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Blockchain Games: What On and Off-chain factors affect the volatility, returns, and liquidity of Gaming Crypto Tokens

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Abstract

Blockchain games took the internet by storm as they offered a new way for users to play video games, own the assets in those games, and benefit monetarily from their efforts. Through Non-Fungible Tokens (NFTs) and cryptocurrencies, new, Web3 games ushered in a unique asset class for retail and institutional investors to diversify into and benefit from. This paper uses cross-sectional data from 30 blockchain gaming companies to identify on and off-chain factors that affect the company's token volatility, returns, and liquidity. A multiple linear regression found the percentage of tokens dedicated to a company's private sale and rewarding users, the length of a token's vesting period, if the token has a fixed supply, and tokens based on the Solana or Polygon blockchains positively affect the volatility of that token. Conversely, the Monthly Active Users of the game, the token's market capitalization, the amount of funds raised by the company, and the game genre negatively affect volatility. Funds raised, game genre, and Solana-based tokens were also significant in the returns model. Lastly, the number of faucets for the game and the percentage of tokens dedicated to rewards and the private sale showed significance in the liquidity model. This paper adds to the literature in the NFT, cryptocurrency, and blockchain gaming spaces.

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1. Introduction

The Metaverse and web3 narrative has had an overwhelming run over the past two years. The Metaverse, as described by Jonathan Lai, a partner at VC firm Andreesen Horowitz, is “a persistent, infinitely-scaling virtual space with its own economy and identity system.” (Vicol 2022). Big tech’s adoption through Facebook’s official renaming to Meta and Twitter integrating NFT technology, among other examples, has furthered the mainstream adoption of blockchain technology (Rodriguez 2021, Chittum 2022). With increasing relevance in day-to-day life, the Metaverse is a concept worth exploring for both its merits and drawbacks in the broader population; in the end, a technological advance is only useful if it gains adoption by the masses. However, achieving the necessary adoption has not been easy; non-technical users can easily be dissuaded from web3 due to complex concepts around token standards, wallet addresses, transaction types, and more. That said, one vertical of web3 that is pushing the boundaries of adoption is undoubtedly the Blockchain Gaming sector.

There are several aspects to the Metaverse, but what is indistinguishable from the web3 Metaverse, particularly in Blockchain Games, are Non-Fungible Tokens (NFTs). An NFT is a digital asset that initially comes from a token standard of Ethereum, aiming to distinguish each token with various signs (Wang et al. 2019). The different signs come in the form of metadata for the token that separates it from the rest of the tokens, such as a digital file (photos, videos, audio files, virtual land, video game items), ID number, ownership history, and more. Placing these tokens on a public ledger, such as a blockchain, allows NFTs to hold specific characteristics such as verifiability, transparency, and tradability that other assets may not have. Due to this, people may have copies of NFTs, but the actual original NFTs, their owners, and their characteristics are available for the world to view if they wish to do so. There have been several prominent examples of NFTs, such as the artist Beeple selling digital art for $69 million or Twitter Cofounder Jack Dorsey auctioning off his first-ever tweet for $2.9 million (Ante 2021). Although these are large, individual transactions, total NFT sales in 2021 reached an all-time high of $25 billion, with $10.7 billion being spent in Q3 alone, up 8x from the previous quarter (Howcroft 2022, Beck 2021). NFTs can span multiple use cases, from digital art to ticketing, music, and more. Nevertheless, the opportunities within gaming are exciting to explore as it provides ownership records of items in games and promotes an economic marketplace in the game's ecosystem – benefiting both developers and players.

Although NFTs hold prime importance in Metaverse applications like Blockchain Gaming, the backbone of any Metaverse economy comes from its native token. Since 2016, startups all over the world, blockchain and non-blockchain related, have used tokens as a form of assets to raise money – this process is known as an Initial Coin Offering (ICO). In an ICO, the token issuer will sell cryptographically secured digital assets, or tokens, to investors to fund their operations and for investors to benefit from realizing their returns on an open market faster than a traditional IPO or other exit processes (Howell et al. 2019). The ICO market grew exponentially in 2017 and early 2018, raising approximately $31 billion between January 2016 and August 2019 (Howell et al. 2019).

While raising money, startups needed to decide what utility or another purpose the tokens would serve to guarantee their value and the value that investors and the general public would receive. Three types of tokens emerged as candidates: medium of exchange, security, and utility tokens. The medium of exchange and security tokens are discussed in further detail in Sections 2.1 and 2.2. Utility tokens are of primary importance to understanding the Metaverse and Blockchain Gaming as they are used to accrue value to token holders through their use cases in an ecosystem. For example, if a token is issued for a Metaverse startup, it may accrue value through its use in marketplace fees or cosmetic upgrades. The value attached to the token will be realized by investors that trade on an open market and thus enable the formation of micro-economies in each company's ecosystem (Howell et al. 2019).

The combination of NFTs and Utility tokens to form Blockchain Games has ushered in a new way to enjoy video games with more transparency, decentralized ownership of assets, and a real, functioning economy beyond the game itself. Sky Mavis, a blockchain gaming startup, pioneered this sector by creating the first popular blockchain game Axie Infinity. Axie Infinity is a pokemon-like game built on the blockchain that allows players to battle against each other and earn tokens as rewards. The Axies are the pokemon-like creatures that are represented as NFTs and are required to play the game, i.e., users need to purchase three NFTs to play. When winning battles, players receive the in-game currency, Smooth Love Potion (SLP), a crypto token that is openly tradeable against other crypto tokens or fiat currencies. At Axie Infinity's height in 2021, players made nearly $500 per month on average simply by playing the game (Mourya 2021). The phenomenon of earning from playing video games was brought possible by the blockchain and is commonly referred to as Play-To-Earn (P2E). However, the price of SLP and Axie Infinity's governance token, AXS, has crashed significantly from its highs due to unsustainable token economics within the game. For SLP, the price is down 99.1% from its all-time high, and AXS has fallen 94% from its all-time high. Even though the market is currently in a downturn, i.e., Ethereum (ETH) is down 67.4% and Bitcoin (BTC) 69.8% from their respective all-time highs, the betas of blockchain gaming tokens have been quite significant. Prices of SLP, AXS, ETH, and BTC were retrieved from CoinGecko on November 6, 2022.

Since blockchain games account for more than 50% of the web3 industry's usage, and the gaming landscape has raised $4 billion in 2021 and $6.9 billion as of Q3 2022, investors cannot avoid its impact on the future of web3. However, many current blockchain games have failed to construct sustainable economies that can retain long-term value in their native tokens. As a result, this paper investigates relationships between on and off-chain factors with blockchain gaming token volatility, returns, and liquidity. To investigate this relationship, this paper uses a cross-sectional study with pricing and fundamental data on 30 blockchain gaming tokens for companies that have some element of gameplay, employ NFTs, and have a native token that is liquid and tradeable.

In this study, multilinear regression models are used with a variety of on and off-chain factors against the following dependent variables: volatility of the token between January and June 2022, monthly volatility of the token averaged over its age, return percentage of the token one year after its launch, and Amihud's Liquidity Factor (detailed in Section 3). The regression models were constructed with only off-chain variables against a dependent variable and only on-chain variables against the same dependent variable, with some control variables standard across both regressions.

The results validated some of the hypothesized effects of certain factors for their impact on volatility, returns, or liquidity. For example, on-chain variables such as the percentage of token supply dedicated to private investors and rewards, the vesting period of these tokens, games based on the Polygon blockchain, and tokens with a fixed supply all have significant positive effects on both volatility measures ($p<0.05$). On the other hand, off-chain variables such as the game's genre (in this case, strategy and gambling games) negatively affect the volatility of a token ($p<0.05$) along with their monthly users ($p<0.10$). Other variables, such as the tokens market capitalization (in this case, if the token's market cap is above the median in the sample) and the amount of funds the gaming companies has raised both positively affect volatility at the 10% significance level.

At the returns level, off-chain variables such as the market cap and funds raised positively affect the one-year returns of tokens ($p<0.05$). Conversely, on-chain variables, such as if the game is based on the Solana blockchain ($p<0.05$) and if the game is based on the Polygon blockchain ($p<0.10$), have overall adverse effects on the returns of that token. In the end, several hypotheses on returns were invalidated by the results. They showed that more investigation needs to be done to understand how game fundamentals can have long-term effects on token prices.

Lastly, off-chain variables had no significant impact on the liquidity measure of tokens. However, several on-chain variables showed positive effects on liquidity, such as the amount of faucets (number of ways the token is minted/released into circulation) and the private sale percentage ($p<0.05$). Negative effects were shown by the percentage of tokens dedicated to rewards ($p<0.05$).

Following the introduction will be eight more sections. Section 2 of the paper provides an industry background and a thorough overview of the concepts addressed in this paper to contextualize the results. Section 3 reviews literature relevant to NFTs, Crypto tokens, ICOs, Blockchain Games, and financial concepts used to guide the models employed in this study. Section 4 goes through the variables used in this study and the cleaning for the final data set used for the regression analysis. The hypotheses for this study are also mentioned in Section 4. Section 5 covers the regression models employed in detail and the tested hypotheses. Section 6 reports the results from these regressions before summarizing and concluding in Section 7. Lastly, Sections 8 and 9 are the references and appendix, respectively.

2. Industry Background

While blockchain gaming provides real-world utility from in-game economies, the concepts of functioning in-game economies and users making money off of in-game items are not novel. For example, the famous First-Person Shooter (FPS) game Counter-Strike: Global Offensive (CS:GO) has an entire economy based on cosmetic upgrades and items users can trade. Some players may randomly draw items from games or purchase keys with fiat money to open in-game 'boxes.' All the items involved in this process: the box, items, and keys can be listed on the Steam (the game's publisher) marketplace for other users to buy (Su et al. 2021). However, some items tend to be traded on a peer-to-peer basis as the value of some rarer skins may not be accurately reflected on the Steam marketplace. The information asymmetry here creates lucrative opportunities for some users. However, it also forces them to transact off the game, commonly using methods like Paypal to complete the transaction off a trust-based system. Users attach value to cosmetic items not only from their looks but other rarity statistics and how they were retrieved. Nevertheless, a direct dollar-item exchange rate is not transparent, and the item's pricing history is also hidden. Although these items are not core to CS:GO's gameplay, active users pay attention to cosmetics, and some even make a living off them.

Furthermore, some Massively Multiplayer Online (MMO) games create a system where infinite demand can be "artificially stimulated in order to match productive supply." (Higgins 2016). Higgins (2016) noted that these systems create in-game objects around both the obsolescence of desirability (once you possess the item, there is already something more appealing just a few steps ahead) and obsolescence of function (as you gain levels or begin working toward higher tier gear, your current equipment becomes ineffective relative to the challenges you are facing). Therefore, there is always a requirement to get newer, better items with more utility as the user progresses. Although these games may also have cosmetic-focused items, their primary intent is for the enjoyment of the game. The critical difference between this system and CS:GO's is that MMOs will have some central, in-game currency that backs the value of these objects. Some games offer the ability to purchase extra in-game currency with fiat money, whereas others simply remain in their native ecosystem. For the latter, any fiat-to-game currency transactions, and vice versa, will happen off the market in a peer-to-peer fashion. However, exchange rates are likely subjective in this case and are, again, not transparent. That said, EVE Online (a popular MMO game) created a direct exchange rate for US Dollars to ISK – their in-game currency. The exchange rate held stably due to ISK's in-game utility and was thus able to support EVE's thriving in-game economy (Higgins 2016).

Knowing now of the extent to which in-game economies operate and thrive, how can web3 and blockchain make a difference? As stated briefly, the decentralization of assets (both tokens and NFTs), price transparency, verifiability, and P2E opportunities are all benefits that blockchain games can offer. To understand these concepts, readers should first have a rudimentary knowledge of blockchain technology, cryptocurrency tokens, and the progress made in this industry to enable blockchain games. We will begin this background knowledge by describing the types of tokens and their consensus mechanisms.

2.1 Medium of Exchange Tokens

Medium of exchange or store of value tokens, like Bitcoin or Litecoin, were the first coined cryptocurrencies. Bitcoin was first developed and deployed in 2008 after a paper published by Satoshi Nakamoto (2008) described a peer-to-peer, digital payments network that would hash a ledger of transactions onto an "ongoing chain of hash-based proof-of-work.". The network, in this case, refers to a decentralized ledger of transactions held and verified by the public and is, therefore, unhackable. These cryptocurrencies store value, exchange value, and reward individuals for keeping up the network and verifying transactions.

In layman's terms, an example of the Bitcoin blockchain, detailed by Fairfield (2008), can be considered a book of transactions. A new page is added to the book, and people can write new transactions on this page, but this book is the ultimate source of truth. However, knowing everyone has access to the book would cause concern as people could tamper with it – individuals could rip out a page, alter or erase transactions, add a new page earlier, and more. However, in this case, if a page is changed, then people would know as the logical ordering of pages would be different, i.e., page 2 would go to page 4 instead of 3. Furthermore, all earlier pages are laminated and sealed, so they are impossible to alter. The blockchain works similarly to this book – everyone has a copy of the blockchain, and each person constantly checks one copy against the other to ensure no unplanned alterations or fraudulent activity.

The process that adds new blocks to the blockchain, particularly in the Bitcoin network, is known as mining. For this process, powerful computers compete with each other to solve complex mathematical problems. When the problem is solved, a new block is ‘mined,’ and the computers that solved the problem are awarded a specific amount of Bitcoin. Once mined, miners can transfer or exchange these Bitcoins, and “every transaction generates an entry into the blockchain’s ledger.” (Anascavage and Davis 2018). The entries all follow the same structure where there is a timestamp for each transaction, the transaction details, and a hash of the current transaction along with the hash of the previous transaction. Because of this structure, verifying data with other copies of the blockchain becomes easy, and the transaction hashes are encrypted to ensure the security of those involved in the transaction (Anascavage and Davis 2018). The particular mining and verifying process described here is known as a consensus mechanism, and this consensus mechanism is known as Proof-of-Work (PoW).

PoW revolves around using computing power to generate blocks and prevent fraudulent activity. Miners are incentivized to provide this computing power through Bitcoin rewards, thus imbuing Bitcoin with fundamental value as long as the network is utilized. Since Bitcoin emerged as the first cryptocurrency and the backbone of blockchain, investors attach enough value to it such that its price action acts as an index for the broader crypto market.

2.2 Security Tokens

Although Bitcoin holds value for keeping up the network, its fundamental value is hard to assess, knowing that investors treat it as a medium of exchange and store of value similar to gold. As a result, security tokens emerged to fractionalize ownership of an asset that already has value, such as real estate, company equity, a painting, and more. These tokens are “digital, liquid contracts” that use the blockchain for their verification, i.e., their ownership stake is preserved on the ledger and for liquidity/open trading in crypto markets. Examples of security tokens are Blockchain Capital (BCAP) and Science blockchain (Liebkind 2021).

Tokens like these also opened up new fundraising opportunities for both startups and mature companies – instead of going through a traditional, lengthy IPO process, they could participate in an Initial Coin Offering (ICO), as detailed in the Introduction. However, Craig (2021) notes that the rise in scam companies and Ponzi schemes led to a "terrible downfall in the popularity of ICOs.". As a result, another fundraising method called the Initial Exchange Offering (IEO) emerged. The caveat here is that although the company still issued tokens to investors, it was conducted on a centralized crypto exchange, such as Coinbase or Binance, and promised investors that this token would be listed and that they would get their token allocations. Earlier, ICOs operated in a void where some investors never received tokens after transferring fiat money. Others would receive it but would not be able to trade on any particular market – IEOs set out to change that (Craig 2021).

However, in 2019, Decentralized exchanges (DEXs) came into the picture, including notable examples such as Uniswap and SushiSwap. These exchanges did not have regulatory requirements such as Know-Your-Customer (KYC). Further, they operated off an Automated Market Maker (AMM) model instead of a traditional order book model. Where regular exchanges match buy and sell orders to set prices, an AMM contains a smart contract that pools liquidity from users and determines the prices of assets in that pool from an algorithm. Decentralized exchanges and smart contracts are discussed further in Section 2.3, but their relevance here is that they gave rise to the successor of IEO, the

Initial DEX Offering (IDO). IDOs were completely permissionless, did not require significant fees for listing, and did not have several regulatory requirements. Like IEOs, IDOs issue tokens that are immediately available for trading. Furthermore, DEXs do not hold user funds, are rarely susceptible to cyber attacks, and investors can access their tokens with their decentralized wallets (where they genuinely have custody of their assets). Since many Decentralized Autonomous Organisations offer their tokens publically, a large community of users holds governance over how to list a company instead of a few central authorities (Craig 2021). IDOs were used in many of the tokens studied in this paper; however, some companies also went through traditional equity financing rounds with token allocations after a company launched their token.

2.3 Utility Tokens

The Bitcoin blockchain's primary purpose is to keep a ledger of transactions that permits exchanges between two parties. However, blockchain technology has evolved to do much more than that – including deploying executable code onto the blockchain that could facilitate more methods of exchange other than just cryptocurrency, i.e., Bitcoin. Vitalik Buterin co-founded Ethereum in 2014 with the intent to create a "solution for all use cases of blockchain that don't have a specialized system to turn to." (Marr 2018). In that sense, Buterin and other developers created Ethereum as a blockchain that allowed users to build programs, known as decentralized applications (dApps), that can serve a variety of use cases, financial and non-financial, and that all benefit from the decentralized database that is blockchain.

The evolution of Ethereum presented fundamental differences from Bitcoin; for example, the entire consensus mechanism is based on a Proof-of-Stake (PoS) system instead of PoW. In the PoS system, computing power is not used to validate transactions and create new blocks. Instead, any individual with a certain amount of tokens can 'stake' or offer their tokens as collateral for a chance to become a validator and earn rewards through transaction fees on the network. For Ethereum, this amount is 32 ETH (the native token, Ether, used to support the Ethereum blockchain). Each block is created through a random validator who then confirms transactions and verifies block information in return for fees that accrue based on the amount of staked ETH the validator owns (Marr 2018). The fees that accrue for validators are supplied by any user performing transactions on Ethereum – these are known as 'gas fees' that users must pay to keep the network running. For example, if a user sends ETH from one wallet to another, that will incur a gas fee that gets automatically paid to validators. Another example of when gas fees are paid is if a user buys or sells an NFT; in this case, the transaction is with a dApp and not another user but is still a transaction on the network. One might wonder how a transaction with an application is validated without human interaction, and the answer is through smart contracts. Ethereum ushered in the ability to develop and deploy smart contracts, programs stored on the blockchain that run when predetermined conditions are met. These programs automate agreements between parties so that no mediator needs to intervene. For example, purchasing ETH with Bitcoin on Uniswap involves interacting with a smart contract. Here, a user will send Bitcoin to the smart contract, which will verify the amount received, check the price of ETH in Bitcoin, and send back the correct amount of ETH. Neither the user nor Uniswap will need to execute this transaction; they just pay a gas fee.

The gas fee is paid in ETH, which is why the Ether token has utility in this network – it supplies validators with rewards and is also needed to perform any transaction. ETH is, therefore, the perfect example of a utility token: a token where value accrues to token holders from its use within a network, application, or platform (Howell et al. 2019). Other examples of utility tokens include Solana (SOL), Polygon (MATIC), and Binance Coin (BNB), which are the backbones of the Solana, Polygon, and Binance Smart Chain networks, respectively. However, not all utility tokens are used to support entire networks. The tokens analyzed in this paper are all utility tokens, serving various functions within the games they originate.

2.4 PoS Blockchains

Although Ethereum is the largest PoS blockchain by market capitalization, it has its fair share of drawbacks that limit its mass adoption. Firstly, due to Ethereum's design, when the network is experiencing high amounts of traffic by worldwide use, gas fees become exorbitant. Gas fees are typically determined from the supply and demand for the network's validation requests. Therefore, when the demand exceeds the number of validators by a large magnitude, gas fees will skyrocket, making each transaction extremely expensive. For example, between Jan 2021 and May 2022, Ethereum's average daily gas fee was approximately $40 per transaction, and the highest daily average in May 2022 was about $196.63 per transaction (Nibley 2022).

Secondly, transaction speeds are critical for blockchains to scale. Ethereum boasts more transactions per second (TPS) than Bitcoin: 20 TPS as opposed to Bitcoin's 3-4. However, comparing these networks to traditional payment rails like Visa or Paypal shows that there is still much more development needed to improve the scalability of these networks – Visa boasts around 1667 TPS, whereas Paypal does about 193 (Mechkaroska et al. 2018).

As a result, other blockchains were developed to solve these scalability problems that Ethereum faces. Many of these networks are referred to as Layer 1 (L1) blockchains, as they are the base networks upon which transactions are verified. Solana, for example, is an L1 blockchain with negligible gas fees (less than a penny's worth) and boasts around 3000 TPS. On the other hand, Polygon is a blockchain created to scale Ethereum by supporting multiple scaling solutions. One such scaling solution, a Layer 2 protocol, scales Layer 1 blockchains by processing transactions off of the Layer 1 before finally submitting them to the Layer 1 for its security and validation. To a user, their transaction may have been processed extremely quickly and for minimal cost. However, the transaction would not have officially occurred until it was reflected in a Layer 1 block. Because of this, Polygon offers meager gas fees and boasts a throughput of around 7000 transactions per second (Bybit Learn 2022).

There are merits and drawbacks to each PoS blockchain aside from transaction speed and gas fees. However, in terms of blockchain games, Ethereum, Solana, Polygon, and Binance Smart Chain (BSC) collectively account for almost 70% of all blockchain games created (Chua et al. 2022). Although BSC currently hosts 36% of all games, Ethereum still maintains its dominance for having the highest NFT transaction volume of the four networks, which can be used as a proxy for overall gaming activity (Chua et al. 2022).

2.5 Play-To-Earn and Blockchain Games

PoS blockchains, utility tokens, and NFTs combined are the building blocks that make blockchain games and P2E possible. Taking advantage of these technologies allows for the decentralization of in-game assets and open trading. Decentralization served prime importance for gamers as the in-game items they own are currently still under custody by the game/publisher itself. At any point, the game could ban users' accounts and seize their in-game items with no recourse. Therefore, giving ownership back to the user reduces their risk of losing their assets, which may be significantly high for those whose income is derived from trading in-game items.

The open trading of assets allows users to gain easier trading, transparent sales and trading data, and real-life utility from their efforts in a game. Furthermore, it eliminates the need to operate in secondary markets as software guarantees sales through smart contracts, not through another party who may commit fraud. As a result, P2E emerged as a novel business model where gamers are "rewarded in cryptocurrencies for playing a specific title, generally as a function of their performance." (Vicol 2022). The P2E space is still in its infancy, but Axie Infinity pioneered this concept. However, as mentioned earlier, both AXS and SLP (the game's native tokens) crashed significantly due to unsustainable token economics.

What characterizes stability in in-game economies like Axie Infinity is the balance of its rate of asset issuance with the rate of asset consumption/demand. Asset issuance methods range from token minting mechanisms, i.e., generating more tokens for the circulating supply, to reward distributions and token vesting schedules (Chung 2022). These aspects primarily relate to the token's economic design, discussed more in Section

2.6, and are commonly referred to as 'faucets.' Conversely, asset consumption can come from marketplace fees/taxes, crafting, utilities, rare collectibles, donations, etc. These aspects of a game are referred to as 'sinks.' Therefore, a balance of sinks and faucets is required to maintain a healthy equilibrium of prices within a virtual economy; however, this is conditional on gamers' use of the sinks (Chung 2022).

For example, Axie Infinity had two notable sinks and three faucets. Once sink came through a 4.25% tax on Axie Marketplace Sales, where all Axie NFTs and other in-game items/utilities were bought and sold. The additional sink was through fees on 'breeding' Axies – the action users would take to combine two Axie NFTs, some amount of AXS, and some amount of SLP to generate a new Axie NFT. On the other hand, the most significant faucet was P2E rewards – the SLP rewards minted for players completing battles or achieving progress in the game. Axie also had staking rewards and competition rewards – a fixed amount of AXS or SLP the game will give to players locking their tokens or winning competitions (Sky Mavis 2020).

Staking, in most games, is different from staking in the PoS consensus mechanism. This type of staking encourages investors to lock up their tokens in a staking pool (typically from a smart contract deployed by the game developers), so they can earn rewards over time. These tokens are typically a fixed percentage of the tokens the game has minted, and their primary purpose is to reward users over time for removing tokens from circulation. However, the rewards distributed to users push more tokens into circulation, so the rate of rewards (APR or APY) should be adjusted according to the number of tokens staked and the size of the staking pool. Some games or web3 projects may offer certain perks for staking their token; for example, staking FTT, FTX Exchange's native token, can unlock a reduction in fees for trading (prior to their collapse). However, others will simply distribute tokens as rewards to investors who trust in the game enough to lock up their tokens for a fixed period (i.e., a few weeks to years), with more tokens being rewarded relatively during the more extended lock-up periods. Axie Infinity's staking program allows users to stake their AXS to earn AXS rewards daily – the current APR as of writing is 45%. Therefore, if a user simply locked up their AXS tokens for a year, they would earn 45% more AXS tokens and could potentially see an increasingly high ROI if the AXS price was constant or grew.

Although staking rewards are guaranteed to increase inflation for a token, companies attempt to keep inflation at a stable and easily-estimated rate based on the token design. Conversely, Axie Infinity's P2E rewards vary based on game activity: the more active users they have, the more SLP is minted to reward users. At the game's height in Q4 2021, the amount of SLP minted exceeded the amount of SLP burned/utilized by almost 300% (Axie World 2021). The continued issuance rate relative to the utilization rate caused severe hyperinflation in SLP, which was eventually responsible for its over 99% crash. Although the sinks existed and were being used, it was not enough to balance out the faucets. Additionally, AXS was not rewarded to users through P2E but through staking and competitions. Therefore, its price did not drop as significantly and quickly but experienced a steady decline as its utility was still associated with Axie's failing in-game economy.

Axie Infinity set an example for how to build a P2E blockchain game and how their interpretation of P2E was flawed. Several more games followed a similar, dual token system (one token acted as the game's governance token and the other a reward/utility token) which also failed or have yet to prove themselves. Although the economic design is essential in the sustainability of blockchain games, their enjoyment and gameplay cannot be ignored. If a game is played with the sole reason of earning, then the game's tokens will constantly experience high volatility and extreme price action as inflation sets in. As Newzoo reports in their 2022 report on blockchain gaming and the Metaverse, "The early market for blockchain games is overrun by titles that feature rudimentary gameplay without sustainable economics." (Vicol 2022)

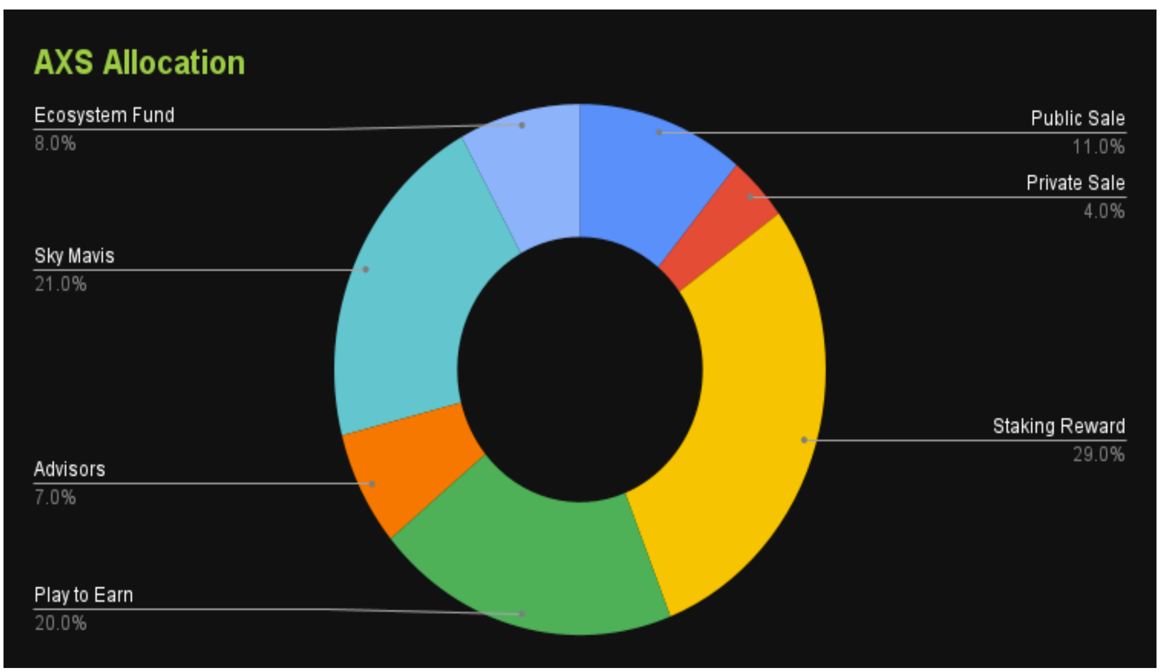
Furthering this narrative, Chung (2022) reports that many crypto gaming economies, like Axie Infinity, extract value through their utility token (i.e., SLP). In the early stages of the game, this model works since value extraction is attractive due to the limited supply of the utility token. However, this attracts more users due to the lucrative nature of the game, leading to rapid population growth and a meaningful increase in economic activity that accrues value to the game's treasury. Unfortunately, the rapid population growth eventually leads to unsustainable value accrual as the utility token collapses due to hyperinflation. With it, economic activity dries up, and marginal treasury value accrual diminishes, leading to the economy's ultimate demise (Chung 2022).

Ultimately, the space is still young. Economical design and gameplay can be mitigated as the industry matures. Furthermore, creating complex and enjoyable gaming experiences is a lengthy and delicate process that should not be accelerated for faster financial gain through crypto tokens.

2.6 Tokenomics Explained

Token economics, commonly referred to as 'tokenomics,' of a token is the "catch-all for the elements that make a particular cryptocurrency valuable and interesting to investors." (Stevens 2022). It is the most crucial consideration for a game or company when it comes to fundraising and ensuring the longevity and sustainability of a token. Companies must decide what fraction of their total token supply will be dedicated to a particular purpose. Typically, the tokens dedicated to launching the token during an offering will be a small fraction of the tokens minted. The price of those initially circulating tokens allows for the calculation of two market capitalizations for the company: circulating market capitalization and fully diluted (all tokens circulating) market capitalization. However, that is only one consideration of the tokenomics for a company. To understand the most common token allocations in blockchain gaming, we can refer to Axie Infinity's AXS allocations in Figure 1, taken from CoinGecko's Tokenomics section on AXS.

Figure 1: AXS Allocation

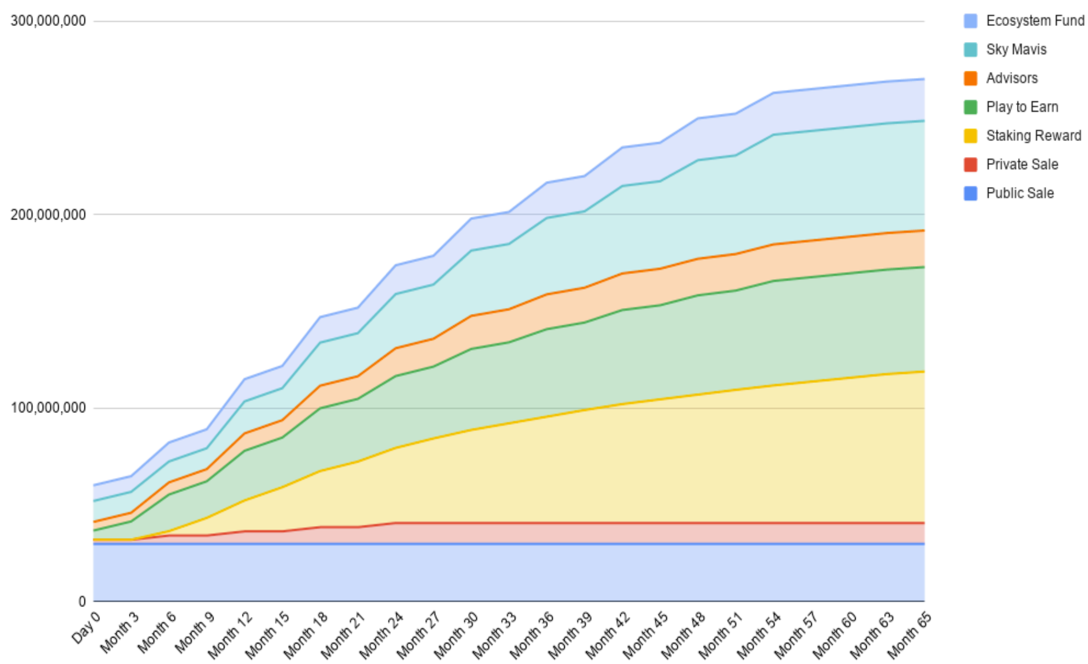


Source: CoinGecko AXS Tokenomics Section

Starting with the highest allocations, Staking Rewards refers to the rewards described in Section 2.5 – rewards distributed to users for locking up their tokens. Next is the 21% allocation dedicated to Sky Mavis – this refers to the tokens saved for the company itself for its balance sheet (which can be considered part of its treasury). The Play To Earn allocation consists of all the AXS faucets that are rewarded to users for playing the game. Public Sale refers to the number of tokens initially dedicated to AXS's IDO for general circulation. Ecosystem Funds typically are tokens allocated to a specific treasury, managed by the company's core team, to grow the game's ecosystem. Axie Infinity mentions that their principles for their ecosystem fund are "Clear value added to the broader Axie Infinity community and KPIs and goals that unlock funds (if applicable)." (Sky Mavis 2021). Advisors are the tokens saved for private investors such as individuals, angels, or larger firms, but these investors take a more hands-on role with the company. Lastly, private sale tokens are reserved for the early, strategic investors of the company, akin to a seed investment into a startup.

Each of these token allocations is not immediately accessible by the relevant party – they go through their respective vesting periods, so tokens are gradually released into circulation. Token release schedules vary from company to company. However, we can use AXS's token release schedule as an example, shown in Figures 2 and Table 1 below, taken from Sky Mavis' Axie Infinity Whitepaper (2021).

Figure 2: Axie Infinity's AXS Release Schedule



Source: Sky Mavis (2021) Axie Infinity Whitepaper

Table 1: Tabled overview of AXS Allocations and Release Status

Token Amount	Total Supply	Pct. Allocated	Release Status
Play and Earn	54,000,000	20%	35% Unlocked
Staking Rewards	78,300,000	29%	35% Unlocked
Ecosystem Fund	21,600,000	8%	40% Unlocked
Sky Mavis	56,700,000	21%	40% Unlocked
Advisors	18,900,000	7%	40% Unlocked
Public Sale	29,700,000	11%	Unlocked
Private Sale	10,800,000	4%	Unlocked
Total Amount	270,000,000	100%	

Source: Sky Mavis (2021) Axie Infinity Whitepaper

Figure 2 shows that most of the allocations release linearly over 85 months from day 0 (AXS launch date). In this sense, the Sky Mavis team does not have access to these tokens because they have yet to be unlocked by the smart contract that deployed the AXS token. Once deployed, the program will start counting and slowly give each party access to the promised tokens. The private sale percentage is the only allocation that has a cliff before a linear vesting period. In month 3, private investors gained access to 20% of their tokens; by month 24, they would have unlocked 100% of their allocation. Many token release schedules use equity vesting principles, but companies also must consider various considerations to slow down inflation while sustaining demand for the token.

3. Literature Review

This paper extends the existing literature on cryptocurrency, NFTs, blockchain games, and their relationship with market effects. Furthermore, this paper will review the literature on traditional measures of volatility, returns, and liquidity as these measures are employed in this study. Although several academic papers and digital resources have been referenced in Section 2, this section aims to elaborate on some of these studies that are crucial to this paper's objectives. Lastly, a discussion of this paper's contributions to the industry will follow the literature review to provide the necessary context before reviewing the data used in this study.

3.1 Literature on NFTs and Cryptocurrency

The first literature to discuss is Caginalp and Caginalp's 2018 study on *Valuation, Liquidity Price, and Stability of Cryptocurrencies*. Many cryptocurrencies like Bitcoin and Ethereum do not explicitly follow traditional valuation metrics, i.e., projecting cash flows. Their function may vary from security to a payment or utility token within a game. Therefore, Caginalp and Caginalp showed that the price of cryptocurrencies would likely be subject to liquidity and momentum; instead of fundamental valuation. However, this research sets the foundation for using factors beyond speculation to guide investments into particular crypto tokens since many of these projects involve cash flows – akin to valuing early-stage startups. That said, the primary cryptocurrency analyzed in this study was Bitcoin and its price history, thus showcasing a rather simplistic overview of the types of valuations and stability that cryptocurrency can offer today.

Howell et al. (2019) continue the investigation of more cryptocurrencies by analyzing multiple crypto tokens of all types and primarily looking at their effectiveness in financing growth through ICOs. They used a sample of over 1500 ICOs that raised around $12.9 billion and had characteristics such as offering mechanisms, ICO design features, operating sectors, and more. After regressing these ICO features against indicators of success (future employment and growth rate), they found that utility tokens are associated with a 20-36% increase in employment and that ICO issuers have lower failure rates when the executive team has a lockup (vesting) period for sale of its ICO tokens. However, Myalo et al. (2019) furthers this study by showing that the volatility of the leading cryptocurrencies (Bitcoin and Ethereum) has a significant impact on the success of an ICO. Therefore, there is a need to investigate the success of ICOs further to control for market impacts on a company's fundamental success (Howell et al. 2019).

Pivoting to NFTs, Ante (2021) investigated the effects of Bitcoin and Ethereum price action on the NFT market to establish a relationship between NFTs as an asset class and cryptocurrencies. They used 1231 daily observations of the volume in NFT sales, the number of blockchain wallets holding or interacting with NFTs on a particular day, and the prices of ETH and BTC on those days. After employing a VAR model, they found that BTC price shocks trigger an increase in NFT sales, whereas ETH price shocks reduce the number of active NFT wallets. Overall, they found that the "larger cryptocurrency markets affect the growth and development of the smaller NFT market, but there is no reverse effect." (Ante 2021). The primary limitation of this study is that the demand in the NFT market can be either underestimated or overestimated as NFT sales are not always between two parties – they can be between two wallets owned by the same user. Furthermore, more investigation is necessary across time to show market effects when sentiment is not highly bullish for NFTs and cryptocurrency, as in 2021.

Overall, these three studies highlight the importance of both market effects on NFT and token success, such as liquidity and volatility. Some fundamental factors of the company, such as vesting periods, affect token success through time. Much of the blockchain gaming-specific literature was detailed in Section 2.5 and showed the importance of sustainable value accrual through sinks and faucets for a game to succeed.

Because previous scholarly work does not address these factors specifically for blockchain games, this paper's model can provide new insights for this space that expand upon existing literature for ICOs and NFTs. A balance between market-related factors (off-chain) and fundamental factors (on-chain) is required to comprehensively understand what can affect blockchain token returns, volatility, and liquidity.

3.2 Literature on Returns, Volatility, and Liquidity Measures

Sections 2 and 3.1 focused on the literature and context for blockchain, blockchain applications, and P2E games. This section will provide the background for the dependent variables used in this study that measure the effects of on and off-chain factors on overall investment decisions. One crucial factor in making investment decisions, particularly into riskier assets like NFTs or blockchain gaming tokens, is the volatility of that asset. Token fundamentals, market factors, and macroeconomic factors such as inflation can influence volatility. In *On the Economic Sources of Stock Market Volatility*, Engle et al. (2008) Used long historical time series stock market data, observed daily, and macroeconomic variables sampled monthly or quarterly. They employed a GARCH-MIDAS model that allowed them to extract two components of volatility: one about short-term fluctuations and the other about a secular component. They concluded that macroeconomic fundamentals (inflation and industrial production growth) play a significant role in forecasting volatility in both long and short horizons (Engle et al. 2008). Several factors that affect stock prices have seen similar effects in the crypto market, such as economic conditions and monetary policy (Rakesh et al. 2022). Due to this correlation, the same frameworks concluded from this study can be used in analyzing the volatility of blockchain gaming tokens.

Expanding the literature on volatility, Lowry et al. (2010) found that the volatility of initial returns (post-IPO) is higher for firms that are more difficult to value because of increased information asymmetry. Similarly, the tokens analyzed in this study all contain performance from their launch (i.e., 1yr % return); however, valuation metrics differ considerably from IPO stocks. Information asymmetry still exists for some projects more than others due to data availability constraints; therefore, looking at short-term vs. long-term gains and sustainability for these projects may add to the literature about initial periods of volatility after a token launch (through ICO, IDO, or IEO).

So far, Lowry et al. and Engle et al. have discussed frameworks of volatility and returns that can be applied to influence investment decisions into crypto. The last measure of importance is liquidity. To measure the liquidity of tokens, this study uses the *illiquidity premium* defined in *Illiquidity and Stock Returns: Cross-Section and Time-Series effects* by Amihud (2002). Amihud calculated a stock's illiquidity premium by taking the absolute stock return and dividing it by the dollar volume traded. He showed that illiquidity significantly affects small firm stocks, increasing their investment risk and expected short-term returns. Liquidity can indicate a token's sustainability and longevity, where more liquid tokens present less investment risk and, thus, a lower expected return. Furthermore, more liquid tokens allow investors to quickly enter and exit positions considering that some tokens may only be traded on decentralized exchanges. Less liquid tokens will also incur higher slippage, which results in investors receiving an unequal amount of returned tokens compared to what they sold.

This paper contributes to the literature on the web3 industry and traditional frameworks applied to stock analysis. These frameworks are applied to crypto tokens for a more comprehensive, robustness check of their validity and applicability for a different asset class.

4. Data

The sample for this study includes cross-sectional data on the top 30 blockchain gaming companies by market capitalization. The selection criteria for these companies were that they must have a game with an existing user base, token(s) used in the economy of that game, and integration of NFTs within the game. The criteria were firm as the study intended to investigate the effects of various in-game factors on the game's token(s); as a result, companies that have existing tokens for fundraising purposes, but do not have a launched product, were excluded from this study.

The data for these tokens were collected from a variety of sources. Pricing, volume, and market capitalization data were downloaded from CoinGecko's pricing and charting website. CoinGecko is a cryptocurrency data aggregator that provides live pricing and information on more than 10,000 tokens. User data was either extracted from DappRadar, another data aggregator on decentralized applications, or from various dashboards on Dune Analytics, a user-curated blockchain analytics platform that allows users to query smart contracts with SQL. Fundraising data for these companies was retrieved from business information aggregators such as Crunchbase, Pitchbook, and Chainbroker.io. Lastly, tokenomics and on-chain-related data were extracted from each company's whitepaper and public documentation. After accounting for missing values and cleaning the data, the final sample consisted of 18 blockchain gaming companies, with 27 used for the on-chain regression models that excluded the missing variables (in this case, fundraising data and user growth were limited for some games).

4.1 Dependent Variables

There were four dependent variables used to measure token performance and other metrics that can provide a risk profile of each token for investors. The first two variables were related to the volatility of a token but measured in two-time horizons: January to June 2022 and the average monthly volatility from the token's launch. Volatilities were measured by taking the standard deviation of prices in each given period. Because of the large range of results, both volatility measures were transformed using the natural log. The following dependent variable is the Illiquidity Measure, as described in Amihud (2002). Formula 1, shown below, is used to calculate the Illiquidity Measure:

$$ILLIQ = \frac{1}{N}\sum_{T=1}^{T} \frac{|r_t|}{\$V_t} \qquad (1)$$

Where T is the number of days, \$V is the dollar volume on day t, and r_t is the return on day t. Therefore, a token with a higher illiquidity measure would experience more significant price impacts from either selling or buying pressure. It is important to note that for crypto tokens, companies supply liquidity, but a significant portion comes from users and investors supplying their tokens as liquidity for rewards. This mechanism is detailed in Section 2.5 as staking but can also refer to liquidity mining, which is out of the scope of this study. Liquidity and volatility are important metrics for investors to factor risk into their portfolios. The last dependent variable is the 1-year holding return from the token's launch. Formula 2 shown below, calculates the returns percentage:

$$(launch\ price - price\ on\ day\ 365)/launch\ price = 1\ yr\ return \qquad (2)$$

As with volatility, the returns also had a large range; thus the returns were also standardized with a continuously compounded return shown in Formula 3:

$$ln(1 + 1yr\ return) = logged\ returns \tag{3}$$

The summary statistics of the dependent variables is shown below in Table 2 for all 27 observations, and Table 3 for the 18 observations used in off-chain regressions:

Table 2: Dependent Variable Summary Statistics with all observations

Statistic	N	Mean	St. Dev	Min	Max	Q25	Q50	Q75
janjunvol	27	-1.017	2.016	-9.010	1.258	-1.512	-0.727	0.069
monthlyvol	27	-0.642	2.008	-8.729	1.635	-0.927	-0.195	0.287
amihudliquidity	27	5.866	0.842	3.841	7.400	5.295	6.056	6.403
1yr_return	27	-0.163	2.428	-3.827	6.880	-1.866	-0.710	1.811

Table 3: Dependent Variable Summary Statistics with limited observations

Statistic	N	Mean	St. Dev	Min	Max	Q25	Q50	Q75
janjunvol	18	-0.407	0.907	-2.188	1.258	-1.174	-0.133	0.076
monthlyvol	18	-0.067	0.853	-1.276	1.635	-0.832	0.086	0.295
amihudliquidity	18	5.726	0.944	3.841	7.400	4.941	5.805	6.295
1yr_return	18	-0.515	2.572	-3.827	6.880	-2.061	-1.238	1.015

4.2 Independent Variables

As detailed previously, the variables in this study have been separated into off-chain and on-chain factors to run regressions, respectively. This section will detail the independent variables for both categories.

4.2.1 Off-Chain

Off-chain variables refer to the factors of a blockchain gaming company that are not related to the blockchain or token design of the game's token(s). Firstly, the companies' market capitalizations were retrieved and normalized using the natural log. Along with market capitalization, a dummy variable labeled *largemarketcap* was created and assigned 1 for companies with a market capitalization above the median ($35.4 million) and 0 for otherwise. It is hypothesized that games with a larger market cap should have high returns (to achieve that market cap in the first place), lower volatility, and higher/deeper liquidity.

After considering the market capitalization, more game-specific off-chain metrics were gathered for this regression analysis. Firstly, monthly active user (*mau*) data was collected from sources such as Dune Analytics and DappRadar, which calculated the number of users a game has from smart contract interactions linked to the game. However, there are some limitations to the validity of this data: actual monthly active users may not be fully reflected only from the smart contract interaction side, but some games have off-chain elements with users not having to interact with NFTs. Furthermore, several blockchain wallets can be shared by the same person, so if unique wallet addresses are not taken into account, then user data can be significantly inflated. That said, an average of the *mau*'s from the year of the game's launch was calculated for each game when that data was available. A year from launch was used to be consistent with other independent variables that relied on time-series data and with *1yr_return*'s time horizon. Unfortunately, some games did not have a full year's worth of data, so some games had *mau* data projected based on historical growth, or the latest *mau* figures were taken from September 2022. The last user metric was the average monthly user growth (*usergrowth)*, taken from the respective game's *mau* data in the same time horizon. However, due to a lack of historical *mau* data for four games, four observations were dropped in regressions that used *usergrowth*. Higher growth and larger MAUs can act as a proxy for how much the token is being used in a game's ecosystem. However, if growth is too significant, it may be unsustainable. If there are too many MAUs, it can also shine a light on the game's economic weaknesses at scale: similar to what happened to Axie Infinity, detailed in Section 2.5. The hypothesis for these variables would be that higher growth figures and more MAUs would result in greater returns, lower volatility, and higher/deeper liquidity.

The next off-chain factor was the number of funds the blockchain gaming company has raised (*fundsraised*) either through a token offering method, private sales, or traditional equity investment rounds. The range of data collected was also extreme in this case, so the natural log of *fundsraised* was calculated and used in the regression analysis. Since there was limited data on eight companies, those observations were dropped for some off-chain regressions. The more funds a gaming company has raised can indicate investor trust and sentiment around the longevity and economic viability of the game. Therefore, more funds raised may equate to higher returns, lower volatility, and higher/deeper liquidity.

The last off-chain factors were dummy variables representing the game's genre: five of the most popular game genres were selected for this study. Firstly, *isMMO* shows one if the game is a Massive Multiplayer Online game, similar to World of Warcraft or EVE Online. Next, *isFPS* represents First-Person Shooter games similar to Counter-Strike: Global Offensive and *isStrat* are Strategy games like Axie Infinity. The last two are *isLifestyle* for lifestyle and general Metaverse-type games like Decentraland and Sandbox and *isGambling* for betting and gambling-focused games. Game genres such as MMO and FPS have had regular, non-web3 videogames that established thriving, sustainable in-game economies. Therefore, looking at the genre's explanatory power on sustainability measures such as volatility and liquidity could yield valuable insights for prospective investors.

Summary statistics of the above off-chain variables are available for 27 observations (without *fundsraised* and *usergrowth*) and 18 observations in Tables 4 and 5:

Table 4: Independent Variable (Off-Chain) Summary Statistics w/o fundsraised and usergrowth

Statistic	N	Mean	St. Dev	Min	Max	Q25	Q50	Q75
marketcap	27	17.487	1.727	14.493	21.113	16.316	17.358	18.223
largemarketcap	27	0.481	0.509	0	1	0	0	1
mau	27	9.144	2.562	4.710	14.550	7.373	9.626	10.484
isMMO	27	0.259	0.447	0	1	0	0	0.500
isFPS	27	0.185	0.396	0	1	0	0	0
isStrat	27	0.370	0.492	0	1	0	0	1
isLifestyle	27	0.370	0.492	0	1	0	0	1
isGambling	27	0.148	0.362	0	1	0	0	0

Table 5: Independent Variable (Off-Chain) Summary Statistics w/ fundsraised and usergrowth

Statistic	N	Mean	St. Dev	Min	Max	Q25	Q50	Q75
marketcap	18	17.956	1.850	14.493	21.113	16.714	17.470	18.791
largemarketcap	18	0.444	0.511	0	1	0	0	1
mau	18	9.635	2.832	4.710	14.550	8.096	9.661	11.373
usergrowth	18	0.124	0.265	-0.213	0.723	-0.112	0.121	0.260
fundsraised	18	16.173	1.545	14.346	19.555	15.425	15.747	16.422
isMMO	18	0.278	0.461	0	1	0	0	0.750
isFPS	18	0.111	0.323	0	1	0	0	0
isStrat	18	0.389	0.502	0	1	0	0	1
isLifestyle	18	0.389	0.502	0	1	0	0	1
isGambling	18	0.167	0.383	0	1	0	0	0

4.2.2 On-Chain

On-Chain variables refer to the factors that have a direct relationship to the blockchain, token economics design, and smart contracts. Beginning these factors are dummy variables for the blockchain the game is based on, either Ethereum (*ethbased*), Solana (*solbased*), Binance Smart Chain (*bscbased*), or Polygon (*polygonbased*). As explained in Section 2.5, different blockchains have their merits and drawbacks. Therefore, investigating the network's effect on each token could yield interesting insights into the sentiment and technology of these other blockchains. Initially, these variables were to be included as controls; however, some blockchains showed explanatory power for effects on all independent variables.

The following three factors are related directly to the P2E dynamics of the game, as detailed in Section 2.5. The number of *sinks*, *faucets*, and a dummy variable for if the sinks are greater than faucets (*sinksgreaterthanfaucets*) were manually retrieved from combing each company's whitepaper. The hypothesis for these variables is that greater sinks than faucets should correlate with higher returns, lower volatility, and higher liquidity. As an extension of this hypothesis, greater sinks and lesser faucets should have similar outcomes. This is because greater utility for the token corresponds to more sinks, and inflationary pressure can be managed with fewer faucets.

Subsequently, the company's whitepaper recorded aspects of the game's tokenomics. Several of these factors are detailed in Section 2.6, including the percentage of tokens dedicated to rewards (*rewardspct*) which consist of staking, P2E, competitions, and other reward categories. Along with the rewards percentage, a dummy variable (*highrewardspct*) was created to check if the rewards percentage of a company's token was higher than 25% – the median in this study's sample. The hypothesis is that a higher rewards percentage may result in higher volatility, lower returns, and higher/deeper liquidity. This would seem intuitive, given that rewarded tokens without significant utility (or sinks) would result in sustained, continuous selling pressure. As the game gets more users, more rewards get distributed overall due to their efforts in-game, increasing the token's circulating supply. A sustained increase in circulating supply, and selling pressure from users cashing out rewards, causes the token to experience hyperinflation and highly volatile conditions, as seen with SLP in Section 2.5. Higher liquidity would result from the increased circulation of token supply that the liquidity incentives from the company would sustain. This is a crucial point to consider if the token is not traded on a Centralised Exchange, and if they are, it will still be significant depending on its relative CEX vs. DEX trading volume. Suppose users or investors continue to supply liquidity. In that case, they gain rewards that could offset the price drop of the token and return a significant upside if the token has positive returns. However, if the incentives are insufficient to offset the loss, the investors may simply sell off their tokens and exit completely, resulting in lower liquidity over time.

Additional tokenomics elements included the percentage of tokens dedicated to private investors, strategic investors, or advisors (*private_sale_pct*), the vesting period of these tokens in days (*vestingperiod*), and whether the vesting period was shorter than three years (*shortvesting*). The last factors relating to the token are the current percentage of circulating tokens (*circulatingpct*) and a dummy variable for whether the token has a total fixed supply (*fixedsupply*).

Since many of these elements are determined by the company when building their token and game, linking explanatory power to some may allow companies to understand sustainable token design better. The hypotheses around these tokenomic variables are that higher *private_sale_pct*, lower *vestingperiod* (and, therefore, *shortvesting*), higher *circulatingpct* and a non-*fixedsupply* token would all result in higher volatility, lower returns, and higher liquidity. Furthermore, investors can use these variables to construct an investment framework when analyzing prospective web3 investments. Summary statistics of these variables are available in Table 6 below:

Table 6: Independent Variable (On-Chain) Summary Statistics

Statistic	N	Mean	St. Dev	Min	Max	Q25	Q50	Q75
ethbased	27	0.556	0.506	0	1	0	1	1
solbased	27	0.185	0.396	0	1	0	0	0
bscbased	27	0.259	0.447	0	1	0	0	0.500
polygonbased	27	0.333	0.480	0	1	0	0	1
sinks	27	3.481	1.909	1	9	2	3	5
faucets	27	3.037	1.786	1	9	2	3	3
sinksgreaterthanfaucet	27	0.444	0.506	0	1	0	0	1
highrewardspct	27	0.481	0.509	0	1	0	0	1
rewardspct	27	0.265	0.193	0	0.733	0.140	0.250	0.390
private_sale_pct	27	0.145	0.110	0	0.440	0.079	0.135	0.200
vestingperiod	27	1,072.852	850.462	0	3,650	730	1,034	1,546.500
shortvesting	27	0.556	0.506	0	1	0	1	1
circulatingpct	27	0.001	0.001	0.0001	0.004	0.001	0.001	0.001
fixedsupply	27	0.852	0.362	0	1	1	1	1

4.3 Control Variables

The control variables for this study primarily consist of controlling for overall cryptocurrency returns in the one year from each company's token launch. For example, if a token launched in October 2019, the Bitcoin and Ethereum 1-year % returns were taken from October 2019 to October 2020 for that observation. These returns are represented by the *ethreturns* for Ethereum and *btcreturns* for Bitcoin and are transformed using Formula 3. Summary statistics for these two variables are available in Table 7 below:

Table 7: Control Variables Summary Statistics

Statistic	N	Mean	St. Dev	Min	Max	Q25	Q50	Q75
ethreturns	27	0.068	1.252	-1.149	2.475	-0.876	-0.466	0.367
btcreturns	27	-0.197	0.969	-1.184	1.625	-0.893	-0.508	-0.088

5. Empirical Analysis

This section will describe the empirical methods used to test the hypotheses of this study. To accomplish this, a multiple linear regression will be employed in models testing the explanatory power of both on and off-chain variables on the returns, volatility, and liquidity of blockchain gaming tokens.

This study uses two distinct regression models, one for on-chain variables and one for off-chain variables. The following equations (Formulas 4 and 5) express the two models:

5.1 On-Chain Regression

$$\begin{aligned}\hat{Y}_{it} = {} & \beta_1(ethbased_{it}) + \beta_2(solbased_{it}) + \beta_3(bscbased_{it}) + \beta_4(polygonbased_{it}) + \\ & \beta_5(sinks_{it}) + \beta_6(faucets_{it}) + \beta_7(sinksgreaterthanfaucet_{it}) + \\ & \beta_8(highrewardspct_{it}) + \beta_9(rewardspct_{it}) + \beta_{10}(private\_sale\_pct_{it}) + \\ & \beta_{11}(vestingperiod_{it}) + \beta_{12}(shortvesting_{it}) + \beta_{13}(circulatingpct_{it}) + \\ & \beta_{14}(fixedsupply_{it}) + \beta_{15}(ethreturns_{it}) + \beta_{16}(btcreturns_{it}) + \epsilon\end{aligned} \tag{4}$$

The $\hat{Y}_{it}$ represents a time-varying dependent variable for a blockchain gaming token. This study has four variables: the volatility between January and June 2022, monthly volatility since the token's inception, 1-year % return for the token since launch, and Amihud's liquidity factor. The rest of the model is occupied by the coefficients from each respective on-chain factor and the error term ϵ. Due to multicollinearity, *highrewardspct* was used in place of *rewardspct*. The rest of the on-chain variables have limited multicollinearity, as shown by the correlation heatmap in Appendix A.

Additionally, the percentage of tokens circulating (*circulating_pct)* was scaled by the age of the respective company in days. Scaling the circulating percentage by age controls for time as older companies will tend to have more tokens unlocked for public markets. However, if younger companies have higher circulation in their infancy, it may have unintended effects on volatility due to increased price activity from trading.

5.2 Off-Chain Regression

$$\hat{Y}_{it} = \beta_1(marketcap_{it}) + \beta_2(largemarketcap_{it}) + \beta_3(ethreturns_{it}) + \beta_4(btcreturns_{it}) + \beta_5(mau_{it}) + \beta_6(usergrowth_{it}) + \beta_7(fundsraised_{it}) + \beta_8(isMMO_{it}) + \beta_9(isFPS_{it}) + \beta_{10}(isStrat_{it}) + \beta_{11}(isLifestyle_{it}) + \beta_{12}(isGambling_{it}) + \epsilon \tag{5}$$

The $\hat{Y}_{it}$ for the off-chain regression is the same for the on-chain regression. Because of multicollinearity in some variables, *largemarketcap* was used in most analyses instead of *marketcap*. Furthermore, *ethreturns* was used in place of *btcreturns* due to Ethereum's applicability and effect on dApps being greater than Bitcoin. The rest of the off-chain variables have limited multicollinearity, as shown by the correlation heatmap in Appendix B:

Several off-chain variables needed to be scaled logarithmically due to their sizeable spread. For example, the market cap, monthly active users, and funds raised are logarithmic explanatory values for this model, as detailed in Section 4.2.1.

6. Results

The results section will first dive into the on-chain regression analyses shown in Table 8 below, followed by the off-chain regressions shown in Table 9 below. Each regression analysis has four independent variables to explore effects on, so both sections will be structured in the following sequence: effects on monthly volatility, January to June '22 volatility, 1-year return from token launch, and liquidity.

6.1 On-Chain Regression Results

Table 8: On-Chain Regression Results for all four Dependent Variables

	Dependent variable:			
	janjunvol	monthlyvol	1yr_return	amihudliquidity
	(1)	(2)	(3)	(4)
ethbased	1.063	0.982	−0.705	−2.288
	(1.171)	(1.100)	(1.597)	(2.743)
solbased	3.481	3.591*	−6.543**	−6.735
	(2.027)	(1.908)	(2.771)	(4.747)
bscbased	0.164	0.563	−0.896	−1.217
	(0.971)	(0.931)	(1.353)	(2.273)
polygonbased	4.076***	3.433**	−4.041*	−1.983
	(1.349)	(1.282)	(1.862)	(3.158)
sinks	0.102	−0.009	0.865	0.770
	(0.364)	(0.343)	(0.497)	(0.852)
faucets	−0.364	−0.194	0.160	1.741**
	(0.259)	(0.260)	(0.378)	(0.608)
sinksgreaterthanfaucet	−2.480*	−1.672	1.622	−1.631
	(1.340)	(1.333)	(1.935)	(3.137)
highrewardspct	1.671**	1.627**	−1.831	−4.019**
	(0.757)	(0.710)	(1.031)	(1.771)
private_sale_pct	10.444**	11.364**	0.554	21.762**
	(4.041)	(3.801)	(5.520)	(9.462)
vestingperiod	0.003***	0.003***	−0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
shortvesting	2.218	1.992	−3.404	1.513
	(1.404)	(1.317)	(1.913)	(3.287)
circulatingpct	145.481	373.190	−887.982	838.201
	(482.069)	(476.529)	(691.967)	(1,128.697)
fixedsupply	−4.269**	−4.075**	1.586	−3.684
	(1.579)	(1.501)	(2.180)	(3.697)
ethreturns		0.566*	1.045**	
		(0.296)	(0.430)	
		3		
Constant	−5.200**	−5.469**	3.178	−19.921***
	(2.402)	(2.380)	(3.456)	(5.623)
Observations	27	27	27	27
R^2	0.729	0.778	0.680	0.813
Adjusted R^2	0.459	0.519	0.307	0.626
Residual Std. Error	1.484 (df = 13)	1.392 (df = 12)	2.021 (df = 12)	3.474 (df = 13)
F Statistic	2.694** (df = 13; 13)	3.005** (df = 14; 12)	1.823 (df = 14; 12)	4.349*** (df = 13; 13)
Note:				*p<0.1; **p<0.05; ***p<0.01

6.1.1 January to June Volatility Results

The January to June volatility model was overall significant at the 5% level with a p-value of 0.0309, multiple R^2 value of 0.7794, and adjusted R^2 of 0.522. The model finds that Polygon-based tokens, high rewards percentages, the tokens allocated to a private sale, and the vesting period have positive relationships with logged volatility. Conversely, if the token has a fixed supply, it has a negative effect on logged volatility. All of the relationships above are significant at the 5% level, with vesting periods carrying significance at the 1% level.

We can validate the initial hypotheses from the results that companies with a higher percentage of their tokens dedicated to incentivizing users or fundraising experience higher volatility. For example, a 10.88 percentage point increase in the token's volatility can be attributed to a 1% increase in the company's private sale token allocation. Furthermore, a 1% increase in the tokens dedicated to rewards corresponds to a 1.68 percentage point increase in the token's volatility. Lastly, suppose the vesting period of a token is increased by one day. In that case, the volatility will see a 0.0030 percentage point increase – this is significant as vesting periods typically vary by months or years, so prospective investors can consider them carefully.

One interesting result from this model is that Polygon-based tokens tend to see higher volatility in this period. The coefficient was similar with Solana-based tokens but was only significant at the 10% level – a reason for this may be due to a smaller sample size, as Solana-based tokens accounted for 18.5% of the sample compared to 33% for Polygon-based tokens. However, Ethereum-based and BSC-based tokens have significantly smaller estimates and are not significant for this model. A further investigation into the volatility of the Total Value Locked (TVL) of tokens across all protocols on Polygon and Solana may yield interesting insights to explain the increased volatility of tokens on those networks. The results of such an investigation will allow investors to construct a more accurate risk/return model for the blockchain gaming tokens in question.

6.1.2 Monthly Volatility Results

As with the January to June volatility, the monthly volatility model with on-chain factors was also significant at the 5% level with a p-value of 0.0317, multiple R^2 value of 0.7781, and adjusted R^2 of 0.519. The model finds that all significant variables in the January to June volatility model are also significant for the monthly volatility model and at the same significance levels. However, the model also found Ethereum returns and Solana-based tokens to have statistically significant effects on the monthly volatility – though this significance was at the 10% level.

The hypotheses for the on-chain factors' effects on January to June volatility are similar to that of monthly volatility, with the caveat that monthly volatility is over varying periods based on the token's launch. In this sense, monthly volatility is analyzed as a long-term measure of the token's price action. Both measures can give investors insight into time horizons for different token investments, i.e., either within six months or longer. That said, seeing that the results of both volatility models are very similar, except for slightly different coefficients, it is plausible that both models explain similar time-based effects of the on-chain factors.

6.1.3 1-Year Returns Results

The one-year returns model against on-chain variables was not significant at the 5% or 10% level – the p-value was 0.1517 with a multiple R^2 value of 0.680 and adjusted R^2 of 0.307. However, Ethereum returns over the same period, and if the token was Solana-based, both had statistically significant effects on the logged one-year returns percentage. In this case, if the price of Ethereum increased by 1%, the one-year return of tokens would increase by 1.04 percentage points. Furthermore, if the token were Solana-based, the one-year return would decrease by 6.54%, which is quite a significant drawback for Solana-based tokens.

The other hypotheses for on-chain factors, such as more sinks than faucets, a lower rewards percentage, and a lower private sale percentage would lead to higher, sustainable returns, were inconsistent with the results of this model. There are various reasons for this inconsistency: firstly, the lack of sample size for this study may greatly impact the statistical significance of the model. Furthermore, since many games have yet to prove themselves in a five-year horizon, using a one-year holding period from the token launch may not be the best indicator of long-term, sustainable performance. For example, it typically takes years to build a good quality game, so the on-chain factors that provide utility to the token may not have been built yet, as the company may prioritize game development in its place. In this sense, web3 gaming companies may only have their in-game mechanics priced into their tokens once the utility is already developed and made clear to users and investors.

Lastly, some of these tokens launched towards the end of the crypto bull run, which lasted from around March 2020 to December 2021. For example, BWO, the token representing the game Battle Worlds, only launched in May 2022. Therefore, BWO does not have a full year's worth of data and would also not experience high returns due to an overall market downturn. The model attempted to control this by using Ethereum returns as a control; however, since the Ethereum returns had explanatory power, more control variables should have been explored. As a result, a further investigation into more gaming tokens through a longer time horizon would be necessary to better understand the on-chain factors' effects on long-term returns.

6.1.4 Liquidity Results

The Amihud liquidity factor against on-chain factors yielded a statistically significant model (at the 5% level) with a p-value of 0.0063, multiple R^2 value of 0.813, and adjusted R^2 of 0.626. The model finds that the number of faucets and percentage of tokens allocated for private sale positively influence the logged liquidity factor. Conversely, the logged liquidity factor would decrease if the token had a high reward percentage (above 25%). All of the mentioned factors are statistically significant at the 5% level.

These results validate the hypothesis that more faucets and a higher private sale percentage would result in lower/shallow liquidity through a higher illiquidity premium. Furthermore, a high rewards percentage would typically see higher liquidity due to liquidity incentives; as a result, the companies that designed their tokenomics around high rewards experienced significantly deeper liquidity. As expected, the blockchain network on which the token was deployed had no significant outcome on liquidity.

However, the shorter the vesting period, higher circulating supply, and non-fixed supply of a token had no significant effect on liquidity. Shorter vesting periods have not been demonstrated in past studies to impact token liquidity significantly, but more investigation may be necessary due to the limited sample in this study. However, a token's circulating supply should intuitively affect the liquidity of a token. Still, investors may prefer to move funds elsewhere, i.e., out of the liquidity pool, if there are insufficient incentives in place and the token does not trade heavily/at all on a CEX. As with vesting periods, more data should be collected when analyzing the effects of a token's circulating supply on its liquidity. Additionally, non-fixed supply tokens accounted for only 15% of the tokens analyzed in the sample. The infinite-supply utility tokens emerged as a popular tokenomics model from Axie Infinity; however, it had not proved itself in terms of longevity. Still, if more blockchain games launch with a dual-token system (a governance and utility token), they should be monitored for the effects on liquidity.

6.2 Off-Chain Regression Results

It is important to note that all off-chain regressions had 9 data points dropped due to a lack of data for *usergrowth* and *fundsraised* variables.

Table 9: Off-Chain Regression Results for all four dependent variables

	Dependent variable:			
	janjunvol	monthlyvol	1yr_return	amihudliquidity
	(1)	(2)	(3)	(4)
largemarketcap	1.030*	0.747	4.543**	−4.343
	(0.524)	(0.463)	(1.523)	(2.809)
ethreturns			−0.222	
			(0.935)	
mau	−0.253*	−0.217*	−0.466	0.038
	(0.125)	(0.111)	(0.366)	(0.672)
usergrowth			−3.742	
			(3.059)	
fundsraised	0.387*	0.378*	1.933**	0.806
	(0.194)	(0.171)	(0.683)	(1.040)
isMMO	−1.963*	−1.803**	−5.041	−2.115
	(0.887)	(0.783)	(2.710)	(4.755)
isFPS	−1.059	−1.363*	−1.162	−2.782
	(0.816)	(0.720)	(2.151)	(4.374)
isStrat	−2.632**	−2.572**	−5.953*	−5.150
	(1.003)	(0.885)	(3.042)	(5.375)
isLifestyle	−1.314*	−1.575**	−2.808	−6.128
	(0.702)	(0.619)	(1.859)	(3.761)
isGambling	−2.121**	−2.212**	−3.219	3.799
	(0.935)	(0.825)	(3.413)	(5.011)
Constant	−2.141	−1.798	−23.381**	−23.574*
	(2.220)	(1.960)	(9.627)	(11.901)
Observations	18	18	18	18
R^2	0.613	0.659	0.798	0.593
Adjusted R^2	0.270	0.357	0.508	0.232
Residual Std. Error	0.775 (df = 9)	0.684 (df = 9)	1.803 (df = 7)	4.156 (df = 9)
F Statistic	1.784 (df = 8; 9)	2.178 (df = 8; 9)	2.759* (df = 10; 7)	1.642 (df = 8; 9)

Note: *p<0.1; **p<0.05; ***p<0.01

6.2.1 January to June Volatility Results

The January to June volatility model against off-chain variables was overall not significant at the 5% or 10% level – the p-value was 0.203 with a multiple R^2 value of 0.613 and adjusted R^2 of 0.270. However, all variables except for *isFPS* were significant at the 10% level, with *isStrat* and *isGambling* significant at the 5% level.

Regarding the game genre variables, strategy games and gambling games were found to have significantly negative effects on the volatility in this period – they resulted in a -2.63 and -2.1 decrease in logged volatility, respectively. Although this may indicate that strategy and gambling games result in more price stability, the sample size of gambling games was relatively minor, representing only 16.7% of the tokens studied. That said, gambling games do not necessarily need to care about AAA game quality; they can focus purely on incentivizing users to play their game from a rewards and addiction perspective. Therefore, if enough users are enticed to hold and trade their tokens while remaining an economic participant in their ecosystem, the token price can hold relatively steadily. On the other hand, strategy games need better quality, and players may scrutinize the in-game mechanics used to promote economic stability more heavily. The players' interests should be aligned from a monetary and gameplay standpoint, so these games have adopted similar token models that have performed well.

The more monthly active users a game has also showed significant negative effects on volatility. When the MAUs of a game increase by 1%, logged volatility decreases by -0.253 percentage points. This effect is in line with the hypothesis that more MAUs result in lower volatility of the game's token, as many players actively use it to support their gameplay. Therefore, the token's price does not wholly rely on speculation or macroeconomic indicators; instead, its price reflects the utility it serves to its many MAUs.

The amount of funds the game company raised also significantly affects the volatility of their token at the 10% level. If the funds raised for a company increase by 1%, then volatility in the January-to-June period increases by 0.387 percentage points, which contradicts the hypothesis that more funds raised would result in lower volatility. Since funds raised were one of the variables that had missing values, a smaller sample size may contribute to this contradictory result. However, the result can also be explained through private selling of the token – if a company has higher funds raised, they would have given more tokens/equity to investors who can freely trade their tokens depending on their vesting schedules. Private sellers would have many tokens that, if sold, can impact the price significantly. Therefore, if they decide to sell, and sentiment around the company is still high, there would be large price swings from private selling and public/retail buying.

6.2.2 Monthly Volatility Results

As with the January to June volatility, the monthly volatility model with off-chain factors was also not significant at the 5% or 10% level with a p-value of 0.1338, multiple R^2 value of 0.659 and adjusted R^2 of 0.357. The model finds that all significant variables in the January to June volatility model are also significant for the monthly volatility model, except for a large market capitalization. Furthermore, MMO games, strategy games, lifestyle games, and gambling games were all significant at the 5% level, with strategy and gambling games having the most substantial negative impact on volatility. As with the on-chain monthly volatility model, monthly volatility against off-chain factors shows similar results to the January to June volatility model with the same independent variables.

6.2.3 1-Year Returns Results

The one-year returns model against on-chain variables was overall significant at the 10% level – the p-value was 0.096 with a multiple R^2 value of 0.798 and adjusted R^2 of 0.509. Both funds raised and whether the token had a large market cap had statistically significant impacts on the returns of a token at the 5% level. Firstly, when a company has 1% more funding, the logged returns are 1.93 percentage points higher. This result is in line with the hypothesis that companies with more funding tend to experience greater returns from their token, which can be considered a reflection of both private/institutional and public/retail investor sentiment. Secondly, a token with a large market cap experiences higher logged returns by 4.54 percentage points. This result is also in line with the hypothesis that larger market cap tokens will tend to have greater returns as they had to get to that market cap in the first place, so it is inconsequential.

Furthermore, from the game genre variables, strategy games had the only statistically significant result at the 10% level for a strongly negative impact on returns. Strategy game tokens saw a -5.95 percentage point decrease in the logged returns of a token. Although the model was controlled with Ethereum returns, this result shows that games like Axie infinity and others tend to have lesser returns than their competitors in other game genres. Strategy games started the P2E space but came crashing down the hardest in the most recent market downturn.

6.2.4 Liquidity Results

The Amihud liquidity factor against off-chain factors yielded a not statistically significant model (at the 5% and 10% level) with a p-value of 0.238, multiple R^2 value of 0.593, and adjusted R^2 of 0.232. Additionally, none of the off-chain factors recorded any significant relationship with liquidity within this model. This non-result contradicts all hypotheses for off-chain effects on liquidity and would need to be investigated further, with a larger sample size, to ensure the non-effect is not just a result of the model's (or data) limitations.

7. Conclusions

Blockchain gaming is a new phenomenon that offers unparalleled benefits to players and companies and is worth investigating. Although user sentiment around blockchain technology will vary, its efficacy in providing a new way for players to earn from their in-game efforts has proved itself. More high-rated games from AAA game studios will need to be developed for users to adopt blockchain technology into their daily lives; yet, even without extremely high-quality games, blockchain gaming has attracted a large, diverse user base.

More work needs to be done in this space, and this paper sought to show both the opportunities and drawbacks of blockchain gaming as it stands today. With the introduction of P2E, games focused too much on economic incentives to realize their token design and gameplay would be unsustainable and follow Ponzi scheme-like mechanics. There is merit in the concept of P2E; however, it has not yet proven itself to be a sustainable model.

Because of the economic opportunity established by blockchain gaming, this paper investigated what factors (on and off-chain) determine returns, volatility, and liquidity for blockchain gaming tokens. The results should enable prospective investors with knowledge of blockchain gaming and an understanding of factors to look at in due diligence that can help them during portfolio construction. Past literature has not focused on blockchain gaming specifically as an asset class, but previous work on ICOs, NFTs (and their pricing), and web2 in-game economies allowed for similar frameworks to be applied to this new field for easier understanding.

Thus, this study looked at 27 blockchain gaming company tokens launched between 2018-2022 and analyzed them for their effects on volatility, returns, and liquidity. The results have validated almost all hypotheses for both on and off-chain factor effects on the dependent variables. Notably, tokenomics elements such as the percentages dedicated to a private sale or rewards, whether the token had a fixed supply, the vesting period, and more showed significant effects on volatility and liquidity. Furthermore, the blockchain network the token was based on had some explanatory power for returns, which was a notable result as it showed that tokens might be quite susceptible to network risk in that the token can be correlated to their network's token (such as SOL, ETH, MATIC, etc.) and thus follow similar price movements. These elements mentioned comprised part of the on-chain factors employed in this study.

Conversely, off-chain factors such as the number of funds the company has raised showed significant effects on volatility, returns, and liquidity. Each hypothesis was validated for this variable, except for its impact on volatility, as that contradicted the original hypothesis where volatility would reduce as a function of funds raised. Furthermore, the amount of Monthly Active Users in a game has also shown significant effects on volatility, validating the hypothesis that more active users would lead to less volatility. However, its impact on returns and liquidity was not significant.

Lastly, the study's sample games comprised genres such as First Person Shooters, Massively Multiplayer Online, strategy, gambling, and lifestyle. Therefore, attributing explanatory power to some game genres over others can be helpful for investors to both understand which game genres/economic designs work now and to plan for the future for game genres that have yet to prove themselves. Game genres such as strategy negatively impacted returns significantly and volatility. Apart from strategy games, the gambling genre was also at the same 5% significance level for volatility and had a similarly negative effect. Other game genres also significantly impacted volatility, with some of them at the 10% level. Still, different game genres did not have any significant effects on returns and liquidity.

The study contributes to an overview of the blockchain gaming landscape and literature on particular variable effects that interest investors, game studios, and prospective players of blockchain games. Although the study was limited in sample size, several effects were established successfully. To further investigate blockchain gaming, studies should include more tokens over time while the industry matures. Since the crypto market is in a current downturn, these results could vary through market cycles, so time-based effects of on and off-chain factors would also merit an investigation. Furthermore, this study is relatively rudimentary as more complex off-chain factors such as social media metrics and game quality indicators were omitted. Additionally, on-chain factors such as smart contract audits, token inflation/emission rates, token burn rates, and more were not included. The primary reason for their exclusion was due to time and data availability. As mentioned, the industry is still in its infancy, and as more companies are established and incumbents mature, there will be a larger quantity of data to analyze.

8. References

1. Amihud, Yakov. “Illiquidity and Stock Returns: Cross-Section and Time-Series Effects.” Journal of Financial Markets, North-Holland, Jan. 2002, https://www.sciencedirect.com/science/article/abs/pii/S1386418101000246.
2. Anascavage, Robert and Davis, Nathan. “Blockchain Technology: A Literature Review.” May 3 2018.
3. Ante, Lennart. “The Non-Fungible Token (NFT) Market and Its Relationship with Bitcoin and Ethereum.” SSRN Electronic Journal, June 8, 2021.
4. Axie World. “Axie World | Economics - Charts.” *Axie World*, 2021, https://www.axieworld.com/en/economics/charts. Accessed 1 Dec. 2022.
5. Beck, James, et al. Web3 Report Q3 2021, Consenys Nov. 2021, https://consensys.net/reports/web3-report-q3-2021/. Accessed 1 Dec. 2022.
6. Bybit Learn. “11 Fastest Cryptocurrencies with Blockchains Boasting High TPS.” Bybit Learn, BybitLearn, 22 June 2022, https://learn.bybit.com/blockchain/fastest-cryptocurrencies-high-tps/. Accessed 1 Dec. 2022
7. Caginalp, Carey, and Gunduz Caginalp. “Valuation, Liquidity Price, and Stability of Cryptocurrencies.” Proceedings of the National Academy of Sciences of the United States of America, vol. 115, no. 6, 2018, pp. 1131–34. JSTOR, https://www.jstor.org/stable/26507145. Accessed 1 Dec. 2022.
8. Chittum, Morgan. “Twitter Integrates Nfts with New Profile-Picture Feature.” Blockworks, 20 Jan. 2022, https://blockworks.co/twitter-integrates-nfts-with-new-profile-picture-feature/. Accessed 1 Dec. 2022

9. Chua, Jie Xuan, et al. “Q3 State of Crypto: Market Pulse.” Binance Research, Binance Research, 20 Oct. 2022, https://research.binance.com/en/analysis/3q22-market-pulse. Accessed 1 Dec. 2022
10. Chung, Terry. “Sinks & Faucets: Lessons on Designing Effective Virtual Game Economies.” Medium, 1kxnetwork, 22 Jan. 2022, https://medium.com/1kxnetwork/sinks-faucets-lessons-on-designing-effective-virtual-game-economies-c8daf6b88d05. Accessed 1 Dec. 2022
11. Chung, Terry, and AG. “Value Accrual in Play to Earn Economies.” Value Accrual in Play to Earn Economies, MetaPortal, 7 June 2022, https://metaportal.substack.com/p/value-accrual-in-play-to-earn-economies?s=w. Accessed 1 Dec. 2022
12. Craig, J. “What is an Initial DEX Offering (IDO): How does it compare to an IEO?” Phemex, 20 Oct. 2021, phemex.com/blogs/what-is-a-dex-ido. Accessed 1 Dec. 2022
13. de Best, R. “Amount of funds raised for cryptocurrency initial coin offering (ICO) projects worldwide as of November 2019, by leading industry.” Statista, 11 Feb. 2021, https://www.statista.com/statistics/802925/worldwide-amount-crytocurrency-ico-projects-by-industry. Accessed 1 Dec. 2022
14. D. Mechkaroska, et al., "Analysis of the Possibilities for Improvement of BlockChain Technology," 2018 26th Telecommunications Forum (TELFOR), 2018, pp. 1-4, doi: 10.1109/TELFOR.2018.8612034.

15. Engle, Robert F., et al. “On the Economic Sources of Stock Market Volatility.” SSRN, 31 Aug. 2008, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=971310#.

16. Finneseth, Jordan. “Crypto Projects Raise $30.2 Billion in H1 2022, Surpassing the Total Raised in All of 2021.” Kitco News, 9 Aug. 2022, https://www.kitco.com/news/2022-08-05/Crypto-projects-raise-30-2-billion-in-H1-2022-surpassing-the-total-raised-in-all-of-2021.html. Accessed 1 Dec. 2022

17. Frankenfield, Jake. “What Does Proof-of-Stake (Pos) Mean in Crypto?” Investopedia, Investopedia, 20 Oct. 2022, https://www.investopedia.com/terms/p/proof-stake-pos.asp. Accessed 1 Dec. 2022

18. George, Benedict. “What Is a Dex? How Decentralized Crypto Exchanges Work.” CoinDesk Latest Headlines RSS, CoinDesk, 11 Feb. 2022, https://www.coindesk.com/learn/what-is-a-dex-how-decentralized-crypto-exchanges-work/. Accessed 1 Dec. 2022

19. Gherghelas, Sara. “DappRadar x BGA Blockchain Games Report #7.” DappRadar Blog RSS, 22 Sept. 2022, https://dappradar.com/blog/dappradar-x-bga-blockchain-games-report-7. Accessed 1 Dec. 2022

20. Higgins, David. “Dreams of Accumulation: The Economics of SF Video Games.” Science Fiction Studies, vol. 43, no. 1, 2016, pp. 51–66. JSTOR, https://doi.org/10.5621/sciefictstud.43.1.0051. Accessed 1 Dec. 2022.

21. Howcroft, Elizabeth. “NFT Sales Hit $25 Billion in 2021, but Growth Shows Signs of Slowing.” Reuters, Thomson Reuters, 11 Jan. 2022,

https://www.reuters.com/markets/europe/nft-sales-hit-25-billion-2021-growth-shows-signs-slowing-2022-01-10/. Accessed 1 Dec. 2022

22. Howell, Sabrina T and Niessner, Marina and Yermack, David. “Initial Coin Offerings: Financing Growth with Cryptocurrency Token Sales.” European Corporate Governance Institute (ECGI) - Finance, Working Paper No. 564/2018, Sep. 3 2019, pp. 5.
23. Liebkind, J. “Is 2021 the Year of the Security Token?” Investopedia, 21 Jun. 2021, https://www.investopedia.com/tech/2018-year-security-token. Accessed 1 Dec. 2022
24. Lowry, Michelle, et al. “The Variability of IPO Initial Returns.” Wiley Online Library, The Journal of Finance, 19 Mar. 2010, https://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.2009.01540.x.
25. Marr, Bernard. “Blockchain: A Very Short History of Ethereum Everyone Should Read.” Forbes, Forbes Magazine, 20 Mar. 2018, https://www.forbes.com/sites/bernardmarr/2018/02/02/blockchain-a-very-short-history-of-ethereum-everyone-should-read/?sh=74fd19631e89. Accessed 1 Dec. 2022
26. Mourya, E. “Here's how Axie Infinity players are earning nearly $500/month in crypto rewards.” FXStreet, 19 Aug. 2021, www.fxstreet.com/cryptocurrencies/news/heres-how-axie-infinity-players-are-earning-nearly-500-month-in-crypto-r ewards-202108190844. Accessed 1 Dec. 2022

27. Myalo, Alina and Glukhov, Nikita. “Success of Initial Coin Offering. The Empirical Evidence from 2016-2019.” Aug. 21 2019.

28. Nakamoto, Satoshi. “Bitcoin: A Peer-to-Peer Electronic Cash System.” *Bitcoincash.org*, 2008, https://bitcoincash.org/bitcoin.pdf.

29. Nibley, Brian. “What Is Ethereum Gas? How ETH Gas Fees Work.” SoFi, SoFi, 8 Sept. 2022, https://www.sofi.com/learn/content/what-is-ethereum-gas/. Accessed 1 Dec. 2022

30. Rodriguez, Salvador. “Facebook Changes Company Name to Meta.” CNBC, 29 Oct. 2021, https://www.cnbc.com/2021/10/28/facebook-changes-company-name-to-meta.html Accessed 1 Dec. 2022

31. Sharma, Rakesh, et al. “Is There a Cryptocurrency Price Correlation to the Stock Market?” Investopedia, Investopedia, 4 Oct. 2022, https://www.investopedia.com/news/are-bitcoin-price-and-equity-markets-returns-correlated/#:~:text=Cryptocurrency%20and%20stock%20prices%20are,tend%20to%20trend%20the%20same. Accessed 1 Dec. 2022

32. Sky Mavis. “Axie Infinity Shards - $Axs.” Axie Infinity Shards - $AXS - Axie Infinity, 2021, https://whitepaper.axieinfinity.com/axs. Accessed 1 Dec. 2022

33. Stevens, Robert. “What Is Tokenomics and Why Is It Important?” CoinDesk Latest Headlines RSS, CoinDesk, 25 Oct. 2022, https://www.coindesk.com/learn/what-is-tokenomics-and-why-is-it-important/. Accessed 1 Dec. 2022

34. Su, Yuchen, et al. “The Sub-Dimensional Economy: Building a Second Economy for Humanity in Online Games.” American Academic Press, 2021.

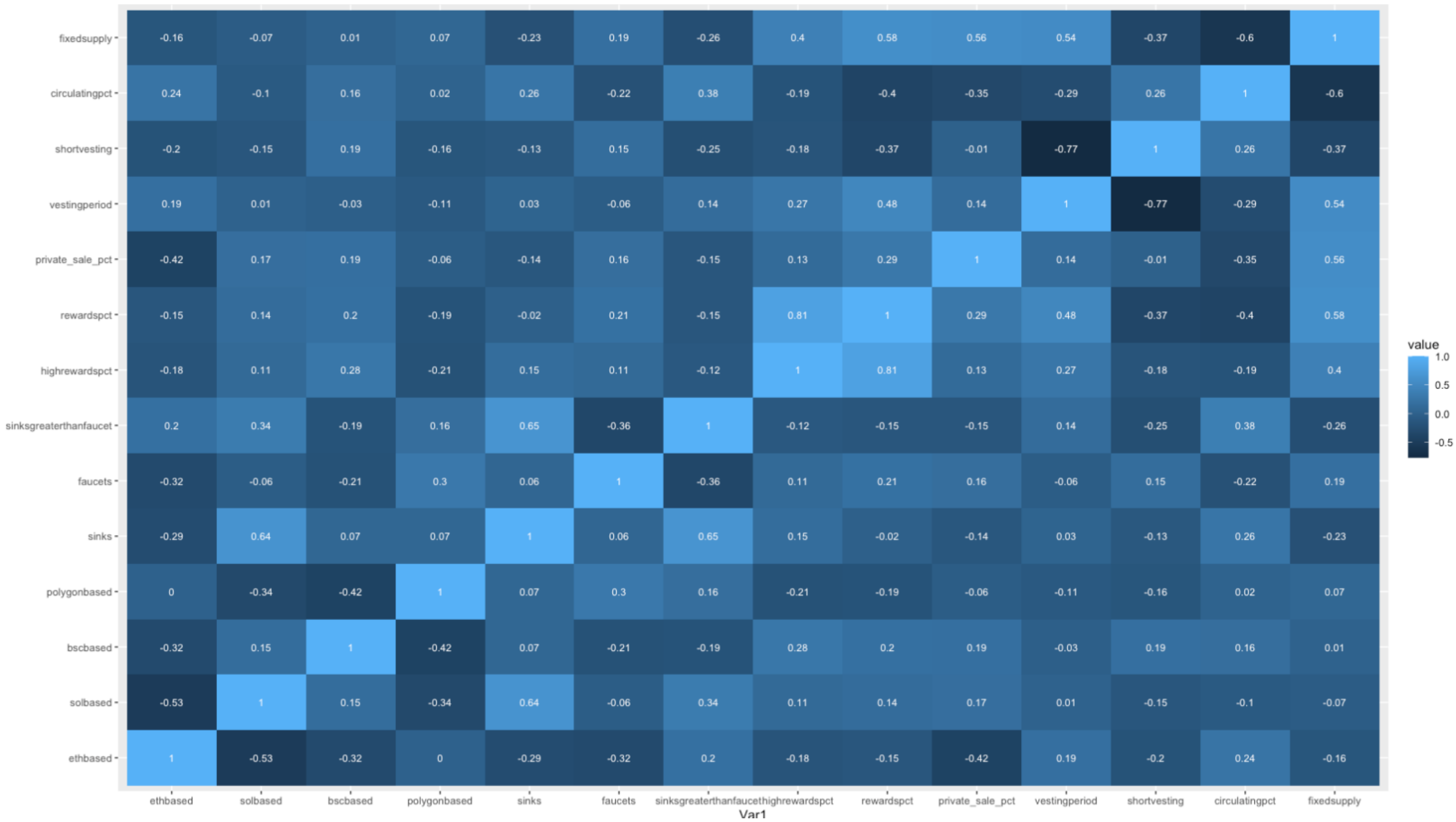
35. Varshney, N. “Someone paid $170,000 for the most expensive CryptoKitty ever.” TNW, 5 Sep. 2018, thenextweb.com/news/most-expensive-cryptokitty. Accessed 1 Dec. 2022

36. Vicol, Mihai. “The Metaverse, Blockchain Gaming, and NFTs: Navigating the Internet’s Uncharted Waters.” *Newzoo Trend Report 2022*, Newzoo, 28 June 2022, https://newzoo.com/insights/trend-reports/newzoo-report-on-metaverse-blockchain-gaming-nft-2022. Accessed 1 Dec. 2022

37. Wang, Qin, Rujia Li, Qi Wang, and Shiping Chen. “Non-Fungible Token (NFT): Overview, Evaluation, Opportunities and Challenges.” May 2019.

9. Appendix

Appendix A – Correlation Heatmap of On-Chain Variables



Appendix B – Correlation Heatmap of Off-Chain Variables