameFi, NFT, Play-to-Earn), which is a linear function of p, of their own lags. $\mathbf{A}_i$

is a $K \times K$ matrix of coefficients for $i = 1, \ldots, p$, and $\mathbf{Y}_{t-i}$ are the $K \times 1$ matrices of lagged returns, with p as the optimal lag lengths to be included.[27] The K-dimensional intercept term is represented by $\mathbf{c}$, and $\mathbf{u}_t$ is a K-dimensional term of white noise.

We estimate the coefficients by iterating seemingly unrelated regressions. Moreover, we adjust our maximum likelihood divisor from $\tilde{T} = T$ to $\tilde{T} = T - \bar{m}$, where $\bar{m}$ is the average number of parameters per equation for $\mathbf{Y}_t$ over the n equations, and T represents the number of error terms. This is to adjust for small-sample degrees of freedom, as our later determined subsamples have 319, 354, and 347 observations, respectively, for subsamples 1, 2, and 3.

After fitting the $VAR(p)$ model, we test whether one variable causes another variable by using "Granger causality" (Granger, 1969). We regress y on lagged y. Variables are considered "causal" if the null hypothesis that estimated coefficients on the lagged values y are (jointly) zero can be rejected.

2.6.2. Data

Next, to research the spillover effects, we create the following four crypto-asset sector indices based on CoinGecko's classification[28]: 1) DeFi, 2) GameFi, 3) NFT, and 4) Play to Earn. CoinGecko's API also provides the token prices, market capitalization, and trading volume in USD, based on a global volume-weighted average price formula.

Appendix Table Chapter 2-13 provides an overview of the tokens included in the respective indices, including their market capitalization in USD. For a token to be considered in any of the four indices, it must be traded for a minimum of seven days with a non-zero trading volume, and have at least a $5 million USD current market capitalization. To build the four indices, we also require a minimum of three distinct tokens in each respective index. This results in a start date of January 17, 2020, and an ending date of April 21, 2023, with a total of 1,191 observations. We create equally weighted indices by taking the average of the log-returns of each token.[29]

Figure Chapter 2-13 plots the respective indices over the sample period. Table Chapter 2-2 shows the descriptive statistics for the sample period for BTC, ETH, and gas, as well as for the four indices. The descriptive statistics show that, despite the high standard deviations

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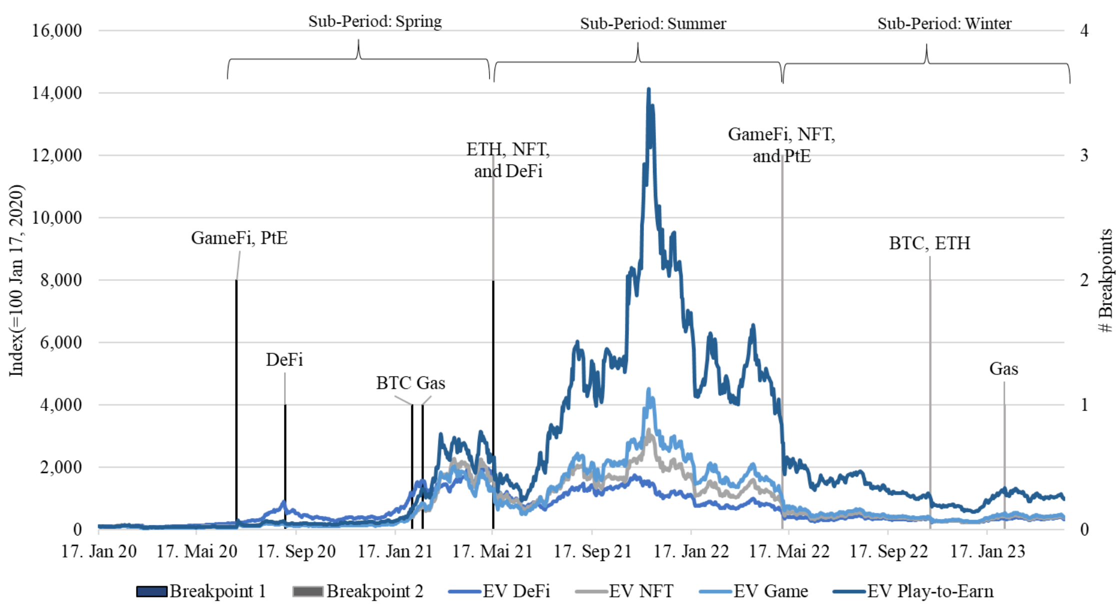
[27] Optimal lag length maximizes the degrees of freedom to estimate the model without incurring the omitted variable problem.
[28] Tokens are categorized according to CoinGecko on April 24, 2023 (available at https://www.coingecko.com/en/categories).
[29] In unreported results, we test our results for value-weighted indices, and find they are not driven by the weighting scheme. The value-weighted index is the sum of the weighted log-returns of each token. The respective weight is calculated based on the average market capitalization of a token over the last fourteen trading days relative to the total market capitalization of all tokens included in the respective index at that time.

for all indices, the returns are positive over the observation period. The distinct higher moments – mostly negative skewness and positive excess kurtosis (fat tails) – reveal that the returns are non-normally distributed. This is supported by the unreported Jarque-Bera test.

Figure Chapter 2-13: Crypto-Asset Price Charts and Structural Breakpoints

These figures show the development of prices for the equally weighted crypto sector indices (DeFi, GameFi, NFT, and Play-to-Earn) (see Panel A), and Bitcoin (BTC), Ethereum (ETH), and gas prices (see Panel B), including structural breaks based on the Clemente-Montañés-Reyes test. The two structural breakpoints were selected at the date when three structural breaks coincided for the crypto sector indices, BTC, ETH, and gas. All time series are indexed to 100 at the beginning of the observation period January 17, 2020 to April 21, 2023.

Panel A: Crypto Sectors



Panel B: Bitcoin, Ethereum, and Gas

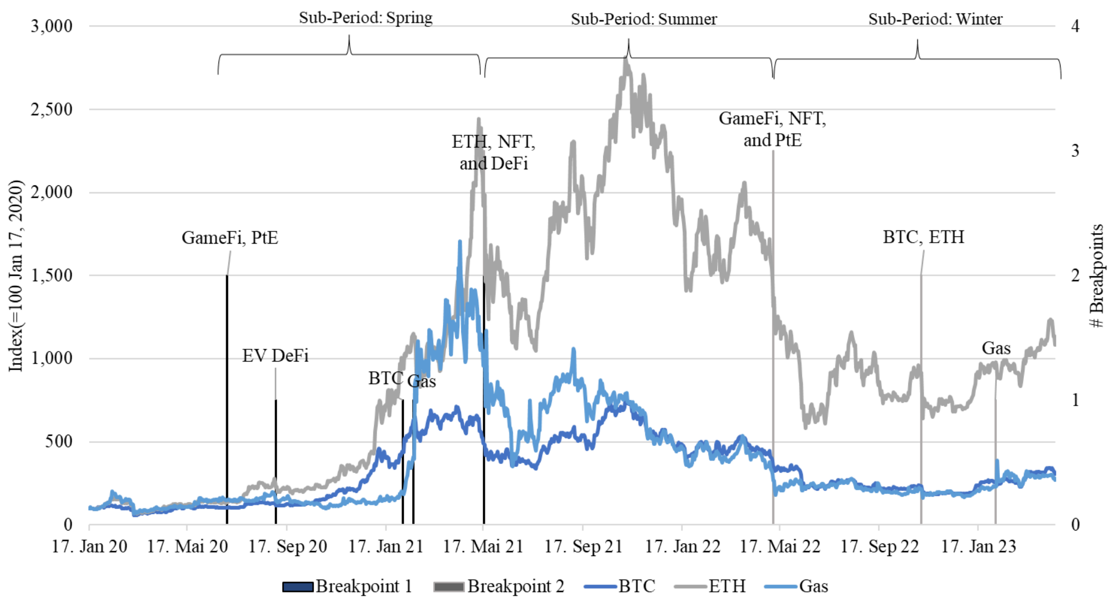


Table Chapter 2-2: Descriptive Statistics

This table shows the descriptive statistics (mean (Mean), median (Median), standard deviation (Std), minimum (Min), maximum (Max), skewness (Skew), and Kurtosis (Kurt)) for BTC, ETH, and gas, as well as the equally weighted DeFi, NFT, GameFi, and Play-to-Earn indices for the period January 18, 2020 to April 21, 2023, with a total of 1,119 observations. In unreported results, we calculate Jarque-Bera (JB) test statistics, and find all are larger then 9.21. We thus reject the null hypothesis of normally distributed returns at the 1% level for all coins and indices.

	Mean	Median	Std	Min	Max	Skew	Kurt
BTC	0.0009	0.0011	0.0376	-0.4337	0.176	-1.39	19.76
ETH	0.002	0.003	0.0502	-0.5631	0.2194	-1.46	18.81
Gas	0.0008	0.0005	0.0688	-0.6002	0.76	1.16	27.39
DeFi	0.001	0.0061	0.0531	-0.5792	0.2126	-2.02	19.26
GameFi	0.0012	0.0013	0.0698	-0.5015	0.6975	0.86	20.65
NFT	0.0011	0.0051	0.0598	-0.6743	0.2653	-1.85	20.97
Play-to-Earn	0.0019	0.0017	0.0707	-0.5699	0.6873	0.69	20.56

2.6.3. Empirical Results

Because we are interested in how the GameFi sector evolved over time, we first analyze whether the log return time series for the indices (DeFi, NFT, GameFi, and Play-to-Earn), and for BTC, ETH, and gas, are stationary. To this end, we use a series of unit root tests on the log-returns, including the traditional Dickey–Fuller no trend-stationary test, the Zivot and Andrews test, and the Clemente-Montañés-Reyes (CMR) test. This ensures the estimation is reliable and the results are not spurious, which could lead to poor understanding of any subsequently applied VAR model results.

As Table Chapter 2-3 shows, the test statistics for all time series are stationary, and are thus integrated at $I(0)$ at the 1% level (see Table 3, columns "Dickey–Fuller," "Zivot-Andrews," and "CMR (AO)"). CMR tests the unit root of a time series under possible structural breaks, and considers the existence of up to two such breaks (Clemente et al., 1998; Perron and Vogelsang, 1992). This is a key point, because the crypto market evolves rapidly. The dynamics can also change quickly and severely, because of, e.g., Bitcoin halving events, the introduction of derivatives (2011) and ETFs (2021), and bubbles and crashes, such as the 2017 boom (2018 crash) and 2020 boom (2021 crash).

Table Chapter 2-3: Stationary and Structural Break Tests

This table shows the results for our stationary test and our structural break test using the Dickey–Fuller no trend-stationary test, the Zivot-Andrews stationary test, and the Clemente-Montañés-Reyes unit root test with double mean shifts. It also shows the AO model breakpoint analysis for BTC, ETH, and gas, as well as the equally weighted DeFi, NFT, GameFi, and Play-to-Earn indices.

	Dickey–Fuller	Zivot-Andrews	CMR (AO)	Break Date 1	Break Date 2
BTC	-35.96***	-16.25***	-9.40***	06-Feb-21	07-Nov-22
ETH	-37.11***	-16.22***	-10.20***	17-May-21	07-Nov-22
Gas	-39.13***	-16.16***	-17.26***	19-Feb-21	07-Feb-23
DeFi	-37.07***	-15.43***	-10.05***	03-Sep-20	17-May-21
GameFi	-32.62***	-15.66***	-13.87***	05-Jul-20	9-May-22
NFT	-35.31***	-14.51***	-10.16***	17-May-21	9-May-22
Play-to-Earn	-32.41***	-15.61***	-13.72***	05-Jul-20	9-May-22

Applying CMR methodology, we identify two major breakpoints: The first is during February to May 2021 (BTC, ETH, Gas, DeFi, and NFT), and the second in May 2022 (DeFi, GameFi, NFT, and Play-to-Earn). These breakpoints can also be seen visually in Figure 13. The exact dates are set to the date when three structural breaks coincided for the sector indices, BTC, ETH, and Gas, which occurred on May 17, 2021, and May 9, 2022. From an economic standpoint, this may have occurred as the concept of GameFi began to take shape during the first half of 2021, when GameFi overtook DeFi as the new emerging crypto-asset sector.[30]

The GameFi "hype" ended when the total number of active users fell by about 13%, and GameFi investment amounts declined by about 90% month-over-month from April to May 2022. At the same time, Ethereum's high gas fees and network congestion issues continued to slow growth.[31]

[30] See, for example, https://news.coincu.com/73220-overview-gamefi-2021-prediction-2022/.
[31] See, for example, https://cryptoslate.com/can-mays-biggest-gamefi-crash-victims-survive-the-bear-market-may-monthly-report/.

We therefore label the three time periods as follows: the *Spring* period refers to the period before the first breakpoint, July 5, 2020, to May 17, 2021, the period when the first large GameFi projects emerged. The *Summer* period begins after the first breakpoint (May 18, 2021), and extends until the second breakpoint (May 9, 2022). This is when GameFi was overtaking DeFi in fund inflows and popularity. The *Winter* period begins after the second breakpoint (May 10, 2022), when the sharp decline in the crypto-asset market started. It lasts until the end of the observation period (April 23, 2023).

Before estimating the VAR model, we choose the optimal lag-length (p) using Final Prediction Error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (BIC), and the Hannan and Quinn information criterion (HQIC) lag-order selection statistics. We choose $p = 1$, which is supported by most criteria for each subperiod. We find it is the optimal choice between giving up degrees of freedom and enduring the omitted variable problem.

Next, we estimate our VAR(1) models to assess Granger causality, with endogenous variables BTC, ETH, Gas, DeFi, GameFi, NFT, and Play-to-Earn for the full sample, as well as separately for *Spring*, *Summer*, and *Winter* (see Table Chapter 2-4). Because of the breakpoints, it is important to test the subperiods separately. Otherwise, we may be "diluting" distinct subperiod relationships by only interpreting the results for the full sample period.

Table Chapter 2-4: Granger Causality

This table shows the results for the Granger causality Wald test χ^2 estimators, using the estimation results of the VAR(1) model with endogenous variables BTC, ETH, Gas, DeFi, Game, NFT, and Play-to-Earn (equally weighted indices) for the subperiods *Spring*, *Summer*, and *Winter*. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The Granger causality relationship is shown from *Origin* (columns) to *Receiver* (rows).

	Origin						
Receiver	**BTC**	**ETH**	**Gas**	**DeFi**	**GameFi**	**NFT**	**Play-to-Earn**
Sub-Period: *Spring*							
BTC	-	3.18*	7.84***	0.02	0.02	0.05	0.02
ETH	5.21	-	11.45***	0.03**	0.24	0.29	0.06
Gas	5.63**	11.67***	-	1.83	0.44	1.83	0.03
DeFi	2.64	5.94**	5.96**	-	0	1.12	0.4
GameFi	2.57	3.91**	2.54	0.41	-	1.8	1
NFT	8.68***	10.33***	3.9**	0	0.95	-	0.09
Play-to-Earn	1.86	5.67**	2.11	0.46	0.73	0.81	-
Sub-Period: *Summer*							
BTC	-	0.27	0	0.96	3.31*	3.09*	0.68
ETH	1.14	-	0.02	2.74	0.49*	0.22	0.75
Gas	0.02	0.79	-	0.09	1.46	0.91	0.19
DeFi	0.4	1.48	0	-	1.34	0.57	1.15
GameFi	0.05	0.66	0.81	0.12	-	3.29*	0.02
NFT	0.05	0.95	0.61	0.17	1.51	-	0
Play-to-Earn	0	0.69	1.37	0.18	0.71	2.2	-
Sub-Period: *Winter*							
BTC	-	0.04	1.5	0.16	0.33	1.24	0.8
ETH	0.37	-	3.77	0.86*	0.42	1.92	1.84
Gas	1.54	0.18	-	3.43*	1.78	2.16	0.02
DeFi	0.72	0.64	1.81	-	0.27	0.61	0.6
GameFi	0.29	1.15	1.94	3.31*	-	0	0.24
NFT	0.6	1.05	1.23	3.07*	0	-	0.18
Play-to-Earn	0.66	1.06	1.39	2.86*	0.01	0	-

During the *Spring* period, when the GameFi market was still in its infancy, we find support for the prediction that ETH Granger causes the DeFi, GameFi, NFT, and Play-to-Earn market, and, to some extent, BTC and Gas. We do not find that the aforementioned markets Granger cause BTC (see Table 4, Subperiod: *Spring*). We interpret these results as a sign that the GameFi market was young and immature, and mostly determined by the movements of the leading crypto-assets, BTC and ETH, and the crypto market at large. In line with Luu Duc Huynh (2019), we also find evidence that Bitcoin received spillover effects from Ethereum (and gas) using a comparable early sample period.

The dynamic described previously changed rapidly during the *Summer* period, when GameFi skyrocketed in popularity. In fact, none of the DeFi, GameFi, NFT, or Play-to-Earn markets showed Granger causality by BTC, ETH, or gas (see Table Chapter 2-4, Subperiod: *Summer*). On the contrary, we find that BTC and ETH are Granger caused by GameFi, and that NFTs Granger cause GameFi. The latter may be explained by the earlier emergence of the NFT market, and by NFTs becoming an increasingly integral part of GameFi.

During the *Winter* period, we find, similarly to the *Summer* period, that the DeFi, GameFi, NFT, and Play-to-Earn markets seem to have become emancipated from the major crypto-assets (BTC and ETH). They continue to not be Granger caused by them (see Table Chapter 2-4, Sub-period: *Winter*). However, GameFi no longer Granger causes BTC or ETH, but DeFi is emerging as an important factor in the crypto market. It Granger causes not only ETH and gas, but also the GameFi, NFT and Play-to-Earn sectors. The relationship between DeFi and ETH/Gas may be attributed to the fact that many DeFi projects are using the Ethereum blockchain, which is powered by gas (a proxy for transaction costs).

In sum, the dynamics in the crypto space, and especially the GameFi sector, are changing rapidly, driven by, e.g., media attention, fund in- and outflows, and technological advances. Not surprisingly, we find that, after GameFi's introduction, the sector was driven by general market movements in the crypto space (*Spring* period). Strikingly, only a short time later, it was growing exponentially, and its dynamics caused spillovers to Bitcoin and Ethereum (*Summer* period). During the subsequent *Winter* period, the GameFi sector seems to be independent from Bitcoin and Ethereum, and is only obtaining spillovers from the DeFi sector.

2.7. Conclusion

GameFi and gaming guilds have become one of the most promising avenues in the digital asset space. Replacing in-game currencies with crypto-assets, and creating NFTs from in-game assets, has literally been a game changer. This is because shifting from a structure that maximizes extraction of value *from* players, to one that maximizes value *for* players, is a recipe for success, if done right. Players are rewarded for time and effort invested with assets they own and can trade.

Gamers always valued these types of in-game assets, but were generally unable to safely transact with peers. These changes have also provided opportunities for game developers to collect royalties on every NFT transaction, which can lead to intriguing new business models. Lastly, the ability to use NFTs outside an actual game, and to interact with smart contracts (using DeFi), has led to imaginative solutions to in-game hurdles.

However, the hype over blockchain gaming, guilds, and in-game NFTs have pushed prices to unsustainable levels, from a financial perspective. Guilds helped democratize access and enable gaming communities to widen participation. But future success in monetary terms depends on the overall success of their partnered games. If a particular blockchain game fails, or the demand for its NFT assets is suddenly reduced, the *SubDAO* that is dedicated to the monetization of that game's assets will inevitably suffer. This, by default, may affect the performance of its superordinate *DAO*. Thus, the primary economic drivers ensuring the success of gaming guilds are inherently connected to the success of the blockchain gaming industry and its native tokens as a whole. We note that blockchain gaming guilds have the advantage of diversifying their NFT investments across different games, and gaining exclusive early access to the newest games on the scene. This ultimately increases their value proposition.

GameFi has shown the capability to contribute to reducing income inequalities by allowing monetization while gaming. However, it has become apparent that this can be a double-edged sword, especially when the tokenomics are not well designed, or the financial gameplay is not appealing enough to attract players. Furthermore, a sharp decline in cryptocurrency prices in 2022 dramatically reduced blockchain gaming activity, which suggests their success is largely tied to earning potential. Current blockchain games have been designed with economic incentives first, and entertainment and game quality second. For more enduring success, industry developers should shift perspective, and take sufficient time to plan and design appealing projects. They should aim to avoid overly ambitious roadmaps, which can mislead players and the markets. However, the continued heavy investment of venture capital into the sector during the bear market signals the continued promise of GameFi. Many market participants still seem to see potential beyond the challenges faced by GameFi and blockchain-based games.

Appendix B. Supplemental Information for Chapter 2

Table Chapter 2-5: Literature Overview

This table summarizes the current literature in decentralized finance (DeFi) (Panel A) and non-fungible tokens (NFTs) (Panel B).

#	Article Title	Authors	Year	Journal Name	Research Type
Panel A: Decentralized Finance (DeFi)					
1. Micro-level					
1.1. Smart Contracts					
1	Smart Contract Templates: Legal Semantics and Code Validation	Clack	2018	Journal of Digital Banking	Theoretical
1.2. Tokens					
2	Built to Fail: The Inherent Fragility of Algorithmic Stablecoins	Clements	2021	Wake Forest Law Review	Theoretical
3	Are DeFi Tokens a Separate Asset Class from Conventional Cryptocurrencies?	Corbet et al.	2023	Annals of Operations Research	Empirical
4	Towards Understanding Governance Tokens in Liquidity Mining: A Case Study of Decentralized Exchanges	Fan et al.	2023	World Wide Web	Empirical
5	Perpetual Contract NFT as Collateral for DeFi Composability	Kim et al.	2022	IEEE Access	Theoretical
6	Stablecoins 2.0: Economic Foundations and Risk-based Models	Klages-Mundt et al.	2020	Proceedings of the 2nd ACM Conference on Advances in Financial Technologies	Theoretical
7	A DeFi Bank Run: Iron Finance, IRON Stablecoin, and the Fall of TITAN	Saengchote	2021	SSRN	Descriptive
8	A Taxonomy of Cryptocurrencies and Other Digital Assets	van der Merwe	2021	Review of Business	Descriptive
1.3. DeFi Apps					
9	An Analysis of Uniswap Markets	Angeris et al.	2019	Cryptoeconomic Systems Journal	Empirical
10	A Theory of Automated Market Makers in DeFi	Bartoletti et al.	2021	Logical Methods in Computer Science	Theoretical
11	DeFi Protocols for Loanable Funds: Interest Rates, Liquidity and Market Efficiency	Gudgeon et al.	2020	Proceedings of the 2nd ACM Conference on Advances in Financial Technologies	Empirical
12	Trust in DeFi: An Empirical Study of the Decentralized Exchange	Han et al.	2022	SSRN	Empirical
13	New Crypto-Secured Lending System with a Two-Way Collateral Function	Kim	2021	Ledger Journal	Theoretical

(continued)

Table Chapter 2-6: Literature Overview—*continued*

14	Deconstructing Decentralized Exchanges	Foundation, L. X. L., Legal Counsel at Interstellar and Stellar Development	2019	Stanford Journal of Blockchain Law & Policy	Descriptive
15	The Rise of Decentralized Cryptocurrency Exchanges: Evaluating the Role of Airdrops and Governance Tokens	Makridis et al.	2023	Journal of Corporate Finance	Empirical
16	Decentralized Finance (DeFi) Projects: A Study of Key Performance Indicators in Terms of DeFi Protocols' Valuations	Metelski and Sobieraj	2022	International Journal of Financial Studies	Empirical
17	Mitigating Loan Associated Financial Risk Using Blockchain Based Lending System.	Reno et al.	2021	Applied Computer Science	Empirical
18	Review of Decentralized Finance Applications and Their Total Value Locked	Stepanova and Erins	2021	TEM Journal	Empirical
2. Meso-level					
2.1. Multichain Scaling					
19	Scaling Decentralized Finance	Shekhawat et al.	2021	Journal of Analysis and Computation	Theoretical
3. Macro-level					
20	Fintech, Cryptocurrencies, and CBDC: Financial Structural Transformation in China	Allen et al.	2022	Journal of Money Laundering Control	Descriptive
21	BeFi Meets DeFi: A Behavioral Finance Approach to Decentralized Finance Asset Pricing	Bennett et al.	2023	Research in International Business and Finance	Descriptive
22	Grasping Decentralized Finance Through the Lens of Economic Theory	Chiu et al.	2022	Canadian Journal of Economics	Theoretical
23	An Analysis of the Return–Volume Relationship in Decentralised Finance (DeFi)	Chu et al.	2023	International Review of Economics and Finance	Empirical
24	An Introduction to Decentralized Finance (DeFi).	Jensen et al.	2021	Complex Systems Informatics and Modeling	Descriptive
25	Risk Analysis in Decentralized Finance (DeFi): A Fuzzy-AHP Approach	Kaur et al.	2023	Risk Management	Empirical

(continued)

Table Chapter 2-7: Literature Overview—*continued*

26	Time-frequency Extreme Risk Spillover Network of Cryptocurrency Coins, DeFi Tokens and NFTs	Qiao et al.	2023	Finance Research Letters	Empirical
27	Decentralized Finance: On Blockchain- and Smart Contract-Based Financial Markets	Schär	2021	Federal Reserve Bank of St. Louis	Descriptive
28	Decentralized Finance & Accounting – Implications, Considerations, and Opportunities for Development	Smith	2021	The International Journal of Digital Accounting Research	Theoretical
29	Maximizing the Time Value of Cryptocurrency in Smart Contracts with Decentralized Money Markets	Tien et al.	2020	IEEE International Conference on Blockchain	Empirical
30	Web 3.0 Tokenization and Decentralized Finance (DeFi)	Treleaven et al.	2022	SSRN	Descriptive
31	Dynamic Connectedness Between Non-Fungible Tokens, decentralized Finance, and Conventional Financial Assets in a Time-frequency Framework	Umar et al.	2022	Pacific Basin Finance Journal	Empirical
32	Disclosure, Dapps and DeFi	Brummer	2023	Stanford Journal of Blockchain Law and Policy	Theoretical
33	Blockchain Disruption and Decentralized Finance: The Rise of Decentralized Business Models	Chen and Bellavitis	2020	Journal of Business Venturing Insights	Descriptive
34	Emerging Canadian Crypto-Asset Jurisdictional Uncertainties and Regulatory Gaps	Clements	2021	Banking and Finance Law Review	Descriptive
35	Smart contracts: will Fintech Be the Catalyst for the Next Global Financial Crisis?	Duran and Griffin	2021	Journal of Financial Regulation & Compliance	Theoretical
36	DeFi: Shadow Banking 2.0?	Allen	2023	William and Mary Law Review	Theoretical
37	Regulating Blockchain, DLT and Smart Contracts: A Technology Regulator's Perspective.	Ellul et al.	2020	ERA Forum	Theoretical
38	Legal Implications of a Ubiquitous Metaverse and a Web3 Future	Garon	2022	SSRN	Theoretical
39	The SEC, Digital Assets, and Game Theory	Guseva	2020	Journal of Corporation Law	Empirical
40	Decentralized Finance: Regulating Cryptocurrency Exchanges	Johnson	2021	William & Mary Law Review	Theoretical
41	Importance of Anti-money Laundering Regulations Among Prosumers for a Cybersecure Decentralized Finance	Kirimhan	2023	Journal of Business Research	Theoretical
42	Regulation of Decentralized Finance in the United States: What to Expect in Crypto	Koster and Lapidus	2022	Banking Law Journal	Descriptive

(continued)

Table Chapter 2-8: Literature Overview—*continued*

43	Blockchain Entrepreneurship Opportunity in the Practices of the Unbanked	Larios-Hernández	2017	Business Horizons	Empirical
44	Decentralized Finance (Defi) – The Lego of Finance	Popescu	2020	Social Sciences and Education Research	Descriptive
45	The Unintended Consequences of the Regulation of Cryptocurrencies	Sauce	2022	Cambridge Journal of Economics	Empirical
46	Financial Crime in the Decentralized Finance Ecosystem: New Challenges for Compliance	Wronka	2023	Journal of Financial Crime	Empirical
47	Decentralized Finance	Zetzsche et al.	2020	Journal of Financial Regulation	Theoretical
48	Is Decentralized Finance (DeFi) Efficient?	Momtaz	2022	SSRN	Empirical
49	Cryptocurrencies and Decentralized Finance	Makarov and Schoar	2022	National Bureau of Economic Research	Theoretical
50	Impact of Social Metrics in Decentralized Finance	Piñeiro-Chousa et al.	2023	Journal of Business Research	Empirical
51	Price Co-Movements in Decentralized Financial Markets	Park et al.	2022	Applied Economics Letters	Empirical
52	Anti-Money Laundering Regulation of Cryptocurrency: UAE and Global Approaches	Al-Tawil	2022	Journal of Money Laundering Control	Descriptive
53	Decentralised Finance's Timocratic Governance: The Distribution and Exercise of Tokenised Voting Rights	Barbereau et al.	2023	Technology in Society	Empirical
54	Decentralized Finance (Defi) – The Lego Of Finance	Popescu	2020	Social Sciences and Education Research	Descriptive
55	Powered by Blockchain Technology, DeFi (Decentralized Finance) Strives to Increase Financial Inclusion of the Unbanked by Reshaping the World Financial System	Abdulhakeem and Hu	2021	Modern Economy	Theoretical
56	Decentralized Finance—A Systematic Literature Review and Research Directions	Meyer et al.	2022	SSRN	Descriptive
57	Herding Behavior in Conventional Cryptocurrency Market, Non-fungible Tokens, and DeFi Assets	Yousaf and Yarovaya	2022a	Finance Research Letters	Empirical
58	Static and Dynamic Connectedness Between NFTs, Defi and Other Assets: Portfolio Implication	Yousaf and Yarovaya	2022b	Global Finance Journal	Empirical

(continued)

Table Chapter 2-9: Literature Overview—*continued*

Panel B: Non-fungible Tokens (NFTs)					
1. Review					
59	Non-fungible tokens (NFTs): A Bibliometric and Systematic Review, Current Streams, Developments, and Directions for Future Research	Nobanee and Ellili	2023	International Review of Economics and Finance	Descriptive
60	The Illusion of the Metaverse and Meta-economy	Vidal-Tomás	2023	International Review of Financial Analysis	Descriptive
2. NFT Market					
61	The Economics of Non-Fungible Tokens.	Borri, Liu and Tsyvinski	2022	SSRN	Empirical
62	Non-Fungible Tokens (NFTs) as an Investment Class	Mazur and Polyzos	2022	SSRN	Empirical
63	NFTs, DeFi, and Other Assets Efficiency and Volatility Dynamics: An Asymmetric Multifractality Analysis	Chowdhury et al.	2023	International Review of Financial Analysis	Empirical
64	Return and Volatility Properties: Stylized Facts From the Universe of Cryptocurrencies and NFTs	Ghosh et al.	2023	Research in International Business and Finance	Empirical
65	What Drives the Volatility of Non-fungible Tokens (NFTs): Macroeconomic Fundamentals or Investor Attention?	Jiang and Xia	2023	Applied Economics Letters	Empirical
66	Non-fungible Tokens: A Hedge or a Safe Haven?	Ko and Lee	2023	Applied Economics Letters	Empirical
67	The Economic Value of NFT: Evidence From a Portfolio Analysis Using Mean–variance Framework	Ko et al.	2022	Finance Research Letters	Empirical
68	Mapping the NFT Revolution: Market Trends, Trade Networks, and Visual Features	Nadini et al.	2021	Scientific Reports	Empirical
69	Investor Experience Matters: Evidence from Generative Art Collections on the Blockchain	Oh et al.	2022	SSRN	Empirical
70	Investment in Virtual Digital Assets Vis-A-Vis Equity Stock and Commodity: A Post-Covid Volatility Analysis	Sharma et al.	2022	Virtual Economics	Empirical
71	Diversification Benefits of NFTs for Conventional Asset Investors: Evidence from CoVaR with Higher Moments and Optimal Hedge Ratios	Umar et al.	2023	Research in International Business and Finance	Empirical

(continued)

Table Chapter 2-10: Literature Overview—*continued*

72	Dynamic Dependence and Predictability Between Volume and Return of Non-Fungible Tokens (NFTs): The Roles of Market Factors and Geopolitical Risks	Urom et al.	2022	Finance Research Letters	Empirical
73	The Role of the Media in Speculative Markets: Evidence from Non-Fungible Tokens (NFTs)	White et al.	2022	SSRN	Empirical
74	The Behavior and Determinants of Illiquidity in the Non-fungible tokens (NFTs) Market	Wilkoff and Yildiz	2023	Global Finance Journal	Empirical
75	The Hedge and Safe Haven Properties of Non-fungible Tokens (NFTs): Evidence from the Nonlinear Autoregressive Distributed lag (NARDL) Model	Zhang et al.	2022	Finance Research Letters	Empirical
76	Non-Fungible Tokens: Blockchains, Scarcity, and Value	Chohan	2021	SSRN	Descriptive
3. Asset Pricing					
77	Non-fungible Token Artworks: More Crypto than Art?	Anselmi and Petrella	2023	Finance Research Letters	Empirical
78	Non-fungible token (NFT) Markets on the Ethereum Blockchain: Temporal Development, Cointegration and Interrelations	Ante	2022	Economics of Innovation and New Technology	Empirical
79	Fertile LAND: Pricing Non-fungible Tokens	Dowling	2022	Finance Research Letters	Descriptive
80	Land Valuation in the Metaverse: Location Matters	Goldberg et al.	2021	SSRN	Empirical
81	Prediction and Interpretation of Daily NFT and DeFi Prices Dynamics: Inspection Through Ensemble Machine Learning & XAI	Ghosh et al.	2023	International Review of Financial Analysis	Empirical
83	Price Determinants of Non-fungible Tokens in the Digital Art Market	Horky et al.	2022	Finance Research Letters	Empirical
83	Infinite but Rare: Valuation and Pricing in Marketplaces for Blockchain-Based Nonfungible Tokens	Kireyev and Lin	2021	SSRN	Empirical
84	Alternative Investments in the Fintech Era: The Risk and Return of Non-fungible Token (NFT)	Kong and Lin	2021	SSRN	Empirical
85	Non-Fungible Tokens (NFTs): A Review of Pricing Determinants, Applications and Opportunities	Kräussl, and Tugnetti	2022	SSRN	Descriptive
86	Spatial Heterogeneity and Non-fungible Token Sales: Evidence from Decentraland LAND Sales	Yencha	2023	Finance Research Letters	Empirical

(continued)

Table Chapter 2-11: Literature Overview—*continued*

4. Tokens					
87	Does Unit of Account Affect Willingness to Pay? Evidence from Metaverse LAND Transactions	Nakavachara and Saengchote	2022	Finance Research Letters	Empirical
88	Dissecting Returns of Non-fungible tokens (NFTs): Evidence from CryptoPunks	Wang et al.	2023	North American Journal of Economics and Finance	Empirical
5. Behavioral Finance					
89	NFTs and Asset Class Spillovers: Lessons from the Period Around the COVID-19 Pandemic	Aharon and Demir	2022	Finance Research Letters	Empirical
90	The Role of Oil Price in Determining the Relationship Between Cryptocurrencies and Non-fungible Assets	Bani-Khalaf and Taspinar	2023	Investment Analysts Journal	Empirical
91	Digital Art and Non-fungible-token: Bubble or Revolution?	Boido and Aliano	2023	Finance Research Letters	Empirical
92	Is Non-fungible Token Pricing Driven by Cryptocurrencies?	Dowling	2022	Finance Research Letters	Empirical
93	Does Utilizing Smart Contracts Induce a Financial Connectedness Between Ethereum and Non-fungible Tokens?	Gunay and Kaskaloglu	2022	Research in International Business and Finance	Empirical
94	Time-frequency Extreme Risk Spillover Network of Cryptocurrency Coins, DeFi Tokens and NFTs	Qiao et al.	2023	Finance Research Letters	Empirical
95	The Return and Volatility Connectedness of NFT Segments and Media Coverage: Fresh Evidence Based on News About the COVID-19 Pandemic	Umar et al.	2022a	Finance Research Letters	Empirical
96	Return and Volatility Connectedness of the Non-fungible Tokens Segments	Umar et al.	2022b	Journal of Behavioral and Experimental Finance	Empirical
97	COVID-19 Impact on NFTs and Major Asset Classes Interrelations: Insights from the Wavelet Coherence Analysis	Umar et al.	2022c	Finance Research Letters	Empirical
98	Dynamic Connectedness Between Non-Fungible Tokens, Decentralized Finance, and Conventional Financial Assets in a Time-frequency Framework	Umar et al.	2022d	Pacific Basin Finance Journal	Empirical
99	Volatility Spillovers Across NFTs News Attention and Financial Markets	Wang	2022	International Review of Financial Analysis	Empirical
100	Are Non-fungible Tokens (NFTs) Different Asset classes? Evidence from Quantile Connectedness Approach	Xia et al.	2022	Finance Research Letters	Empirical

(continued)

Table Chapter 2-12: Literature Overview—*continued*

101	Herding Behavior in Conventional Cryptocurrency Market, Non-fungible Tokens, and DeFi Assets	Yousaf and Yarovaya	2022a	Finance Research Letters	Empirical
102	Static and Dynamic Connectedness Between NFTs, Defi and Other Assets: Portfolio Implication	Yousaf and Yarovaya	2022b	Global Finance Journal	Empirical
103	The Relationship Between Trading Volume, Volatility and Returns of Non-Fungible Tokens: Evidence from a Quantile Approach	Yousaf and Yarovaya	2022c	Finance Research Letters	Empirical
6. Regulatory & Societal Factors					
104	Space Transition and the Vulnerabilities of the NFT Market to Financial Crime	Al Shamsi et al.	2023	Journal of Financial Crime	Theoretical
105	Performing Wash Trading on NFTs: Is the Game Worth the Candle?	Bonifazi et al.	2023	Big Data and Cognitive Computing	Empirical
106	Beyond the Bubble: Will NFTs and Digital Proof of Ownership Empower Creative Industry Entrepreneurs?	Chalmers et al.	2022	Journal of Business Venturing Insights	Descriptive
107	Non-fungible Token-enabled Entrepreneurship: A Conceptual Framework	Chandra	2022	Journal of Business Venturing Insights	Theoretical
108	The Treachery of Images: Non-fungible Tokens and Copyright	Guadamuz	2021	Journal of Intellectual Property Law and Practice	Theoretical
109	Non-fungible Tokens: A Bubble or the End of an Era of Intellectual Property Rights	Kraizberg	2023	Financial Innovation	Theoretical
110	Detecting Wash Trading for Nonfungible tokens	Serneels	2023	Finance Research Letters	Empirical
111	From the Artist's Contract to the Blockchain Ledger: New Forms of Artists' Funding Using Equity and Resale Royalties	van Haaften-Schick and Whitaker	2022	Journal of Cultural Economics	Descriptive
112	Metaverse-enabled Entrepreneurship	Weking et al.	2023	Journal of Business Venturing Insights	Theoretical
113	Exploring Gender and Race Biases in the NFT Market	Zhong et al.	2023	Finance Research Letters	Empirical
114	Tokenized: The Law of Non-Fungible Tokens and Unique Digital Property	Fairfield	2021	SSRN	Theoretical

Table Chapter 2-13: Index Constituents

This table provides an overview of the respective index constituents for the DeFi, NFT, GameFi, and Play-to-Earn indices. To be included in an index, a token must have a regular trading volume of greater than zero for no more than seven trading days, and a market capitalization on April 24, 2023 of above $5 million USD. Market capitalization (Market Cap) is calculated in millions as of April 24, 2023.

	Market Cap	***DeFi***	***GameFi***	***NFT***	***Play-to-Earn***
BTC	16,443	NO	NO	NO	NO
ETH	1,842	NO	NO	NO	NO
Gas	5.15	NO	NO	NO	NO
0x	19.16	YES	NO	NO	NO
1inch	15.46	YES	NO	NO	NO
aave	36.63	YES	NO	NO	NO
amp-token	13.24	YES	NO	NO	NO
aurora-dao	153.25	YES	NO	NO	NO
badger-dao	6.16	YES	NO	NO	NO
balancer	5.94	YES	NO	NO	NO
band-protocol	11.42	YES	NO	NO	NO
barnbridge	12.59	YES	NO	NO	NO
bella-protocol	37.07	YES	NO	NO	NO
chainlink	244.73	YES	NO	NO	NO
coin98	10.26	YES	NO	NO	NO
compound-governance-token	14.89	YES	NO	NO	NO
curve-dao-token	57.92	YES	NO	NO	NO
dai	135.92	YES	NO	NO	NO
dodo	9.92	YES	NO	NO	NO
dydx	139.87	YES	NO	NO	NO
frax	9.81	YES	NO	NO	NO
frax-share	17.65	YES	NO	NO	NO
gains-network	12.28	YES	NO	NO	NO
gmx	29.98	YES	NO	NO	NO
havven	33.01	YES	NO	NO	NO
injective-protocol	111.18	YES	NO	NO	NO
joe	14.78	YES	NO	NO	NO
just	18.14	YES	NO	NO	NO
kava	11.79	YES	NO	NO	NO
kyber-network-crystal	11.24	YES	NO	NO	NO
lido-dao	48.45	YES	NO	NO	NO
linear	10.65	YES	NO	NO	NO
liquity	18.28	YES	NO	NO	NO

(continued)

Table Chapter 2-14: Index Constituents—*continued*

	Market Cap	*DeFi*	*GameFi*	*NFT*	*Play-to-Earn*
loopring	27.50	YES	NO	NO	NO
maker	16.89	YES	NO	NO	NO
nest	5.37	YES	NO	NO	NO
osmosis	11.20	YES	NO	NO	NO
pancakeswap-token	119.72	YES	NO	NO	NO
republic-protocol	13.66	YES	NO	NO	NO
reserve-rights-token	7.10	YES	NO	NO	NO
rocket-pool	7.03	YES	NO	NO	NO
serum	12.68	YES	NO	NO	NO
spell-token	8.20	YES	NO	NO	NO
staked-ether	10.92	YES	NO	NO	NO
stargate-finance	11.25	YES	NO	NO	NO
sushi	23.55	YES	NO	NO	NO
terra-luna-2	42.30	YES	NO	NO	NO
the-graph	45.03	YES	NO	NO	NO
thorchain	46.49	YES	NO	NO	NO
uma	6.20	YES	NO	NO	NO
uniswap	71.89	YES	NO	NO	NO
venus	5.38	YES	NO	NO	NO
wrapped-nxm	6.25	YES	NO	NO	NO
yearn-finance	19.30	YES	NO	NO	NO
yfii-finance	6.69	YES	NO	NO	NO
apecoin	86.08	NO	YES	YES	NO
cocos-bcx	66.76	NO	YES	YES	NO
enjincoin	21.30	NO	YES	YES	NO
ethernity-chain	5.15	NO	YES	YES	NO
internet-computer	36.94	NO	YES	YES	NO
magic	29.09	NO	YES	YES	NO
my-neighbor-alice	19.14	NO	YES	YES	NO
alien-worlds	6.08	NO	YES	YES	YES
axie-infinity	50.99	NO	YES	YES	YES
gala	217.38	NO	YES	YES	YES
immutable-x	33.02	NO	YES	YES	YES
mobox	10.03	NO	YES	YES	YES
smooth-love-potion	8.62	NO	YES	YES	YES
stepn	51.52	NO	YES	YES	YES
the-sandbox	118.87	NO	YES	YES	YES
yield-guild-games	7.96	NO	YES	YES	YES
audius	39.32	NO	NO	YES	NO

(continued)

Table Chapter 2-15: Index Constituents—*continued*

	Market Cap	*DeFi*	*GameFi*	*NFT*	*Play-to-Earn*
bakerytoken	6.76	NO	NO	YES	NO
chiliz	62.89	NO	NO	YES	NO
contentos	6.30	NO	NO	YES	NO
ethereum-name-service	17.59	NO	NO	YES	NO
fetch-ai	50.54	NO	NO	YES	NO
flow	63.57	NO	NO	YES	NO
origin-protocol	5.73	NO	NO	YES	NO
playdapp	19.17	NO	NO	YES	NO
project-galaxy	13.28	NO	NO	YES	NO
radicle	6.47	NO	NO	YES	NO
render-token	90.56	NO	NO	YES	NO
superfarm	5.29	NO	NO	YES	NO
theta-token	13.82	NO	NO	YES	NO
decentraland	82.81	NO	NO	YES	YES
verasity	11.70	NO	YES	NO	NO
volt-inu-2	13.85	NO	YES	NO	NO
illuvium	8.60	NO	YES	NO	YES
mines-of-dalarnia	13.92	NO	YES	NO	YES
wax	8.61	NO	NO	NO	YES
wemix-token	7.98	NO	NO	NO	YES

Chapter 3: PolitiFi: Just Another Meme, or Instrumental for Winning Elections?

3.1. Citation:

Proelss, J., Schweizer, D., & Sevigny, S. (2025) PolitiFi: Just Another Meme, or Instrumental for Winning Elections? *Finance Research Letters*, *72*, 106533. doi:10.1016/j.frl.2024.106533

3.2. Abstract:

As the 2024 U.S. presidential election looms, the intersection of cryptocurrency and political finance has garnered significant interest. This study explores the new crypto category of PolitiFi, which merges politics and finance and is linked to political figures and agendas. Our analysis underscores the strategic deployment of these tokens to enhance visibility, shape narratives, and appeal to younger, more technologically adept voters within the crypto sphere. The alignment of cryptocurrency adoption with voter demographics highlights PolitiFi's potential to redefine political engagement and campaign strategies, and influence election outcomes. Empirical analyses show that PolitiFi's development has exhibited a distinct trajectory, rapidly demonstrating independence and a critical decoupling from other meme coins in the cryptocurrency market.

3.3. Introduction

As the 2024 U.S. presidential election approaches, a notable shift has occurred: Former President Donald Trump, previously critical of cryptocurrencies (see 2019 Twitter post)[32], has embraced them (see 2024 Truth Social post)[33] to outpace President Joseph Biden in fundraising. This shift reflects broader trends in the integration of digital assets into politics, exemplified by the rise of PolitiFi, a new crypto trend merging politics and finance. PolitiFi tokens, often meme coins associated with political figures or movements, serve campaign purposes like raising awareness, shaping narratives, soliciting crypto donations, and appealing to younger, tech-savvy voters. Notable tokens include MAGA (Trump) and BODEN (Biden).

Trump's ventures into crypto, selling digital trading card non-fungible tokens[34] and accepting crypto payments, likely influenced his decision to accept crypto contributions for his 2024 campaign.[35] His pledge to free Silk Road creator Ross Ulbricht (CoinDesk,

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[32] See https://x.com/realDonaldTrump/status/1149472282584072192.
[33] See https://truthsocial.com/@realDonaldTrump/112503319133425856.
[34] See https://opensea.io/collection/trump-digital-trading-cards.
[35] See https://www.donaldjtrump.com/crypto.

2024) and support for making the future of crypto "made in the USA" (Benzinga, 2024) further cement his alignment with the crypto community. As a result, tokens like "Make America Great Again" (MAGA) surged up to about 100x in value since 2023 (reaching a market cap of about $750m), with Trump outpacing Biden in fundraising as of April 2024 (BNN Bloomberg, 2024)[36].

A key aspect of this landscape is the role of internet memes and meme coins in shaping political discourse. Memes, driven by humor and virality, serve as valuable marketing tools. They unite communities via "social currency" (Benaim, 2018), and when combined with cryptocurrencies, can sway retail investors and voters alike (Elsayed et al. 2024). Political meme coins leverage this appeal, allowing campaigns to spread messages rapidly (Beskow et al., 2020). However, these communities may devolve into echo chambers dominated by ill-informed members, leading to significant market disruptions, as seen with meme stocks like GameStop (Pedersen, 2022; Aloosh et al., 2022).

We build on Bonaparte and Kumar's (2013) insight that political activism reduces information-gathering costs, lowering barriers to participation, a dynamic also seen in PolitiFi. These tokens simplify political engagement, particularly for younger, tech-savvy individuals by offering a decentralized and accessible platform for political participation. Hong, Kubik, and Stein's (2004) work on sociability and Grinblatt et al.'s (2011) research on financial literacy suggest that individuals inclined to use cryptocurrencies are also likely to participate politically through PolitiFi. Guiso et al. (2008) highlight that trust influences market participation, and in PolitiFi, trust in political figures translates to trust in their associated tokens. Akerlof and Shiller's (2016) emphasis on narrative economics highlights how compelling stories and emotional appeal can drive the widespread adoption of financial tools like PolitiFi, even when individuals have limited understanding of the risks involved.

PolitiFi represents a novel intersection of decentralized finance and political engagement, with the potential to shift political power away from elite donors, as Ansolabehere et al. (2000) discuss. This aligns with Rogers' Diffusion of Innovation theory (2003), positioning PolitiFi as a tool first adopted by opportunistic political campaigns, like Trump's, before spreading to mainstream political finance strategies.

To understand PolitiFi's potential, it is critical to recognize the overlap between U.S. voting demographics and crypto adoption patterns. In the 2020 election, younger voters (ages 18-24) showed a turnout rate of 51.4%, compared to 76% for those over 65 (Pew Research Center, 2023). Millennials and Gen Z, the same groups more likely to engage with cryptocurrencies (Campino and Yang, 2024), constitute an underrepresented yet vital

[36] See https://www.bnnbloomberg.ca/trump-leads-biden-in-monthly-campaign-fundraising-for-first-time-1.2075243.

demographic. With approximately 20% of individuals aged 18-44 involved in cryptocurrency, and with higher ownership among African-Americans (33%) and Hispanics (32%) (Paradigm, 2024), PolitiFi holds the potential to bridge this voter engagement gap. This convergence of crypto and political participation presents a unique opportunity for campaigns to sway traditionally underrepresented voter bases through targeted crypto-friendly narratives, adding an additional layer to candidates' outreach strategies.

We explore the dynamics of how PolitiFi could influence political engagement and campaign strategies through two primary channels: Candidate viability and narrative-shaping. For candidate viability, we measure the price movements of PolitiFi tokens, such as MAGA or BODEN, act as proxies for market sentiment on electoral prospects. Previous research shows that cryptocurrency prices are linked to investor sentiment and social media activity (Kraaijeveld and De Smedt, 2020; Phillip et al., 2018). We hypothesize that major campaign events, such as President Biden's withdrawal from the race, will cause sharp declines in related token prices, reflecting the strong connection between PolitiFi tokens and candidate reduced viability.

Second, narrative-shaping can be analyzed through token price reactions to key political events. Campaigns that align themselves with the crypto community should experience increased engagement with their PolitiFi tokens, which serve as extensions of their messaging. However, isolating the impact of pre-announced events like Trump's Bitcoin 2024 conference appearance is challenging due to anticipatory market effects. In contrast, unanticipated events, such as the assassination attempt, offer clearer insight into PolitiFi's dynamics. This event, framed by Trump's campaign as a demonstration of strength and resilience, triggered measurable price surges, illustrating the power of narrative control. We hypothesize that positive narratives, such as campaign victories or strategic successes, will lead to price spikes, reflecting increased optimism. Even dramatic and potentially negative events, like the assassination attempt, can be reframed to enhance market confidence through effective narrative spinning, driving unexpected price gains.

Our findings reveal that PolitiFi tokens, while initially regarded as meme tokens, have matured into financial instruments that directly reflect market sentiment, voter behavior, and candidate viability. The empirical evidence shows that PolitiFi tokens react significantly to key campaign events, suggesting that these tokens are a real-time gauge of voter sentiment, especially within younger, tech-savvy demographics. The ability of PolitiFi to engage with previously underrepresented voter bases, particularly among minorities and lower-income groups, provides a new mechanism for political campaigns to broaden their outreach. As PolitiFi gains traction, the expanding institutional acceptance of crypto at large, signaled by major players like BlackRock and Fidelity offering e.g. crypto related Exchange Traded Funds, underscores its growing legitimacy within mainstream finance.

Although still in its early stages, PolitiFi's capacity to drive both financial and voter engagement positions it as a transformative tool in U.S. political campaigns. The integration of decentralized fundraising and active voter sentiment tracking through token movements offers a unique dual impact on electoral outcomes. Given that candidates who outspend their opponents are more likely to win, PolitiFi tokens hold the potential to influence fundraising dynamics and empower campaigns to attract decentralized, crypto-friendly donor bases. The implications extend beyond the U.S., with PolitiFi potentially evolving into a global model for campaign finance, offering a decentralized alternative to traditional elite donor structures.

3.4. PolitiFi's Role in the Crypto Ecosystem

PolitiFi is a recent spinoff of meme coins, a rapidly evolving trend where politics, finance, and cryptocurrency converge. PolitiFi essentially began in August 2023 with the introduction of the MAGA coin, inspired by Trump's "Make America Great Again" campaign. Over the following months, many other PolitiFi meme coins were launched, inspired by both President Biden (Jeo Boden: BODEN; Jill Boden: JILLBODEN) and Donald Trump (Doland Tremp: TREMP; Pepe Trump: PTRUMP). As of May 23, 2024, they reached a total market cap of about $850 million.

Our next objective here is to analyze how PolitiFi is integrated within the crypto ecosystem. We turn to empirical data to estimate a general vector autoregression (VAR) model without restrictions in order to measure spillovers. We then use the estimation results to investigate the relationships between the variables.

We compare PolitiFi with Bitcoin and Ethereum, the two leading digital asset and meme coins, because it evolved from that space, as well as from the U.S. Economic Policy Uncertainty (EPU) Index. Past research on spillovers in the digital asset space focused on specific tokens, coins, and volatility (see, e.g., Katsiampa et al., 2019; Koutmos, 2018; and Omane-Adjepong and Alagidede, 2019). Our aim, in contrast, is to carve out how PolitiFi is incorporated into the crypto space during different periods, because the dynamics change so rapidly.

We estimate a $VAR(p)$ model that allows for multiple independent variables without enforcing a distinct Granger causal relationship. We follow the research design of Proelss et al. (2023):

$$\mathbf{Y}_t = \mathbf{A}_1\mathbf{Y}_{t-1} + \mathbf{A}_2\mathbf{Y}_{t-2} + \cdots + \mathbf{A}_p\mathbf{Y}_{t-p} + \boldsymbol{c} + \mathbf{u}_t \tag{1}$$

where $\mathbf{Y}_t$ is the $K \times 1$ vector of our five endogenous return variables (BTC, ETH, PolitiFi, Meme Coins, EPU), which is a linear function of p of their own lags. $\mathbf{A}_i$ is a $K \times K$ matrix of coefficients for $i = 1, .., p$ and $\mathbf{Y}_{t-i}$ are the $K \times 1$ matrices of lagged returns, with p as the optimal lag lengths to be included.[37] The K-dimensional intercept term is $\mathbf{c}$, and $\mathbf{u}_t$ is a K-dimensional white noise term. After fitting the VAR(1) model, we use "Granger causality" (Granger, 1969) to test whether one variable causes another. We regress y on lagged y. Variables are considered "causal" if we can reject the null hypothesis that estimated coefficients on the lagged values y are (jointly) zero.

3.4.1. Data

We create the following two equally weighted crypto-asset sector indices based on CoinGecko's Top-PolitiFi Index and Top GMCI Meme Index constituents. We obtain BTC and ETH prices by using CoinGecko's API. To build the two indices, we also require a minimum of two distinct tokens in each respective index. This leads to a start date of November 23, 2023, and an end date of March 31, 2024, with a total of 131 observations. Finally, we also include the daily EPU Index.

Figure Chapter 3-1 plots the respective indices over the sample period. Table Chapter 3-1 shows the descriptive statistics for the sample period for BTC and ETH, as well as for PolitiFi, Meme Coins, and EPU.[38]

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[37] Optimal lag length maximizes the degrees of freedom to estimate the model without incurring the omitted variables problem.
[38] The index is the daily U.S. EPU index (available at https://www.policyuncertainty.com/us_monthly.html).

Figure Chapter 3-1: Crypto-Asset Price Developments

This figure illustrates the price trajectories of equally weighted crypto indices (PolitiFi and Meme Coins), alongside Bitcoin (BTC), Ethereum (ETH), and the Economic Policy Uncertainty (EPU) index. A structural break, identified via the Clemente-Montañés-Reyes test, is also depicted. All time series are indexed to a base value of 100, spanning the observation period of November 23, 2023, to March 31, 2024

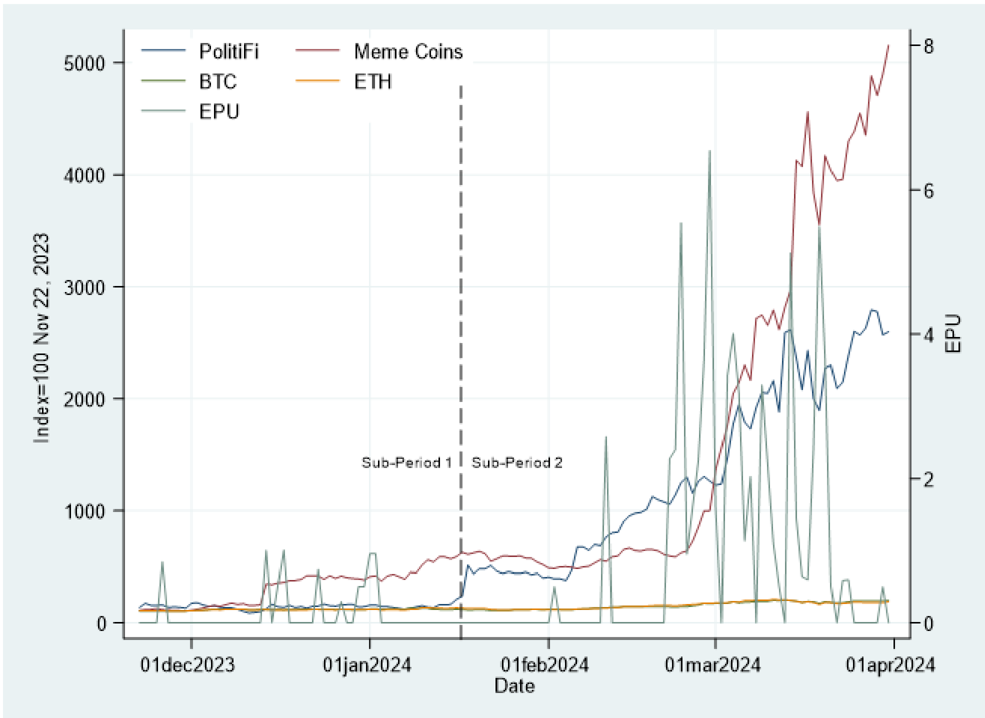


Table Chapter 3-1: Descriptive Statistics

This table shows the descriptive statistics mean (Mean), median (Median), standard deviation (Std), minimum (Min), maximum (Max), skewness (Skew), and kurtosis (Kurt) for Bitcoin (BTC) and Ethereum (ETH), the equally weighted indices for PolitiFi and Meme Coins, and the economy policy uncertainty (EPU) index spanning the observation period of November 23, 2023, to March 31, 2024, with a total of 131 observations.

	Mean	Median	Std	Min	Max	Skew	Kurt
BTC	3.41%	1.11%	15.28%	-17.62%	116.83%	3.54	24.96
ETH	3.62%	1.87%	12.68%	-15.77%	115.55%	5.58	48.12
PolitiFi	0.56%	0.32%	2.87%	-8.24%	9.75%	0.14	4.59
Meme Coins	0.53%	0.37%	3.03%	-10.06%	10.86%	0.18	4.88
EPU	0.61	0.00	1.28	0.00	6.54	2.61	9.66

3.4.2. Empirical Results

Because we are interested in how the PolitiFi sector has evolved over time, we first analyze whether the time series for the indices (PolititFi and Meme Coins), and for BTC, ETH, and EPU, are stationary. To this end, we use unit root tests on the returns (Dickey-Fuller no trend-stationary test, the Zivot and Andrews test, and the Clemente-Montañés-Reyes (CMR) test). This ensures our estimation is reliable and the results are not spurious, which could lead to poor understanding of any subsequently applied VAR model results.

Table Chapter 3-2: Stationary and Structural Break Tests

This table shows the results for our stationary test and structural break test using the Dickey-Fuller no trend-stationary test, the Zivot-Andrews stationary test, and the Clemente-Montañés-Reyes unit root test with single mean shifts. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

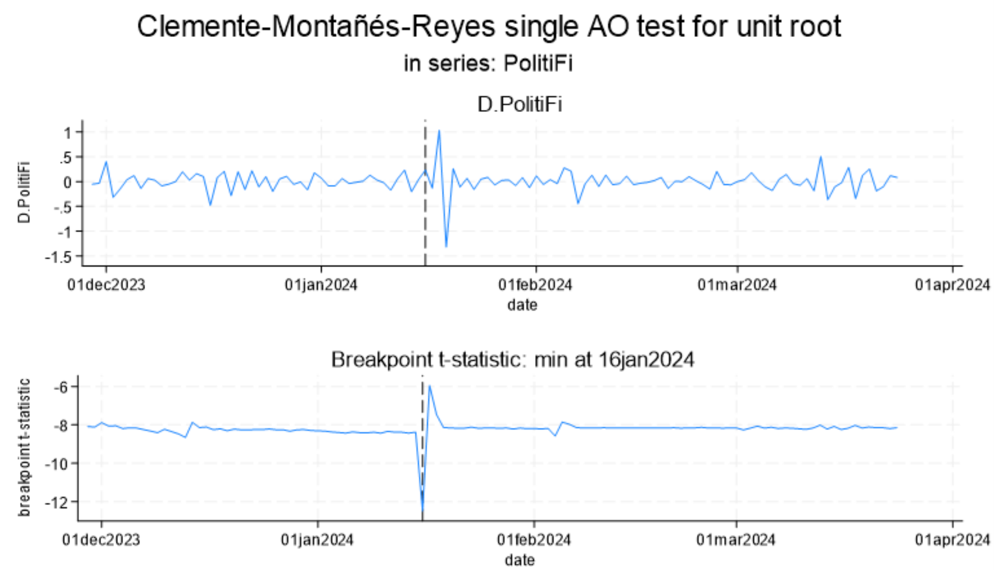
	Dickey-Fuller	Zivot-Andrews	CMR (AO)
PolitiFi	-11.401***	-11.766***	-12.494***
Meme Coins	-13.415***	-11.895***	-11.569***
BTC	-12.921***	-13.357 ***	-4.353***
ETH	-12.722***	-6.352***	-9.669**
EPU	-6.253***	-4.704*	-2.575

As Table Chapter 3-2 shows, the test statistics for all time series are stationary. The Zivot-Andrews and CMR tests of the unit root consider one structural break in mid-January 2024 for the PolitiFi time series (Clemente et al., 1998). This corresponds to the week when the number of constituents doubled from three to six, marking the point where PolitiFi began to take shape and gain increased media coverage.

Crypto markets are known for their rapidly changing dynamics, due to events such as the Bitcoin halving and the introduction of the Bitcoin ETF. As visually represented in Figure Chapter 3-2, we establish the PolitiFi breakpoint as January 16, 2024. Therefore, we analyze the entire period, as well as two subperiods: pre-breakpoint (*subperiod 1*), and post-breakpoint (*subperiod 2*).

Figure Chapter 3-2: Structural Break Test

This figure presents the results of the Clemente-Montañés-Reyes structural break test, including the corresponding *t*-values.



Before estimating the VAR model, we determine optimal lag length (p) by using several selection criteria: final prediction error, Akaike's information criterion, Schwarz's Bayesian information criterion, and the Hannan-Quinn information criterion. For each subperiod, most criteria indicate that $p = 1$ is optimal. This represents a balance of the trade-off between preserving degrees of freedom and minimizing the omitted variables bias.

The results of the VAR(1) models in Table Chapter 3-3 reveal significant insights across the two subperiods. In *subperiod 1*, which precedes the widespread media coverage and public discussion of PolitiFi tokens, we find evidence that meme coins Granger cause PolitiFi (see Yousaf et al. (2023) for additional insight into the relation between meme coins and other crypto assets). This suggests that PolitiFi tokens were not initially clearly differentiated from meme coins. However, this dynamic shifts markedly after the identified breakpoint. During *subperiod 2*, which coincides with increased public interest in the U.S. presidential election (according to Google Trends and the higher media coverage of PolitiFi-related tokens), we no longer observe any Granger causation between meme coins and PolitiFi. This is a strong indicator that PolitiFi quickly established a distinct presence in the crypto ecosystem.

Table Chapter 3-3: Granger Causality

This table shows the results for the Granger causality Wald test χ^2 estimators, using the estimation results of the VAR(1) model with endogenous variables Bitcoin (BTC) and Ethereum (ETH), the equally weighted PolitiFi and Meme Coins indices, and the economic policy uncertainty (EPU) index for the entire sample period (*Entire Period*) and two subperiods: *subperiod 1* (pre-January 16, 2024), and *subperiod 2* (post-January 16, 2024). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The Granger causality relationship is shown from *Origin* (columns) to *Receiver* (rows).

	Origin				
Receiver	**PolitiFi**	**Meme Coins**	**BTC**	**ETH**	**EPU**
Entire Period					
PolitiFi	-	3.81*	0.02	0.63	0.05
Meme Coins	0.15	-	0.05	0	7.45***
BTC	0.22	2.03	-	0.56	1.22
ETH	0.59	3.77*	1.06	-	3.27*
EPU	0.65	0.04	9.04***	6.13**	-
Subperiod 1					
PolitiFi	-	4.48**	1.6	0.45	0.36
Meme Coins	0.47	-	0.09	0.09	0.76
BTC	0.11	0.91	-	0.93	0.22
ETH	0.42	1.49	0.3	-	2.97*
EPU	0.37	1.88	0.49	0.01	-
Subperiod 2					
PolitiFi	-	0.08	0.66	2	0.45
Meme Coins	0	-	0.29	0.73	24.35***
BTC	0.04	0.35	-	0.01	0.79
ETH	0.27	0.24	0.89	-	3.81*
EPU	0.61	0.7	8.26***	7.72***	-

Additionally, we see during *subperiod 2* that Bitcoin and Ethereum Granger cause EPU (see Katsiampa et al. (2019) for spillover effects). This may be attributable to ongoing discussions surrounding crypto-related policies, the introduction of Bitcoin ETFs, pending approval of Ethereum ETFs, and the Bitcoin halving event, which were prevalent in the press. Notably, EPU only Granger causes meme coins and Ethereum during this subperiod, further highlighting the evolving interdependencies within the crypto market.

3.5. Channels of Influence

We test our two channels of political campaign influence on PolitiFi tokens by conducting event studies in response to Kamala Harris replacing President Biden as the Democratic Presidential Nominee (candidate viability) and the assassination attempt on Donald Trump (narrative-shaping) for two separate groups of PolitiFi tokens either related to the Republican or Democratic party (see Table Chapter 3-4). We find that after President

Biden’s withdrawal from the race, PolitiFi tokens related to him experienced a statistically significant drop of about 45%. This aligns with reduced candidate viability. Conversely, tokens associated with Trump and the Republican party increased about 15%, also statistically significant at the 1%-level, following the assassination attempt. This increase reflects how the campaign successfully leveraged the narrative to their advantage. These results provide preliminary evidence on the relationships and possible channels through which political campaigning influences PolitiFi tokens.

Table Chapter 3-4: Testing the Channels of Political Campaign Influence on PolitiFi Tokens

This table presents the results of four event studies examining the price impact on PolitiFi tokens related to the Republican and Democratic parties (Token Type) following two key events: 1) the assassination attempt on Donald Trump on July 13, 2024, and 2) Kamala Harris replacing Joe Biden as the Democratic Presidential Nominee on July 21, 2024. '#Tokens' denotes the number of tokens associated with each party. 'AARE' represents the average abnormal returns and are caculted on the [0;1] event window. Abnormal returns are calculated using a three-factor model, incorporating Bitcoin, Ethereum, and an equally weighted Meme Coins index, consistent with the analysis in Table 3. The estimation window spans from May 1 to June 30, 2024, for both events, with a minimum of 25 observations per token to ensure reliable estimates. 'Patell' and 'Patell adj.' show the *t*-statistics based on the methodology of Patell (1976) and Kolari and Pynnönen (2010) respectively. We employ the Patell and adjusted Patell tests, as Gao et al. (2024) demonstrate that these methods perform best for small sample sizes, event-induced volatility, and non-normal returns. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Event	Token Type	#Tokens	AARE	Patell	Patell adj.
Trumps Assassination Attempt on July 13, 2024	Republican	13	15.2%	3.748***	2.346**
	Democrat	5	-8.8%	-1.245	-0.926
Harris Replacing Biden as Presidential Nominee on July 21, 2024	Republican	13	-1.2%	-0.721	-0.452
	Democrat	5	-45.3%	-6.69***	-4.977***

3.6. Conclusion

Examining the intersection of politics and meme coins reveals that PolitiFi has rapidly become a significant factor in political campaigns, influencing voter behavior, financing, and outcomes. In federal elections, where billions are raised and spent, financial resources are crucial for candidate success. PolitiFi represents a groundbreaking change in political finance. By leveraging digital assets, meme culture, and the financial power of cryptocurrencies, it can energize younger voters and fundamentally alter the strategies and outcomes of political campaigns.

Our complementary empirical findings indicate that the dynamics within the cryptocurrency market can swiftly transform, influenced by factors such as media coverage, regulatory developments, and the U.S. presidential election campaign. These elements collectively contribute to crypto's evolution and volatility. Not surprisingly, during the initial phase of PolitiFi's introduction (*subperiod 1*), we noted that its price dynamics were significantly influenced by developments in meme coins. However, in the subsequent phase (*subperiod 2*), PolitiFi exhibited a strong, distinct evolution, becoming decoupled from the price movements of meme coins, Bitcoin, and Ethereum. Additionally, we identified two potential channels—candidate viability and narrative-shaping—through which political campaigns can influence PolitiFi. While PolitiFi presents a compelling tool for political campaigning, it remains in its early stages, and various crypto market factors, such as bear markets or high volatility, may negatively impact its long-term success (see Bonaparte, 2023). On October 15, 2024 the Trump campaign's launch of the 'World Liberty Financial' (WLFI) token introduced new dynamics into the PolitiFi landscape. Despite initial excitement, the token raised less than $12 million against its ambitious $300 million target (Sigalos, 2024). The token's governance framework is notably restrictive, as it prohibits holders from selling unless approved by collective governance vote, mitigating speculative trading and framing the token as a governance tool rather than an investment asset (World Liberty Financial, 2024). This non-transferability may reflect a strategic approach to comply with regulatory frameworks, presenting an intriguing use case within campaign finance law. This approach highlights PolitiFi tokens' potential to serve as legally complex tools that facilitate political financing within cryptocurrency, offering campaigns a new way to leverage digital assets while navigating regulatory restrictions. Future research should examine the impact of election outcomes on PolitiFi tokens and identify key events driving token behavior. Additionally, exploring regulatory frameworks around cryptocurrencies in campaign finance will be crucial to address transparency and legal compliance issues.

Conclusion

This thesis has explored the transformative potential and multifaceted challenges of blockchain technology and cryptocurrencies through three interconnected lenses: Bitcoin's alignment with Environmental, Social, and Governance (ESG) criteria, GameFi's role in expanding blockchain utility, and PolitiFi's innovative application in political finance. Each chapter contributes distinct insights into how cryptocurrencies address inefficiencies in centralized systems while simultaneously unveiling new paradigms for financial and societal transformation.

The first chapter critically evaluated Bitcoin's compliance with ESG principles, emphasizing its environmental, social, and governance dimensions. On the environmental front, Bitcoin's energy-intensive proof-of-work (PoW) mechanism has been a major source of criticism. However, this study challenges exaggerated claims about Bitcoin's environmental harm by presenting a nuanced analysis of its energy consumption and carbon emissions. A novel forecasting model revealed that prior estimates were often overstated due to flawed assumptions that failed to properly model mining dynamics. Furthermore, the study highlighted the potential for Bitcoin mining to integrate renewable energy sources and stabilize power grids by consuming surplus energy. Socially, Bitcoin demonstrates potential to enhance financial inclusion for unbanked populations, offering secure, transparent, and decentralized financial services. From a governance perspective, Bitcoin's decentralized architecture exemplifies accountability, transparency, and stakeholder participation, positioning it as a model of governance innovation. These findings underscore Bitcoin's broader societal benefits, suggesting that its environmental challenges must be assessed from a holistic viewpoint, alongside its contributions to social and governance advancements.

Building on this, the second chapter examined GameFi as a case study in expanding blockchain's practical applications. By integrating decentralized finance (DeFi), non-fungible tokens (NFTs), and gaming, GameFi platforms create decentralized digital economies where players and developers can monetize in-game assets and interactions. Empirical evidence showed that GameFi enables economic empowerment and engagement, particularly among younger, tech-savvy demographics. However, the study also identified key challenges, such as market volatility, liquidity constraints, and governance vulnerabilities within these ecosystems. Addressing these risks is crucial for ensuring the sustainability and inclusivity of GameFi platforms. The findings suggest that GameFi represents a transformative avenue for blockchain technology, capable of bridging the gap between speculative trading and real-world utility while democratizing access to digital economies.

Finally, the thesis explored PolitiFi tokens, a novel intersection of blockchain technology and political finance. By leveraging blockchain's transparency and decentralization, PolitiFi tokens offer a new mechanism for engaging voters and funding campaigns. The analysis demonstrated how PolitiFi tokens reflect market sentiment and candidate viability, with price movements tied to key campaign events. These tokens also enable real-time voter engagement, reduce reliance on elite donors, and provide innovative tools for narrative shaping. The study highlighted the potential of PolitiFi to engage underrepresented voter demographics, particularly younger and minority groups, through targeted crypto-friendly narratives. While these tokens face regulatory and ethical challenges, their capacity to redefine political engagement positions them as a transformative tool for campaigns, with implications extending beyond the U.S. to global political finance.

Collectively, these findings illuminate the potential of cryptocurrencies to drive transparency, inclusivity, and decentralization across industries. However, significant barriers remain, including regulatory uncertainty, technical inefficiencies, and public skepticism.

This thesis contributes to the growing body of literature critically assessing cryptocurrencies' dualities—their ability to address systemic inefficiencies and their inherent complexities. By examining the ESG dimensions of Bitcoin, the utility expansion through GameFi, and the governance innovation via PolitiFi, this work informs academic and practical discussions on blockchain's evolving role in society. The transformative potential of cryptocurrencies lies in their capacity to foster innovation and inclusivity across diverse sectors. Realizing this potential requires a balanced approach that leverages their strengths while addressing their limitations. As blockchain technology continues to evolve, its ultimate impact will depend on collaborative efforts among researchers, policymakers, and practitioners to navigate these challenges responsibly.

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