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An Empirical Study of Underpricing in Initial Decentralized Offerings

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ABSTRACT

To date, this research represents the first comprehensive exploration of the factors influencing the level of underpricing in Initial Decentralized Offerings (IDOs). Through regression model analysis, I examine the impact of various market and IDO-specific characteristics on IDO underpricing. I find evidence that supports the presence of underpricing in IDOs. Furthermore, my analysis reveals that IDO underpricing is significantly higher during bull market periods compared to bear market periods. Moreover, the research demonstrates that IDOs exhibit significantly higher levels of underpricing compared to ICOs, examined in currently outstanding scientific literature. Additionally, the study uncovers significant evidence indicating that the monetary value of circulating token supply at launch has a negative influence on the level of IDO underpricing. Similarly, the fully diluted market cap at launch, which serves as a proxy for project's size, also exhibits a negative impact on underpricing levels. Finally, the analysis reveals a negative relationship between Duration of IDO measured in days and the level of underpricing in IDOs for crypto projects, while controlling for characteristics outlined in outstanding ICO literature.

Keywords: Initial decentralized offerings, underpricing, cryptocurrencies

JEL codes: C2 Single Equation Models; C21 Cross-Sectional Models; C52 Model Evaluation, Validation, and Selection; G1 General Financial Markets; G10 General; G14 Information and Market Efficiency.

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CHAPTER 1 Introduction

Initial Decentralised Offerings (IDOs) have gained significant attention in the cryptocurrency industry over the past years. IDO is a fundraising mechanism allowing cryptocurrency projects to raise funds by selling tokens directly to investors on decentralized exchange platforms. IDOs permit investors to purchase native tokens directly from the project's smart contract, while offering several advantages in comparison to Initial Coin Offerings (ICOs), including lower fees and greater transparency. There exists a deficiency of research in the topic as this is a rather new phenomena, with the first IDO being launched in 2019. By this study's definition, underpricing in IDOs occurs when the market price at the end of the first trading day is significantly higher than the initial token allocation price. This leads to immediate profits for early investors and a potential loss for the project. While managers may consider underpricing as a good mechanism for attracting investors (Brau and Fawcett, 2006), this results in the company "leaving money on the table" and not being able to raise the optimal amount of capital (Ibbotson and Jaffe, 1975). While this is a well-researched topic for Initial Public Offerings (IPOs) and somewhat for ICOs, there is no scientific literature examining this phenomenon in IDOs. Being the first one of its kind, this study aims to investigate factors that influence IDO underpricing levels and lay grounds for further research in this domain. Studying the mechanics of the fundraising process and the influence of prerequisite characteristics on the magnitude and direction of IDO's underpricing could prove beneficial for all parties involved in these fundraising events, as well as market efficiency as a whole.

As mentioned earlier, in recent years, IDOs have proven to be an effective way to raise capital to fund start-ups and companies due to its accessibility, security and high investor demand. According to available statistics, in the first half of 2021, 242 IDOs were held, raising approximately $2.6 billion. These figures indicate a significant increase in activity comparing to the previous year; the number of IDOs increased by 500 precent, and the amount of funds raised increased by more than 8,800 precent (CoinGecko, 2021). Despite the current global economic decline and the bearish trend of the cryptocurrency market, the popularity of IDOs remains remarkably high among numerous projects seeking funding. This enduring popularity signifies a strong level of confidence in the efficacy of this fundraising method and its resilience to external economic factors.

Given the similarities between IDOs and ICOs, which are relatively more researched in the existing literature, it may be possible to apply methods and frameworks used in currently outstanding ICO literature to investigate factors that influence underpricing in IDOs. For ICOs, Adhami et al. (2018) finds an average level of underpricing of 929.9 percent and a median of 24.7 percent for 140 observations, Momtaz (2018) finds an average of 8.2 percent and a median of 2.6 percent for 302 observations, while Felix, T. H., & von Eije, H. (2019) find average and median underpricing of 108.5 and 32.9 percent for 247 observations, highlighting that the variables trading volume, issue size, market sentiment, a hot issue market and the use of a pre-ICO significantly influence ICO underpricing. Benedetti, H., & Kostovetsky, L. (2021) find evidence of significant ICO underpricing, with an average of 179% increase from the ICO allocation price to the first day's opening market price and a strong correlation between underpricing and activity on public discussion forums, discussing a project before its ICO. Furthermore, Lyandres, E., Palazzo, B., & Rabetti, D. (2019) results show that determinants of ICO underpricing are consistent with most empirical regularities known to characterise IPO underpricing, while some of the discrepancies may be because of differences in institutional settings between the ICO and IPO markets. This allows for intuition to rely on classic economic theory regarding some of the determinates of IDO underpricing.

The primary research inquiry of this paper aims to investigate the key factors contributing to underpricing in IDOs and compare the extent of IDO underpricing with that of ICOs as established in the current scientific literature, while drawing a link in characteristics to underpricing in IPOs and traditional capital markets. To address this research, an analysis of IDO data will be conducted, encompassing projects developed on various blockchains. The initial hypothesis focuses on comparing the average and median magnitudes of underpricing in ICOs and IDOs, as highlighted in existing literature. Second hypothesis focus on exploring the association, either negative or positive, between the prerequisite IDO-specific characteristics, and their impact on underpricing levels.

The research methodology will employ ordinary least squares regression model analysis, conducted through a software called Gretl, utilizing the following dependent variable: Underpricing adjusted for market returns. Multiple control and explanatory variables will be included in the model. Majority of data for the analysis will be sourced from reputable cryptocurrency data providers, specifically Cryptorank.io and Coinmarketcap.com. The study will consider the period from January 2020 to March 2023. While available data will be extracted from the previously mentioned websites and additional sources like tradingview.com, a significant portion of data collection will be collected manually due to the unavailability of Cryptorank.io API.

To mitigate data extraction challenges, only IDOs with a market capitalization of $100,000 USD and above will be considered, resulting in an estimated 600 available observations based on Cryptorank.io data. This limitation is one of the main constraints of the research. Furthermore, observations with missing data points will be excluded, resulting in a final sample size of approximately 450 observations. The analysis will primarily focus on financial factors due to the relative ease of data collection compared to other contributing factors such as social & media attention, marketing strategies, whitepaper characteristics, number of employees in the development team etc.…., which are acknowledged as influential in the existing literature on Initial Coin Offerings. However, extracting aggregated data for these factors is too complex and costly, adding another limitation to the scope of this research. The regression model will include the following variables:

Table 1 All variables included in the model

Variables	Description	Units
MUP (Dependent Variable)	Market adjusted underpricing	Precent
Total raised	The total capital raised during IDO	USD
Volume	Trading volume of a token on its first trading day	USD
Duration IDO	The length of the IDO	Days
Duration Launch	Duration of the token launch	Days
MCS at Launch	Initial monetary value of circulating token supply at launch	USD
Number of Launchpads	Count of launchpads hosting the IDO	Launchpads
Number of Blockchains	Count of blockchains on which the token is launched	Blockchains
FDMC at Launch	Fully diluted market cap of a token at launch	USD
VC	Dummy variable indicating Venture Capital backing	Binary
Sentiment	The crypto Fear and Greed index value	Index
Crowdedness	Count of fund-raising events within a 30-day period prior to the analysed IDO.	Events
NFT (0)	Utility category of a token	Binary
Blockchain service (1)	Utility category of a token	Binary
DeFi (2)	Utility category of a token	Binary
GameFi (3)	Utility category of a token	Binary
Social (4)	Utility category of a token	Binary
Blockchain infrastructure (5)	Utility category of a token	Binary
CeFi (6)	Utility category of a token	Binary
Meme (7)	Utility category of a token	Binary

Note: Table 1 presents the list of all variables included in the regression model, their description and units of measurement, where applicable. Dummy variables based on the category of the token are numbered from 0 to 7. The dependent variable MUP refers to market adjusted underpricing.

First and foremost, I anticipate that the level of underpricing in IDOs will likely be comparable to that of ICOs, given their susceptibility to similar factors' influence. Alternatively, it is possible that IDOs may exhibit slightly lower levels of underpricing due to reduced information asymmetry. However, arriving at a definitive conclusion on this hypothesis proves challenging, given the considerable variability in documented ICO underpricing across scientific papers. The timeframe used for estimation emerges as a critical factor altering the results. Nonetheless, I am committed to addressing this challenge by prioritizing papers with extended and up-to-date estimation windows, considering them more pertinent to my analysis.

My comprehensive analysis of underpricing in IDOs confirms the well-established, although insignificant, negative relationship between the issue size of IDOs and underpricing, consistent with findings from Initial Public Offerings in traditional markets. Moreover, I find that the FDMC at the time of launch exhibits a negative association with the underpricing levels in IDOs, indicating that larger projects experience reduced underpricing. Simultaneously, I confirm a significant positive association between market Sentiment and Crowdedness and the level of underpricing, these findings align with previous research, outlined in the IPO and ICO literature. Furthermore, my study revealed a positive correlation between first-day trading volume and underpricing, aligning with observations from the IPO literature. Additionally, the duration of the IDO demonstrated negative effects on underpricing, highlighting the importance of time-related factors in determining underpricing levels.

In line with my expectations, the analysis revealed a highly significant negative relationship between the monetary value of circulating token supply at launch and underpricing levels. In contrast to my initial expectations, the number of launchpads and the number of blockchains hosting an IDO showed a negative, but insignificant relationship with underpricing levels. Lastly, the examination of different token categories demonstrated varying associations with underpricing. Blockchain service category exhibited a positive association with underpricing, while social category displayed a negative association with underpricing, when compared to NFT category tokens. All other variables and category dummies displayed an ambiguous, inconsistent effect on the levels of underpricing.

CHAPTER 2 Background and Theoretical Framework

2.1 Background

2.1.1 Introduction to Concepts of Blockchain, Smart Contracts and Tokens

A blockchain is a decentralized peer-to-peer network operating independently of a central authority not bound to any specific physical location. Every computer within the network diligently maintains a synchronized replica of the database, ensuring that updates made to the database are seamlessly propagated across all copies in a harmonious and coordinated fashion. The system relies on internal cryptographic algorithms that shape the behaviour of the network nodes, ensuring consistency among the copies. The process of adding new data to the shared database follows a predefined protocol, known as the consensus mechanism. This mechanism serves two purposes: determining how information is appended to the blockchain and facilitating the agreement among the participants of the blockchain network regarding the current state of the shared database. The protocol permits any user to contribute information to the shared database while ensuring the validity of the added data.

Structurally, a blockchain comprises interconnected blocks that contain various data records, such as transactions. Each block maintains a reference to the preceding blocks, forming an unbroken chain that encompasses all transactions within the network. Once a new block is appended to the chain and becomes part of the shared database, it becomes immutable. The interlinking of blocks introduces a high level of resistance against tampering or alteration of newly added data.

One of the key innovations that blockchain introduces are Smart contracts. These self-executing programs automatically fulfil predetermined conditions when specific events occur on the blockchain. As a result, they facilitate efficient automation and error-free execution for various transactions involving value and asset rights transfers within decentralized blockchain networks.

The emergence of Ethereum stands as a remarkable milestone in the evolution of smart contracts, being established in 2014 as a decentralized blockchain ecosystem, Ethereum empowers individuals to craft their own smart contracts, complete with unique ownership rules, transaction formats, and state transition functions. This innovation has unlocked the potential for companies to generate digital tokens, endowed with a range of rights, be it economic, consumer-oriented, or voting. These tokens can then be made accessible to the public through fundraising events such as ICOs, IEOs, and IDOs, all facilitated by smart contracts. This novel approach bypasses the conventional routes of IPOs or acquisition procedures (Andres, 2022), forging new pathways for innovation and financial inclusion.

Furthermore, within the context of smart contract functionality, tokens are different from coins. Unlike coins, which are native digital currencies that operate independently on their own blockchain networks, tokens are built upon existing blockchains and cannot operate independently.

Tokens are essentially constructed on top of established coins, predominantly on the Ethereum blockchain. They typically serve more specific purposes compared to coins and are primarily intended for exclusive use within their respective platforms. Conversely, coins often function as a means of payment for goods or services outside the platform.

Tokens serve various functions within the realm of initial fundraising offerings and as a form of payment within the economic system, indicating ownership or acting as a share equivalent. In the context of project tokens, important organizational details, including rights and opportunities associated with token use, are disclosed in a publicly available document called the White Paper. This document is typically provided to interested investors prior to the project launch and/or during the initial exchange offer (Adhami, 2018).

There are three primary types of tokens, each fulfilling distinct roles (Amsden and Schweizer 2018):

1. Utility Tokens: In decentralized applications (DApps) and blockchain ecosystems, utility tokens are specifically designed for users to access products and services & interact with the platform. They serve as a form of payment, allowing users to purchase goods & services and participate in project activities. The value of a utility token depends on the demand and usage within the underlying platform.

2. Security Tokens: Security tokens represent ownership of an asset or a company, similar to stocks or bonds. They offer investors various rights, including profit sharing, voting, and entitlement to dividends. Compliance with relevant securities regulation is crucial for security tokens, as they operate within the legal frameworks governing traditional financial instruments.

3. Payment Tokens (Cryptocurrencies (coins)): Cryptocurrencies primarily function as digital currencies that facilitate transactions and value transfer across blockchain networks. They often have their own dedicated blockchains, some famous examples include BTC or ETH. Cryptocurrencies serve as both a means of payment and a store of value.

Moreover, it is important to acknowledge that these categories are not mutually exclusive, therefore categorizing specific tokens can be challenging, as many tokens share common attributes. The classification of a token depends on its purpose, functionality, and compliance with applicable regulations.

2.1.2 Theoretical Aspects of Initial Decentralised Offerings

While creating a token is only one of the steps in a project's development, a large challenge lies in selling or transferring those tokens to investors, willing to purchase them. There are 3 main fundraising mechanisms a company can employ to sale their tokens to the public:

1. ICO (Initial Coin Offering): A fundraising method where cryptocurrency start-ups issue and sell tokens to the public through their own website or platform.
2. IEO (Initial Exchange Offering): A fundraising model where token sales are conducted on centralized cryptocurrency exchanges, providing a trusted intermediary between the project and investors.
3. IDO (Initial Decentralised Offering): A fundraising mechanism on decentralized exchanges, allowing cryptocurrency start-ups to directly sell tokens to investors without intermediaries governed by self-functioning smart-contracts (Andres, 2022).

ICOs first gained prominence in 2017, raising millions with Ethereum-based tokens. However, interest waned, partly, due to a very large amount of scam projects, and a new model emerged in 2018. By Q1 2019, initial exchanges offerings (IEOs) were introduced, being based on the ICO model while undergoing strict screening by the intermediary centralized exchanges like Binance, KuCoin, Huobi, and OKEx, imposing increased costs and complexities for the projects. Besides fundraising, IEOs offered the advantage of being listed on the exchange where the token sale occurred. Notable projects like Elrond and Matic Network began as IEOs, growing into multibillion companies. As listing complexities grew and decentralized exchanges like Uniswap and PancakeSwap gained popularity, projects sought simpler and more cost-effective listing options. In 2020, the concept of initial offers on decentralized exchanges (IDO) emerged, marking a new phase in cryptocurrency and project financing.

Decentralized Exchanges (DEXs) embody cryptocurrency and token trading platforms that operate autonomously, free from centralized management or intermediaries. Participants engage in direct trading, leveraging the power of smart contracts and blockchain technology, to guarantee transaction security and reliability. The rise in popularity of DEXs stems from their decentralized nature, effectively mitigating the risks associated with hacking and the potential loss of funds often associated with centralized exchanges. Notably, prominent exchanges like Bitfinex and Binance have suffered substantial thefts of funds over the years, prompting the emergence of DEXs as a compelling alternative for investors and traders.

Initially, IDOs were executed independently, devoid of the involvement of a third party—specifically, a launchpad. Nonetheless, as the cryptocurrency market matured and evolved, launchpads gradually assumed a pivotal role, streamlining and enhancing the IDO process with remarkable efficiency. These launchpads facilitate the organization and execution of token initial offerings. The main reason for their emergence was that the token sales were quiet often over in a matter of seconds, leaving no way for average retail investors to get a stake in the initial offering. Tokens were usually redeemed either by specialized computer algorithms and/or project representatives. While fixing the above issue, launchpads also bridged the gap between start-ups and investors by providing platforms for project launch preparation, due diligence, and marketing.

Moreover, launchpads serve a crucial role in the IDO, fostering transparency and trust in the cryptocurrency market. They facilitate informed decision-making for investors by providing a comprehensive overview of the team, market prospects, technology behind the token and the project as a whole. Additionally, launchpads offer sophisticated mechanisms such as lotteries, auctions, and pre-registrations, ensuring an equitable and impartial distribution of tokens among participants.

The key functions of launchpads are:

1. Vetting and Selection of Projects: Launchpads assess and analyse proposed projects to identify the most promising and reliable options for investors.
2. Transparency Assurance: Launchpads furnish investors with vital project details, including team composition, roadmap, and other pertinent aspects, fostering transparency and engendering trust.
3. Marketing and Promotion: Launchpads actively support projects in their marketing and promotional campaigns, ensuring effective outreach to attract investors and stakeholders.
4. Liquidity Provision: Launchpads play a crucial role in ensuring liquidity for project's tokens on decentralized exchanges following the IDO.
5. Technical Support: Launchpads offer technical assistance and guidance to projects throughout the development and integration of their tokens and smart contracts.

Having understood the core functions of launchpads, let's explore the key stages of conducting an Initial Decentralized Offering. IDO procedures for initial token offerings on decentralized exchanges bear similarities to those on centralized exchanges (IEOs), but with some distinct differences. The main contrast lies in project verification and token sale responsibilities. While IEOs delegate these tasks to the exchange itself, IDOs rely on third-party launchpad platforms for verification, with token sales occurring in a more decentralized manner, on DEXs.

To conduct an Initial Decentralized Offering, it's mandatory to gather a project team and register the company, as well as creating a website where potential investors can familiarize themselves with the company's product or service, along with a comprehensive description of the product development plan, profit distribution, and information on the team and the company owners. Furthermore, it's necessary to develop a white paper, that discusses the specifics of the token sale and the fundraising objectives of the initial decentralized offering as well as the concept of the project itself. In addition, an important step is choosing a blockchain ecosystem for issuing project tokens and developing and auditing a smart contract that will facilitate the IDO process and the subsequent distribution of tokens.

Next, the project needs to select a launchpad where they would like to host their token offering event. Once the IDO application is submitted and approved by the launchpad, the team initiates preparations for the token sale. The project's team and the platform engage in negotiations to determine key IDO details, including the minimum (Softcap) and maximum (Hardcap) financial funding goals, the number of tokens for sale and the token price.

Once the organizational aspects are finalized, the token sale commences on the decentralized platform at a specific date and time for a prespecified duration. During this process, all collected funds remain under the control of the launchpad. If the project does not reach the minimal financial goal (Softcap), investors receive their funds back, in full amount. However, if the goal is reached, the smart contract transfers funds to the project's team for development of the product. Following the end of the token sale, usually, within a few days or right after the end of the token sale, in accordance with the project's preferences, comes a Token Generation Event (TGE), during which, the tokens are generated on the blockchain and distributed to their rightful owners, facilitating their availability for trading on the exchange.

The choice of a decentralized exchange to conduct a token sale is often influenced by the underlying blockchain of the token. For instance, Uniswap is commonly used for ERC-20 tokens (ETH), while PancakeSwap is favoured for BEP-20 tokens (BNB). It is important to note that participating in an IDO does not limit a project's future development or expansion of its ecosystem. Following the token sale, projects can seamlessly pursue listing on other exchanges, including centralized platforms. Moreover, an emerging trend involves projects organizing IDOs on multiple launchpads to attract greater interest and broaden their pool of potential investors. This approach allows investors to independently choose the platform they prefer for participation, whether it's based on Ethereum, Binance Smart Chain, Polkadot, Solana, or any other blockchain ecosystem. However, due to limited token availability during the initial offering, a supply shortage often arises in the face of overwhelming demand from investors. To encourage broader participation, launchpad platforms have implemented fair distribution mechanisms, such as the "whitelist" system, which places certain restrictions on token quantities while ensuring equitable access for the majority of users.

To be whitelisted, users are usually required to complete a series of marketing tasks, which often include:

1. Joining the project's communities across various platforms and social networks.
2. Engaging with project publications through reposts and comments on social networks like Twitter, Telegram, Medium, Discord, and others.
3. Inviting friends to join the project communities, among other activities.

These tasks contribute to generating a “marketing buzz” surrounding the IDO, leading to rapid growth in community size. It is therefore not surprising that projects opting for IDOs can amass hundreds of thousands of social media followers within days. In addition to social media engagement, another criterion for whitelist inclusion is the ownership of a specific number of launchpad’s own tokens. This selection method is preferred, as it simplifies the process and eliminates the need for additional verification. For instance, the renowned IDO platform Polkastarter offers two pools: a general pool and an exclusive pool for POLS (native token of the Polkastarter platform) token holders, where competition is comparatively lower. Typically, there are two stages of whitelisting: one for holders of the launchpad's own tokens and another for the general public. The competition during the second stage can be extremely intense, providing minimal chances of participation in the IDO. Collectively, these two aspects create a powerful marketing effect that stimulates demand for IDO tokens in the secondary market. This represents a significant advantage for investors that sets IDOs apart from other initial offering methods, such as ICOs and IEOs.

2.1.3 Comparison of IDO with other Fundraising Methods

Next, for the purpose of this research, it’s essential to precisely outline the differences among the three methods of fundraising: Initial Decentralised Offering (IDO), Initial Coin Offering (ICO), and Initial Exchange Offering (IEO).

Decentralization stands out as a key distinction. IDOs occur on decentralized exchanges, eliminating the need for centralized management. Smart contracts and automated protocols facilitate a transparent, secure, and efficient token selling and exchange process. Decentralization reduces reliance on intermediaries, enabling direct interaction between projects and investors. ICO offers some decentralization, allowing projects to sell tokens directly to investors. However, compared to IDOs, ICOs lack the same level of security and automation, as projects independently develop and issue their tokens. This can introduce risks related to fraud and incorrect smart contract implementation. In contrast, IEOs adopts a completely centralized approach, with token offerings taking place on centralized cryptocurrency exchanges. While IEOs may provide additional project and smart contract verification, the influence of centralized structures can lead to investment barriers, high fees, and dependence on the exchange’s decisions. It's important to note that user funds' safety lies with the exchange, which can result in complete loss due to risk management errors, exemplified by the bankruptcy of FTX, one of the largest cryptocurrency exchanges, in November 2022.

The collapse of FTX and similar events prompted a re-evaluation of decentralization, shifting attention to secure and transparent decentralized platforms, leveraging smart contracts to minimize fraud risks and providing heightened investor security. ICOs, on the other hand, have faced security issues like fraud and smart contract mis implementation, making them less preferable to IDOs and IEOs. IEOs offer enhanced security through centralized exchange verification, but entail risks associated with reliance on centralized structures.

For IDOs, start-ups must closely collaborate with the projects' communities and investors, investing significant effort in primary marketing and promotion while adapting to decentralized funding and token governance mechanisms. This poses challenges for unprepared teams, but IDOs offer a relatively low entry threshold and minimal bureaucracy.

The same holds true for ICOs, which provide freedom and flexibility but suffer from the rapid growth of fraudulent schemes and security issues that undermine investor trust. Moreover, start-ups must independently establish and maintain ICO infrastructure, incurring high costs and time commitments. Stricter legislation and regulatory pressure present additional barriers to this funding method.

IEOs require projects to pass stringent checks from cryptocurrency exchanges, creating difficulties and inefficiencies. Additionally, the commissions paid to exchanges for conducting IEOs can be significant, reducing attractiveness for start-ups with limited budgets. (Myalo & Glukhov, 2019). Based on the gathered data, a table highlighting the key distinctions among IDO, ICO, and IEO will be shown below.

Table 2 Comparison of characteristics of different fundraising method

Characteristics	IEO	ICO	IDO
Fundraising Location	Centralized Exchange	Project's Website	Launchpad Platform
Level of costs for the issuer	High	Low	Medium
Parties Involved	Centralized Exchange	Project's Team	Launchpad Platform
Due Diligence	Conducted by Centralized Exchange	Not Conducted	Conducted by Launchpad Platform
Security Level	Moderate	Low	High
Marketing Investment	Low - Exchange conducts marketing campaign and attracts investors	High - Marketing is solely done by the company's resources	Medium - Both the launchpad platform and the project participate in attracting investors
Identity Verification Required	Yes	No	No
Token Listing	Occurs immediately after IEO	Project needs to independently contact an exchange for listing	Occurs after a certain period following the IDO (usually 2-3 days)
Liquidity Level	Medium	Low	High

Note: The table provides a comparison of key characteristics between Initial Exchange Offerings (IEOs), Initial Coin Offerings (ICOs), and Initial Decentralised Offerings (IDOs) in terms of fundraising location, level of costs for the issuer, parties involved, due diligence, security level, marketing investment, identity verification requirements, token listing process, and liquidity level. *Adapted sources:* CryptoPotato, 2023; CoinMarketCap, 2023.

2.1.4 Market overview of Initial Decentralised Offerings

To gain a deeper understanding of the current market landscape and explore Initial DEX Offerings (IDOs), I have thoroughly examined the distinctions between IDO, ICO, and IEO, along with their respective advantages and disadvantages. Now, let us briefly delve into the market trends surrounding IDOs to better grasp the current market environment and how it has changed throughout the last few years.

IDOs have emerged as a preferred choice for numerous projects, gaining popularity among start-ups and investors. Its advantages in terms of decentralization, security, and accessibility have led to the displacement of numerous IEO and ICO placements. IDOs offer several notable benefits, including:

1. Accessibility: IDO allows almost any project to attract investments without requiring significant initial capital.
2. Investor Flexibility: Tokens become available for trading on exchanges promptly after the IDO concludes, providing investors with flexibility.
3. High Liquidity: IDO generates instant and substantial liquidity by locking a significant portion of project funds on the DEX.
4. Transaction Transparency: Smart contracts ensure transparent transactions, and token verification is possible beforehand.

However, it is important to consider the short comings of IDO:

1. Lack of Transparency in Project Screening: The project verification process with different launchpads can be opaque, potentially creating opportunities for fraudulent activities.
2. Participation Requirements: High participation requirements, such as holding a large amount of native launchpad tokens, may pose challenges for investors, especially considering the tokens' price volatility.
3. Uneven Share Distribution: Unequal distribution of shares among investors in different rounds can result in mass selloffs shortly after the project lists on exchanges.

However, despite the drawbacks of IDO, it remains the favoured choice for the majority of start-up companies. A significant testament to this preference can be seen in the data provided by Cryptorank.io, a trusted cryptocurrency market aggregator. Over the past two years, there have been a total of 3,195 public token sales, with 82% of them being IDOs as highlighted in Figure 1.

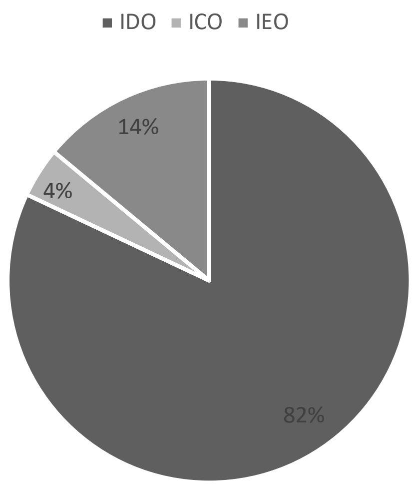

Figure 1 Number of public token sales by type

Adapted Source: CryptoRank, 2023

Throughout this period, start-ups have successfully raised over $2.6 billion through various fundraising methods such as ICOs, IDOs, and IEOs. Nonetheless, IDO prevalence in this domain serves as a testament to the widespread appeal and effectiveness of IDOs as a powerful tool for capital fund raising purposes.

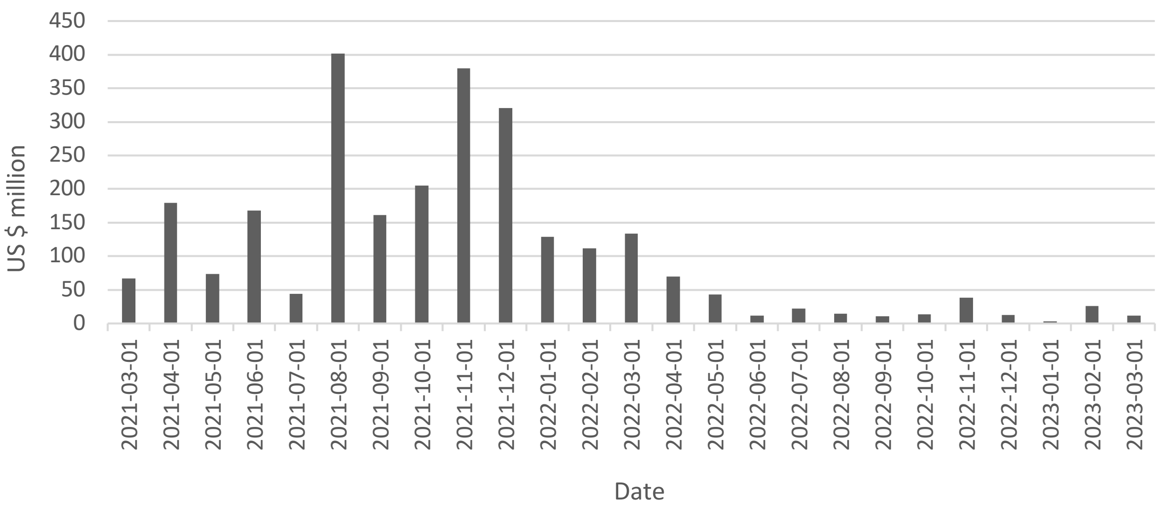

Figure 2 Amount of capital raised in IDOs in the past 2 years

Adapted Source: CryptoRank, 2023

According to CryptoRank.io, notable IDO platforms include DAO Maker, Polkastarter, Seedify, Red Kite, and BSCPad. In total, these five platforms have facilitated over 400 fundraising events, raising approximately 120 million USD. In terms of project categories, the DeFi sector attracted the largest funding rounds, followed closely by GameFi. The GameFi sector experienced a surge in popularity following the success of Axie Infinity, leading developers, and investors to seize the opportunity and capitalise on Play-to-Earn (P2E) and Move-to-Earn (M2E) game trends. However, ecosystem stability remained an unresolved issue in this sector, resulting in the devaluation of many associated tokens during and after the market downturn.

Moreover, IDO returns rely greatly on market conditions and market liquidity levels. Fundraising is much easier during a bullish market compared to a bearish one, resulting in many projects trying to time the market. This results in much lower levels of activity during market downturns and increased activity during bullish periods. However, it's important to note that investing in a bull market doesn't guarantee success, as market dynamics can change rapidly.

2.1.5 The Phenomena of Underpricing

Underpricing refers to the situation in which the offer price of a stock in an Initial Public Offering is set below its first trading day closing price. Theoretically, this phenomenon signifies an unfavourable scenario, as it suggests that the stock was undervalued and introduced to the market at a price below its true value. As a result, underpricing introduces inefficiencies for the issuer and results in "money left on the table", which the issuer could capitalise on if the price was set optimally. This same phenomenon can also be observed in initial offerings in the crypto market. However, it is worth noting that research on the determinants specifically associated with underpricing in ICOs remains limited, and determinants of IDO underpricing are currently unexplored, making insights derived from extensive IPO literature particularly valuable.

Various theories have been proposed to explain the occurrence of positive first day returns in IPOs. The underpricing phenomenon has been the subject of investigation by scholars such as Baron (1982), Beatty and Ritter (1986), and Rock (1986), who have proposed theories that provide insights into the significance of information asymmetry and ex-ante uncertainty. Ex-ante uncertainty refers to the uncertainty surrounding a company's future value following an issuance. This type of uncertainty often arises due to imbalances in information among the participants involved in a transaction. Information asymmetry occurs when one party possesses superior or more comprehensive information compared to the others involved in a transaction.

Akerlof (1970) argues that market participants try to deceive less-informed consumers by presenting low-quality goods as high-quality ones. On the other hand, Löfgren & Persson and Weibull (2002) point out that both buyers and sellers want to reduce uncertainty about the true quality of goods. Moreover, the existence of unequal information raises doubts about a product's actual quality. To address this, buyers seek more information, while sellers use strategies to indicate the quality of their products. According to Welch (1989), IPO issuers can effectively communicate the true value of their offerings by deliberately setting lower prices, which discourages low-quality issuers. Grinblatt and Hwang (1989) support this idea by suggesting that issuers can signal the quality of their firms through the offer price and the proportion of retained stock. According to their model, initiating IPOs with lower prices that are subsequently increased can generate heightened interest in the offerings. Retaining a larger percentage of shares also signals higher future cash flows. Additionally, Rock's (1986) model of underpricing suggests that riskier stocks tend to have higher levels of underpricing. Moreover, in their model, Beatty and Ritter (1986) examined the uncertainty preceding IPOs and discovered a positive correlation between underpricing and the level of uncertainty prior to the issuance. As a result, IPO issuers lower the offer price to attract investors and reduce uncertainty. By effectively conveying quality to investors and minimising uncertainty, issuers can successfully reduce the extent of underpricing. I hypothesise the same may hold true for ICOs as well as IDOs.

2.2 Literature review

The phenomenon of underpricing in IDOs remains completely unexplored in the existing literature. While there are some studies examining the return on investment (ROI) from IDOs and the factors influencing it, the relationship between underpricing and the factors associated with it has not received adequate attention. Certain variables will be drawn from the existing Initial Coin Offering literature, as IDOs and ICOs exhibit similarities, particularly in terms of market variables' influence on outcomes. Moreover, certain aspects of the model will be based on variables outlined in the well-researched classical financial literature on IPOs. Although IDOs and IPOs differ in many aspects, leveraging insights from IPO literature can still prove valuable, as elaborated further. Finally, the model will incorporate additional variables derived from documented assumptions within the crypto community, addressing a crucial aspect that previous research has overlooked.

2.2.1 IPO Literature

IPOs and IDOs exhibit distinct differences in their characteristics. IPOs involve the sale of shares that grant residual rights to shareholders, whereas IDOs offer tokens that confer value and/or specific rights upon token holders. The legal, regulatory, and reporting requirements for these two types of offerings differ vastly. IPOs typically involve the participation of professionals such as accountants, lawyers, and banks, while IDOs primarily engage programmers, who code the smart contracts, in their processes. IPOs, due to their numerous requirements and involvement of multiple parties, undergo a lengthier procedure compared to IDOs. On the other hand, IDOs have a historical track record of being very efficient in raising capital for projects. However, IDOs come with higher risks, including the potential for insider trading and pump-and-dump schemes. In terms of listing tokens on cryptocurrency exchanges, IDOs, similarly to ICOs, have an advantage as they are comparatively easier to list as highlighted by Chohan (2019), especially on decentralised exchanges. Furthermore, IPOs generally have significantly larger transaction volumes compared to IDOs. Moreover, ICOs exhibit a greater degree of information asymmetry than IPOs (Ofir & Sadeh 2020). For the purposes of this study, I hypothesise that the same holds true for IDOs, although the extent of information asymmetry may differ.

Current research suggests that information asymmetry plays a significant role in the underpricing observed in Initial Public Offerings (Baron, 1982; Rock, 1986). In the context of IDOs, the "lemon" problem, characterised by buyers having less information than sellers, is particularly pronounced due to the higher associated risks and the lack of regulation. The principal-agent theory framework highlights the information gap between issuers and underwriters in IPOs (Baron, 1982). Addressing information asymmetry issues can be achieved through collaborations with reputable auditors, venture capitalists, and other trusted partners, as recommended by Beatty and Ritter (1986), Johnson and Miller (1988), Titman and Trueman (1986), and Balvers et al. (1988). Consequently, IPOs backed by venture capital demonstrate significantly higher first-day returns compared to non-venture backed IPOs (Lee & Wahal 2004). Retaining stocks can also be beneficial in mitigating information asymmetry and serve as a quality signalling act, as emphasised by Grinblatt and Hwang (1989). Moreover, Switzer et al. (2022) also finds new evidence on the role of firm size on IPO underpricing.

Furthermore, signalling theory suggests that companies intentionally undervalue their offerings during IPOs to demonstrate their quality (Welch, 1992; Allen & Faulhaber, 1989). Setting offering prices below the true value attracts both informed and uninformed investors and helps avoid fundraising failures, as proposed by Rock (1986).

It is noteworthy that market conditions significantly influence the underpricing phenomenon. In "hot" markets characterised by high investor optimism, firms strategically time their offerings to capitalise on investor confidence (Lerner, 1994; Loughran & Ritter, 1995). Hot markets typically arise when a substantial number of firms initiate public offerings (Loughran et. al 1994).

2.2.2 ICO Literature

Howell et al. (2020) confirms the significance of white papers or disclosure of specific information in ICO successfulness, noting that issuers who disclose more information experience higher liquidity and trading volume of exchange-traded tokens. This paper hypothesis that this is not consistent with IDOs, as they go through screening by the launchpad, which requires mandatory disclosure of standardised information as well as the whitepaper.

Amsden and Schweizer (2018) identify coin tradability as the main measure of ICO success and highlight the negative impact of absence from social media channels like GitHub and Telegram, and a higher percentage of tokens distributed. This paper hypothesis the same holds true for IDOs.

ICO underpricing is explored by several researchers, including Benedetti and Kostovetsky

(2021), Momtaz (2019), Lyandres et al. (2019) and Felix and von Eije (2019). Positive returns for investing in ICOs are found by Benedetti and Kostovetsky (2021), who link performance to Twitter followers and activity. Gächter (2021) emphasises the importance of timing as a crucial driver of ICO success in terms of the total amount raised, even when considering the quality of a project and firm-specific characteristics.

Gächter (2021) employs a comprehensive analysis involving time dummy variables and the Google Trend index, also revealing that ICO underpricing can be significantly influenced by "lucky timing," even when accounting for project quality and firm-specific characteristics. Furthermore, Hu et al. (2019) undertake an extensive examination of over 200 cryptocurrencies, uncovering a strong correlation between their returns and the performance of Bitcoin. This finding suggests that the fortunes of cryptocurrencies are intricately intertwined with the fluctuations of the broader Bitcoin market, emphasising the interconnected nature of digital assets.

2.3 Hypothesis development

Based on the aforementioned findings, it becomes evident that underpricing is a prevalent phenomenon observed in both IPOs and ICOs. Therefore, I posit that the same trend holds true for IDOs. However, it is crucial to acknowledge that the level of information asymmetry, which has been identified as a significant determinant of underpricing according to prior research, is higher in ICOs compared to IDOs. This disparity can be primarily attributed to the absence of standardised procedures and external due diligence conducted on ICO projects, as elucidated in the preceding sections. Considering these insights, this paper presents the following hypothesis:

H1: “*The level of underpricing in IDOs is significantly smaller than in ICOs.*”

Furthermore, I build upon the findings of Amsden and Schweizer (2018), who discovered that a higher percentage of tokens distributed to investors negatively impacts the "successfulness" of an ICO. Considering FDMC at Launch as a proxy for a project’s size, I also build on the findings of Switzer et al. (2022), who outline the relationship between firm’s size and the magnitude of underpricing in IPOs. Drawing on this information, I propose the following hypothesises:

H2a: *“The level of underpricing in IDOs is negatively affected by the monetary value of circulating token supply at launch.”*

H2b: *“The level of underpricing in IDOs is negatively affected by size of fully diluted market cap at launch.”*

By formulating the hypotheses stated above, I aim to delve deeper into the factors contributing to the underpricing phenomenon in IDOs. I also consider all the relevant variables outlined in previous scientific literature as control variables, ensuring a more precise examination of the variables of interest in this research. Moreover, I anticipate that the variables derived from the classical IPO literature, such as volume on the first trading day, venture capital support, crowdedness, and market sentiment, will exhibit a positive influence on the level of underpricing. Additionally, I anticipate that the number of launchpads and the number of blockchain environments where a token is hosted will also positively influence the level of underpricing. Conversely, I predict that the total amount raised, duration of the IDO and duration of the launch, will exert a negative impact on the level of underpricing. Lastly, I anticipate that category variables will have an ambiguous effect.

Unfortunately, I was unable to include social media buzz as a variable in my research due to unavailability of consistent proxies in regard to the period examined in the research. Also, I was unable to include taxonomy as a factor in my study due to the imprecision and inconsistencies in the data provided by most crypto data aggregators. While the data is available, it contains significant errors in approximately 50-60% of the observations, making it unreliable. As a result, I adopt the viewpoint that it is better to exclude this data from the research rather than present misleading findings.

CHAPTER 3 Data and Methodology

3.1 Measure of Underpricing

To assess the degree of underpricing, I employ a widely adopted formula, which is commonly utilised in the literature on IPOs:

[1] Raw underpricing

$$UP = \frac{P_{c,i} - P_{o,i}}{P_{o,i}}$$

In this equation, UP represents the measure of raw underpricing, $P_{c,i}$ denotes the closing price of a token on its first trading day, and $P_{o,i}$ represents the initial offer price of the same token during its IDO. It is important to note that cryptocurrencies are traded continuously, and thus, the closing price used in my analysis refers to the token price provided by cryptorank.io at 00:00 following the commencement of the first trading day. This ensures a consistent and standardized approach when evaluating the extent of underpricing.

Moreover, it is widely acknowledged that a strong correlation exists between the price of Bitcoin and a significant number of other cryptocurrencies (Ciaian, Rajcaniova, & Kancs, 2016; Yi, Xu, & Wang, 2018). I therefore decide to adjust raw underpricing to returns of the CCI30 index, which is composed of a selection of 30 cryptocurrencies that are chosen based on their market capitalization and liquidity, providing a representative snapshot of the broader cryptocurrency market by including a diversified range of largest cryptocurrencies. This serves as a comprehensive robustness assessment for the model. The market's adjustment for underpricing in IDOs is calculated using the following method:

[2] Market-adjusted underpricing

$$MUP = \frac{P_{c,i} - P_{o,i}}{P_{o,i}} - R$$

Where R represents the return of CCI30 index on the first trading of a token after the IDO and is calculated in the following way:

[3] Return of the CCI30 index

$$R = \frac{H_{c,i} - H_{o,i}}{H_{o,i}}$$

Whereabout $H_{c,i}$ represents the closing price of CCI30 index and $H_{o,i}$ represents the opening price of CCI30 index on a given day.

3.2 Methodology

3.2.1 Regression Model

To evaluate the proposed hypotheses, I construct an Ordinary Least Squares (OLS) model with the dependent variable MUP on the left side of the equation, while incorporating all independent variables on the right-hand side. To ensure normality of the regression analyses, the underpricing variable undergoes an additional adjustment through a natural log transformation for some of the models. This step is taken to enhance the conformity of the data to a normal distribution and create a better fit model with a higher adjusted R^2, in line with common practices in the ICO literature. In addition, I conduct a White heteroskedasticity test to investigate the presence of heteroskedasticity. Notably, the test yields substantial evidence to reject the null hypothesis of homoscedasticity. As a result, I adopt robust standard errors, which have gained broad recognition as the standard practice in empirical finance research. The regression analysis model is represented by the following equation (while omitting the category dummies):

[4] General underpricing model

$$
\begin{aligned}
MUP &= \alpha + \beta_1\, Total\ raised + \beta_2\, Volume + \beta_3\, Duration\ IDO + \beta_4\, Duration\ Launch + \beta_5\, MCS\ at\ Launch \\
&\quad + \beta_6\, Number\ of\ Launchpads + \beta_7\, Number\ of\ Blockchains + \beta_8\, FDMC\ at\ Launch \\
&\quad + \beta_9\, VC + \beta_{10}\, Sentiment + \beta_{11}\, Crowdedness + \varepsilon
\end{aligned}
$$

Moreover, it is important to highlight the utilisation of the "GETS" or “kitchen sink” method, whereabout I initially construct a comprehensive model incorporating all variables under consideration. Subsequently, I carefully omit variables that display minimal significance, ultimately yielding a final model where all variables are relevant and demonstrate statistical significance. In this research, I establish a significance threshold based on the 5% critical level. This approach ensures that only meaningful variables are included in the analysis. Lastly, the subsequent two sections will present the independent variables of interest and the control variables included in the model.

3.2.2 Control Variables

I include the following control variables in my models based on the existing research as highlighted in the IPO & ICO literature sections:

Total raised - This continuous variable represents the total amount of capital raised during the IDO. The measurement unit is USD.

Volume - This continuous variable signifies the trading volume of a token on the first day following its launch. The measurement unit is USD.

Category dummies – This categorical variable describes the category to which the token belongs. The variable will be split into the following dummy variables: ***NFT*** (0), ***Blockchain service*** (1), ***DeFi*** (2), ***GameFi*** (3), ***Social*** (4), ***Blockchain infrastructure*** (5), ***CeFi*** (6), and ***Meme*** (7).

Sentiment - This discrete variable ranges from 0 to 100 and denotes the Fear and Greed index value of the cryptocurrency market. The index is composed of various factors, including Bitcoin Volatility (25%), Market Momentum & Volume (25%), Social Media Buzz (15%), Surveys (15%), Bitcoin Market Dominance (10%), and Google Search Trends (10%).

Crowdedness - This continuous variable is calculated as the count of IDOs, ICOs, and IEOs within a 30-day period before and including the date of an IDO being analysed.

VC - this is a dummy variable that represents Venture Capital backing for a certain project. It takes a value of 1 if the project was backed by venture capital, and a 0 otherwise.

3.2.3 Variables of Interest

I include the following variables of interest in my models. Apart from the variables that I include to test the Hypothesises 2a and 2b, I include some variables that have not been previously examined. Some of these variables are factor specific to IDOs only and since this is the first research in such domain, I decided to check for the possible effects of these. Moreover, if the variables are insignificant or irrelevant, they get excluded from the final model through the utilisation of the "GETS" method. List of variables is presented below:

MCS at Launch - this is a continuous variable measured in USD, representing the quantity of tokens available in the market at the time of a token's release, multiplied by the IDO issue price (the monetary value of circulating token supply at launch). Upon token release, only a portion of the total token supply is unlocked and made available in the market, which is referred to as the circulating supply at launch. By multiplying the circulating supply at launch by the issue price, I obtain the monetary value of circulating token supply at launch that is immediately accessible to investors, traders, and users upon the project's launch. The measurement unit is USD.

FDMC at Launch - this is a continuous variable that represents the fully diluted market cap of a token at the time of launch. This variable is calculated by multiplying the total supply of a token by the IDO issue price and serves as a proxy for the project's size. The measurement unit is USD.

Duration IDO - this is a continuous variable that signifies the length of the IDO denominated in days. The variable is calculated by subtracting the start date of the IDO from the finish date.

Duration Launch - this is also a continuous variable that signifies the duration of token launch in days. This variable is calculated by subtracting the finish date of an IDO from the date when the token generation event (TGE) happened, and the token became available for trading.

Number of Launchpads - this is a continuous variable that represents the amount of launchpads where the IDO was hosted.

Number of Blockchains - this is a continuous variable that represents the amount of blockchains on which the token is launched.

3.3 Data

3.3.1 Data Collection and processing

The data for this study was collected from a variety of sources. To obtain IDO specific variables related to underpricing, cryptorank.io served as the primary source. In cases where certain variables, such as total token supply or market cap at the end of the first trading day, had missing values, I supplemented the data using information from coinmarketcap.com. Both cryptorank.io and coinmarketcap.com are widely recognized and trusted sources within the crypto community, having been extensively used in previous research on ICOs.

I extracted data from cryptorank.io and downloaded it straight to excel. However, a considerable portion of the data could not be automatically extracted and required manual collection. For this reason, as well as to ensure the quality and reliability of the data, I made certain considerations during the selection process. Specifically, I focused on observations within the timeframe of January 2020 to April 2023, and only included projects with an initial market cap at launch equal to or exceeding $100,000 USD. This approach helped to exclude many scam tokens with extremely low market caps, which are often considered insignificant in comparison to larger token offerings, resulting in a sample of 600 observations. By implementing these criteria, I aimed to eliminate projects that were prone to limited investor awareness and participation, allowing us to refine the dataset and ensure that the included observations were more representative of substantial projects within the specified timeframe. Furthermore, it is worth acknowledging that the quality of token distribution and tokenomics data provided by most crypto aggregators is generally poor, with evident mistakes in a significant number of observations. Due to the potential endogeneity problems and the impact on the analysis, I made the decision to exclude tokenomics distribution data from my study. By focusing on data that was more reliable and consistent, I aim to ensure robustness and accuracy of the analysis.

Moreover, market variables were sourced from tradingview.com and the CCI30 index websites. I employ variable transformations to ensure that variables take the required form. To compute underpricing and market-adjusted underpricing I follow the methodology outlined in the section 3.1 Measure of Underpricing. To compute the natural logarithm of MUP, I added the constant 2 to all observations in order to deal with negative values. Additionally, I determine the duration of an IDO in days by subtracting the start date from the end date. Similarly, I calculate the launch duration in days by subtracting the IDO end date from the token launch date. Moreover, I calculate the monetary value of circulating token supply at launch by dividing the market cap of a token at the end of the first trading day by its closing price at that time. This calculation allows me to find the token amount of circulating supply at launch, assuming no token burns or emissions on the first trading day, which is usually the case. I then multiply this amount by the token issue price. Next, to calculate the FDMC at launch, I multiply the total token supply by the issue price. This provides an estimate of the market capitalization of a project if all tokens were in circulation. Finally, to determine the crowdedness, I calculate the rolling number of fundraising events (including ICOs, IDOs, and IEOs) within a 30-day period before and including the date of an IDO. This metric helps measure the level of intensity or competition within the fundraising landscape.

Following the transformation and calculation of variables, the data sets are consolidated in Excel using unique identification numbers assigned to each observation. Finally, considering the cross-sectional nature of the data, observations with missing data points, which could not be filled using any available crypto data aggregators were eliminated, resulting in a well-organised and comprehensive final data set consisting of 439 observations.

3.3.2 Summary statistics

Table 3 provides a comprehensive overview of the key statistics related to underpricing, market-adjusted underpricing, and other variables analysed in the regression model. My analysis reveals that the average level of underpricing is a staggering 790%, with a median of 356%. The observed range of underpricing spans from a minimum of -93% to a maximum of 7400%. Interestingly, market-adjusted underpricing shows a higher average level of 805% and a median of 358%, contrary to initial expectations of lower levels compared to raw underpricing. This unexpected result may be attributed to the onset of the bear market in December 2021. To further explore the impact of market conditions, I will present two additional tables highlighting statistical summaries separately for IDOs that took place during the bull market and the bear market.

Table 3 reveals that the average duration of an IDO is 16.22 days, with a median value of 2 days. The average duration of the token launch or TGE (token generation event) following the IDO is 12.91 days, while the median value is 1 day. It is worth noting that these average values may be influenced by outliers, as evidenced by maximum values of 481 and 485 days, respectively. Therefore, I consider the median values to be more representative. Moreover, the average value of the natural logarithm of the monetary value of circulating token supply at launch stands at 14, accompanied by a closely aligned median value of 13.7. This observation indicates a tendency towards a relatively normal distribution of the data, further supported by the range of observations, which spans from a minimum of 6.4 to a maximum of 18.8. Additionally, the average number of launchpads hosting an IDO is 2.18, with a median of 2 launchpads. The average number of blockchain ecosystems on which the observed IDOs released their tokens is 1.5, while the median value is 1 blockchain ecosystem. Surprisingly to the author, the average sentiment, as measured by the fear and greed index, is 44.52, with a median of 40, indicating an overall average market sentiment of "fear" during the sampled period.

Furthermore, the average logarithmic value of FDMC at Launch stands at 17, with the median value closely mirroring it. This observation suggests a tendency towards a relatively normal distribution of data to right-hand side. Notably, the lowest recorded value reaches 11.839, while the highest reaches 22.205, demonstrating the range encompassed by the dataset. Within the same sample a noteworthy 77% of all projects were backed by Venture Capital funds, indicating a relatively high backing ratio compared to IPOs, which averaged 54% during the same period according to Jay R. Ritter (2022). However, it is important to note that my sample excluded super small cap IDOs, which may have an impact on this criterion. Furthermore, the average number of fundraising events (ICO, IEO, IDO) occurring within 30 days before an IDO is 82, with a median of 77 and a range of 5 and 192 fundraising events. Finally, among all the IDOs analysed, 6% of the tokens were related to NFTs, 14% to Blockchain services, 33% to DeFi, 35% to GameFi, 5% to Social, 4% to blockchain infrastructure, 2% to CeFi, and only 0.2% were categorised as Meme tokens.

Several variables, such as MUP, Total raised, Volume, Duration IDO, and Number of launchpads, demonstrate highly positive skewness values, indicating right-skewed distributions with long tails. These variables also exhibit positive excess kurtosis, indicating distributions with heavy tails and pronounced peaks. On the other hand, VC, Sentiment, Crowdedness, Number of blockchains, FDMC at Launch, and MCS at Launch exhibit smaller skewness values in absolute terms, indicating only slight skewness in their distribution. Furthermore, these variables also show slight kurtosis, suggesting distributions with lighter tails and either flattened or moderate peaks. Notably, Duration of Launch stands out with the highest positive skewness and excess kurtosis, suggesting a heavily skewed distribution with excessive peaks, putting forth the need for transformation or outlier handling for this variable to ensure more robust and interpretable results.

Additionally, Duration of IDO and Duration of Launch exhibit the highest standard deviations and coefficient variation values, indicating substantial variability in the data. This implies the possible presence of heterogeneity within the dataset and significant deviations from the average values, also indicating the possibility of outlier existence. Considering these findings, caution should be exercised when interpreting the coefficients associated with these variables in the regression analysis. It may be beneficial to explore transformations or outlier emissions to enhance the interpretability of these variables, as mentioned in the previous paragraph.

Furthermore, variables such as UP, MUP, Total raised, and Volume also demonstrate significant variability. This relatively high variability may result in wider confidence intervals around the estimated coefficients in the upcoming regression analysis, suggesting a broader range of potential values for the true population coefficients. As a result, the coefficients for these variables should be interpreted with caution, and additional scrutiny should be applied to ensure robust and reliable conclusions. I will also consider transforming the depended variable for the regression analysis.

Conversely, variables including MCS at Launch, Number of Launchpads, Number of Blockchains, FDMC at Launch, VC, Sentiment, and Crowdedness exhibit lower levels of variability. The reduced variability implies smaller standard errors and the potential for narrower confidence intervals around the estimated coefficients, which enables more precise interpretations of the relationships between these variables and the outcome variable in the forthcoming regression analysis.

Table 3 Summary statistics of all relevant variables

Variable	Mean	Median	S.D.	Min	Max	C.V.	Observations
UP	7.90	3.56	12.3	-0.934	74.0	1.5534	439
MUP	8.05	3.58	12.7	-0.996	74.0	1.5525	439
Total raised	4.35	2.11	10.2	10000	109	2.3450	439
Volume	12.8	3.65	31.9	45.9	377	2.4857	439
Duration IDO	16.2	2.00	50.4	0.00	481.	3.1096	439
Duration Launch	12.9	1.00	47.2	0.00	485.	3.6548	439
MCS at Launch	14	13.723	1.3597	6.3958	18.811	0.097170	439
Number of Launchpads	2.18	2.00	1.60	1.00	16.0	0.73249	439
Number of Blockchains	1.50	1.00	0.808	1.00	5.00	0.53888	439
FDMC at Launch	17	17.021	1.3517	11.839	22.205	0.079530	439
VC	0.768	1.00	0.423	0.00	1.00	0.55078	439
Sentiment	44.5	40.0	22.6	7.00	95.0	0.50753	439
Crowdedness	81.8	77.0	44.0	5.00	192.	0.53721	439

Note: The table presents descriptive statistics for all variables in the dataset. Natural logarithm is used for MCS at Launch and FDMC at Launch. Mean, Median, S.D. and Max values for Volume and Total raised are presented in millions. These descriptive statistics provide an overview of the central tendency, variability, and range of the variables in the dataset.

I proceeded to divide the observations into two distinct samples: the bull market and the bear market. In my analysis, I considered all the IDOs that took place before December 2021 to be launched during the bull market, while those occurring after December 2021 are classified as being launched during the bear market in accordance with the change of trend in CCI30 around that time. This categorization enables us to gain insights into the differences between these two market environments.

Table 4 presents the summary statistics for the IDOs launched during the bull market, while Table 5 provides the summary statistics for the IDOs that took place during the bear market. As expected, the level of underpricing exhibits a significant difference between these two periods as shown in the table 6, with the average underpricing during the bull market reaching 1070% and the average during the bear market amounting to 433%. The respective median values stand at 603% and 104%. Interestingly, when I split the observations into these groups, the averages of underpricing and market-adjusted underpricing within groups become equal for both periods.

Furthermore, there are significant differences in the duration of IDOs and the time interval between the completion of the IDO and the token generation event (TGE) between the two market periods. In the bull market, the average duration of IDOs is 8.66 days, with a median of 1 day, and the average duration of the token launch is 4.63 days, with a similar median value of 1 day. However, in the bear market, the averages increase to 25.9 days for IDO duration and 23.6 days for token launch duration, with median values of 3 and 2 days, respectively.

Table 4 Summary statistics of variables in the Bull market period

Variable	Mean	Median	S.D.	Min	Max	C.V.	Observations
UP	10.67	6.03	14.2	-0.605	74.0	1.3316	247
MUP	10.68	6.03	14.2	-0.535	74.0	1.3309	247
Total raised	4.23	1.95	11.3	20000	109	2.6741	247
Volume	15.5	6.7	32.1	45.9	377	2.0665	247
Duration IDO	8.66	1.00	23.1	0.00	243.	2.6686	247
Duration Launch	4.63	1.00	14.3	0.00	134.	3.0828	247
MCS at Launch	13.972	13.723	1.3504	6.3958	18.811	0.096646	247
Number of Launchpads	1.94	2.00	1.12	1.00	7.00	0.57707	247
Number of Blockchains	1.61	1.00	0.858	1.00	5.00	0.53354	247
FDMC at Launch	16.847	16.772	1.3773	12.218	22.205	0.081757	247
VC	0.838	1.00	0.369	0.00	1.00	0.44048	247
Sentiment	0.136	0.137	0.0200	0.0604	0.172	0.40741	247
Crowdedness	54.8	61.0	22.3	11.0	95.0	0.41834	247

Note: Category dummy variables are excluded from the table. The table presents descriptive statistics for all observations in the dataset that took place before December 2021, considered to take place during the bull market. Natural logarithm is used for MCS at Launch and FDMC at Launch. Mean, Median, S.D. and Max values for Volume and Total raised are presented in millions. These descriptive statistics provide an overview of the central tendency, variability, and range of the variables in the dataset.

Additionally, during the bear market, there is a higher average number of launchpads utilized, indicating that projects aim to attract more media attention and investor interest by leveraging multiple launchpad platforms. Conversely, during the bull market, there is a higher average number of blockchain ecosystems on which tokens are launched. This suggests that projects may have focused on limiting costs by releasing tokens on a scattering number of blockchain ecosystems. This divergence in approach may be influenced by the market conditions and the strategies employed by projects to optimize their visibility and resource allocation during each respective market phase.

Moreover, the ratio of projects backed by Venture Capitalists (VCs) differs between the bull and bear market periods. In the bull market, 84% of all projects considered were VC-backed, whereas in the bear market, this ratio decreased to 68%. I attribute this disparity to the decreased profitability of IDOs during the bear market, as evidenced by the comparison of average underpricing levels during these two periods. Additionally, the average market sentiment during the bull market was between "Greed" and "Neutral," while in the bear market, the average sentiment was characterized as "Fear." Surprisingly, the variable "crowdedness," which describes the density of fundraising events in the last 30 days, did not change significantly between the two periods.

When comparing the two tables, variables in the Bull market period generally exhibit lower standard deviations and coefficient variations compared to those in the Bear market period. This implies that the data points in the Bull market period are relatively concentrated around the mean resulting in lower general variability.

Table 5 Summary statistics of variables in the Bear market period

Variable	Mean	Median	S.D.	Min	Max	C.V.	Observations
UP	4.33	1.04	7.89	-0.934	60.0	1.8231	192
MUP	4.33	1.06	7.90	-0.996	60.1	1.8222	192
Total raised	4.5	2.6	8.59	10000	87.2	1.9062	192
Volume	9.38	1.77	31.4	568	296	3.3501	192
Duration IDO	25.9	3.00	70.5	0.00	481	2.7191	192
Duration Launch	23.6	2.00	68.1	0.00	485	2.8906	192
MCS at Launch	14.019	13.742	1.3746	10.540	18.085	0.098057	192
Number of Launchpads	2.49	2.00	2.02	1.00	16.0	0.80962	192
Number of Blockchains	1.36	1.00	0.717	1.00	4.00	0.52748	192
FDMC at Launch	17.189	17.217	1.2963	11.839	21.367	0.075418	192
VC	0.677	1.00	0.469	0.00	1.00	0.69240	192
Sentiment	31.3	27.0	14.6	7.00	69.0	0.46816	192
Crowdedness	84.5	70.5	54.6	18.0	192	0.64687	192

Note: Category dummy variables are excluded from the table. The table presents descriptive statistics for all observations in the dataset that took place after December 2021, considered to take place during the bear market. Natural logarithm is used for MCS at Launch and FDMC at Launch. Mean, Median, S.D. and Max values for Volume and Total raised are presented in millions. These descriptive statistics provide an overview of the central tendency, variability, and range of the variables in the dataset.

Another noteworthy observation is that the total amount of capital raised is higher during the bear market compared to the bull market, which contradicts the findings of Geddes, R. (2003) regarding the IPO market. I hypothesize that this is by random chance as the difference is not significant. Moreover, notable differences can be observed in the distribution of tokens across different categories during the two market periods. Specifically, the number of tokens released in categories 2 (DeFi) and 3 (GameFi) underwent significant changes. In the bull market, 42% of all tokens released through IDOs were related to DeFi, while 25% were associated with GameFi. However, during the bear market, these proportions shifted, with 22% of tokens being DeFi-related and a larger portion of 48% being GameFi-related. This shift can be attributed to the emergence of a strong GameFi trend starting in 2022, characterised by the rise of play-to-earn (P2E) and move-to-earn (M2E) concepts.

Moreover, I generate a correlation matrix encompassing all variables within the model to conduct a more thorough analysis of the data and address potential multicollinearity concerns among independent variables. The correlation matrixes are depicted in Figure 3, with all the variables in the original from and in Figure 4, with MUP, MCS at launch and FDMC at launch transformed by taking the natural logarithm.

Let's now analyse the correlation matrixes for the variables in question. In Figure 3, the strongest correlation coefficient with market-adjusted underpricing is observed with volume (0.4), followed by sentiment (0.2). Other coefficients exhibit correlations that are not above 0.1. When examining the highest correlations between independent variables in the model, I find the highest coefficient between the MCS at Launch and FDMC at Launch (0.7). The second and third highest correlation coefficients are between MCS at Launch and Total raised (0.6), and between the FDMC at Launch and Total raised (0.4). It is therefore important to consider the possibility of multicollinearity issues in the regression models, which I will address accordingly, by conducting the Variance Inflation Factor (VIF) tests.

Now, let's examine the correlation matrix shown in Figure 4. I observe that the correlation coefficient of Total raised with the dependent variables increases from 0.0 to -0.1, suggesting a slightly stronger relationship. The coefficients for Duration IDO and Duration Launch also increase from -0.1 to -0.2, indicating a more pronounced association. Additionally, the coefficients of sentiment, crowdedness, and FDMC at Launch show modest increases of 0.1 in the initial direction of the correlation. Furthermore, I observe a decrease in the correlation coefficients between MCS at Launch and Total raised (-0.2), as well as between MCS at Launch and FDMC at Launch (-0.2). However, the correlation coefficients between VC and MCS at Launch, as well as between VC and FDMC at Launch, exhibit a slight increase. Nonetheless, these increases are minimal and fall within an acceptable range, posing no significant concern. I observe a consistent pattern in the coefficients of variables with respect to the proposed dependent variable, as they exhibit increases in their initial direction of correlation. Furthermore, I observe consistent decreases in correlation coefficient of independent variables between each other, reinforcing the notion that the natural logarithm of market-adjusted underpricing is a more appropriate choice as the dependent variable for the subsequent regression analysis as well as natural logarithms of MCS at Launch and FDMC at Launch.

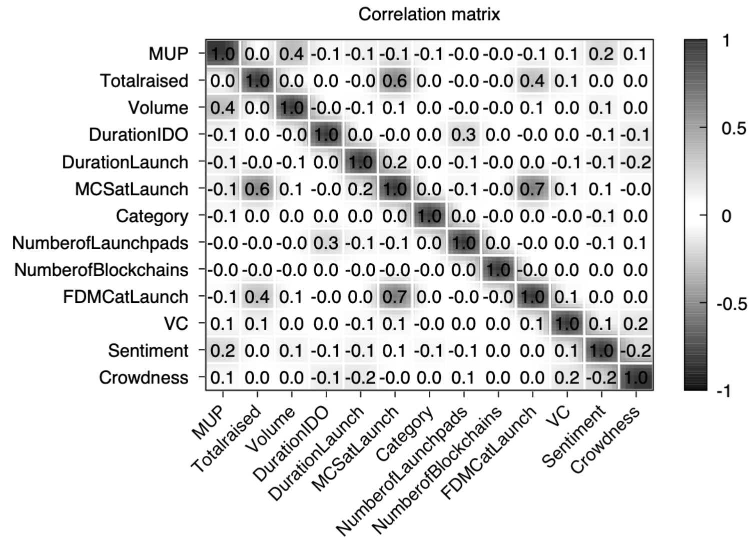

Figure 3 Correlation matrix of variables included in the model

Note: The correlation matrix provides insights into the strength and direction of associations between the MUP variable, and all the other variables included in the model. Correlation coefficients range from -1 to +1.

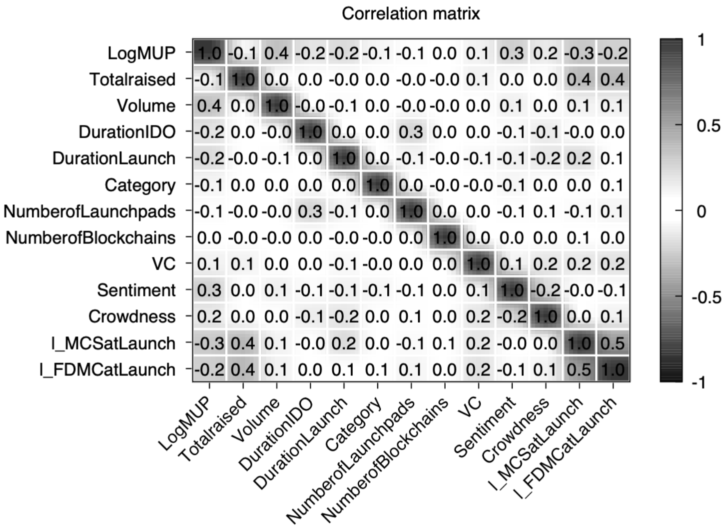

Figure 4 Correlation matrix of transformed variables included in the model

Note: The correlation matrix provides insights into the strength and direction of associations between the MUP variable, and all the other variables included in the model. Correlation coefficients range from -1 to +1.

3.3.3 Outliers

To achieve a more precise fit for the regression analysis and eliminate any anomalous observations, I opted to carefully exclude outliers that deviated significantly from the distribution and lied beyond the tails of a normal distribution, upon the visual observation of the distribution graphs. This was done, with great caution due to a small sample size, by assigning a Z-score to each independent variable that exhibited a high level of variability, as indicated in the summary statistics section. Observations with a Z-score greater than +4 or smaller than -4 were then excluded. While it is generally recognized that a Z-score of 2 or 3 is commonly used to establish this threshold, it is important to acknowledge that in the case of this particular research, a higher threshold of 4 was deemed appropriate. This decision was made considering the unique characteristics of the crypto market, which is still in its nascent stage, characterized by high volatility and relatively unpredictable behavioral patterns. Given these factors, I believe that employing a Z-score of 4 aligns well with the nature of this evolving market.

It is important to acknowledge that the exclusion of any variable from the calculation impacted the Z-score of other variables. Thus, I performed this process only once for each variable in question. In result, 22 observations were omitted from the model. The final number of observations came out to be 417. The outcome of this procedure yielded a notable reduction in the model's skewness and an improvement in the adjusted R^2 value. Additionally, the average standard errors were reduced, resulting in a better fit of the model to the data.

CHAPTER 4 Results

4.1 IDO vs ICO Underpricing

In my research I find that the average level of underpricing in IDOs is equal to 790%, with a median value of 356%. Firstly, I perform a T-test, to check whether the level of underpricing (UP) and the market adjusted level of underpricing (MUP) in IDOs is significantly different from 0. I find that underpricing and market adjusted underpricing in IDOs is indeed highly significant and different from 0, as highlighted in Table 6. Moreover, I also test if the level of underpricing during the bull market is significantly different and higher from that during the bear market period and find evidence in favour of this argument, as highlighted in Table 6. This indicates that underpricing tends to be more pronounced when market conditions are favourable and investor sentiment is optimistic.

Moreover, for ICOs, Adhami et al. (2018) finds an average level of underpricing of 929.9 percent and a median of 24.7 percent for 140 observations, Momtaz (2018) finds an average of 8.2 percent and a median of 2.6 percent for 302 observations, Felix & Eije (2019) find average and median underpricing of 108.5 and 32.9 percent for 247 observations. I perform a T-test, assuming unequal variances, to check whether my findings differ significantly from the level of underpricing observed in ICOs and documented by the authors listed above. I conclude that the average level of underpricing in IDOs is significantly different and higher than the level of underpricing in ICOs presented by Momtaz (2018) and Felix, T. H., & von Eije, H. (2019). Adhami et al. (2018) don't provide the standard deviation of underpricing observed in their sample which doesn't allow me to perform a T-test. Based on these findings, I conclude that IDOs tend to demonstrate higher levels of underpricing compared to ICOs, at least within the examined time periods. This highlights a consistent pattern wherein IDOs are associated with greater degrees of underpricing. I hypothesise that this effect may be attributed to aggressive marketing campaigns intensified by launchpads and greater investor engagement, driven by eagerness to secure a spot on the whitelist, as discussed in the theoretical framework section.

Table 6 T-test mean Underpricing

Subject of Test	T-test statistics	P-value (two-tailed)	P-value (one tailed)
$UP >= 0$	13.488***	<0.0001	<0.0001
$MUP >= 0$	13.496***	<0.0001	<0.0001
$UP_{bull} >= UP_{bear}$	5.936***	<0.0001	<0.0001
$UP_{IDO} >= UP_{ICO}$ Momtaz, (2018)	13.344***	<0.0001	<0.0001
$UP_{IDO} >= UP_{ICO}$ Felix & Eije, (2019)	11.327***	<0.0001	<0.0001

Note: This table represents the results of T-test conducted, testing for mean difference between underpricing or market adjusted underpricing and a list of other values. In the first two rows I perform a one-sample T-test. In rows 3-5 I perform two-sample T-tests assuming unequal variances. *,**,***Significant at 10, 5 and 1 percent, respectively

4.2 Regression Results

Table 7 presents the results of the regression analyses conducted. First two models (Columns 4-5) represent linear relationship between variables, the other models represent logarithmic relationships. My evaluation of variables is based on a comprehensive GETS approach, starting with a full model, and carefully eliminating the least significant and irrelevant variables. This process leads us to a set of final models where all variables demonstrate significance, allowing us to interpret the relationship between the dependent variable and independent variables as more substantial.

Firstly, I observe a negative association between issue size and the level of underpricing, in line with the expectations outlined in Beatty and Ritter (1986) and Miller and Reilly (1987) for IPOs. Next, I find a highly significant and positive correlation between the trading volume on the first day and the level of underpricing, which aligns with my expectations based on Miller and Reilly (1987), Carter and Manaster (1990), and Schultz and Zaman (1994). Furthermore, I discover that Sentiment and Crowdedness exhibit highly significant and positive relationships with the level of underpricing, in line with the findings of Ljungqvist et al. (2006), Campbell et al. (2008) and Ritter (1984) within the IPO market as well as numerus findings in the ICO literature.

Next, out of line with findings from the IPO literature, my findings reveal an ambiguous & unclear association between Venture Capital backing and level of underpricing. When examining IDO-specific variables, I find that the number of blockchains on which a token is launched has a somewhat negligible impact on the level of underpricing, as the effect is negative but lacks statistical significance and has a minimal magnitude of effect. On the other hand, the coefficient estimates for Duration IDO in models 1 and 2 are statistically significant, suggesting that a longer duration of the IDO is associated with lower levels of market-adjusted underpricing. However, in model 3, the coefficient estimate for Duration IDO is not statistically significant.

In model 1, the coefficient estimate for Duration Launch is statistically significant, indicating that a longer duration of the project launch is associated with lower market-adjusted underpricing levels. However, in models 2 and 3, the coefficient estimates for Duration Launch are not statistically significant. The lack of statistical significance in Model 2 and Model 3 suggests that the relationship between the duration of the project launch and market-adjusted underpricing, observed in Model 1, may be due to sampling variation and the association between the duration of the project launch and market-adjusted underpricing may not be consistent across different model specifications.

Of utmost significance, the monetary value of circulating token supply at launch reveals a strong and statistically significant negative relationship with the level of underpricing in all models. This finding provides compelling evidence in support of hypothesis 2a, aligning with my initial expectations. In a surprising turn of events, the number of launchpads where an IDO was hosted exhibits a negligible negative correlation with the level of underpricing, although not statistically significant. As anticipated, the FDMC at launch demonstrates a significant negative association with the level of underpricing, in the prevailing amount of model specifications. This finding suggests that larger projects tend to experience smaller degrees of underpricing in comparison to smaller projects, providing evidence in support of my hypothesis.

Lastly, when analysing the coefficients of tokens categories across models, I only consider the categories Social (4) and Blockchain service (1), to have a substantial effect on underpricing. While the statistical significance of these relationships may somewhat vary across models, I draw the conclusion that launching a token in the Social (4) category, as opposed to the NFT category, is linked to reduced levels of underpricing. Conversely, launching a token in the Blockchain service (1) category is associated with increased levels of underpricing compared to the NFT category.

When comparing models to each other I observe that models 4 and 5 demonstrate relatively modest adjusted R^2 values and large average standard errors. Conversely, models 1-3 exhibit higher adjusted R^2 values and showcase lower average standard errors. Considering these factors and characteristics of variables listed in the summary statistics section, the logarithmic models emerge as more favourable model specifications. Moreover, upon comparing the logarithmic models, it becomes evident that models 2 and 3 stand out with higher adjusted R^2 values pointing to a better model fit, however, only model 1 exhibits normally distributed residuals at 5% significance level (see Appendix B), while all other models fail this test. I will therefore consider model 1 as the final specification of the proposed ordinary least squares analysis and will refer to this model when interpreting the magnitude of the effect of independent variables on the dependent one.

It is crucial to acknowledge that Model 1 does not incorporate the Total Raised variable, which has been recognized as a significant control in previous IPO and ICO research. However, I contend that this variable does not have the same effect in IDO underpricing. This viewpoint stems from the fact that the soft and hard caps for any IDO are predetermined before the event commences and cannot be under or over achieved, in contrast to ICOs, as explained in section 2.1.2 Theoretical Aspects of Primary DEX Offerings. Also, adding Total Raised to the final model does not affect the coefficients of other variables, while its coefficient emerges highly statistically insignificant with a negligible impact. The distinct difference in terms of economic reasoning, the minimal magnitude of effect in all models and insignificance of coefficients in all logarithmic models allows me to deem this variable inconsequential for the purpose of this research and leave it out of the final model.

Following this logic, the analysis reveals that higher trading volumes are associated with a slight increase in underpricing. Specifically, a unit increase in volume corresponds to a statistically significant 0.000025% increase in the level of underpricing. Furthermore, a longer duration of the IDO is found to have a modest but statistically significant negative effect on the level of underpricing. Each additional day of IDO duration is associated with a 0.3% reduction in underpricing. The model also demonstrates that a larger monetary value of circulating token supply at launch denominated in dollars has a statistically significant impact on mitigating underpricing levels.

For every one percentage point increase in the MCS at launch, there is a corresponding 0.14% decrease in the level of underpricing. Additionally, a 1% increase in the FDMC is associated with a notable 0.14% decrease in the level of underpricing. This finding highlights the inverse relationship between FDMC and underpricing, indicating that larger project size leads to reduced underpricing levels. Moreover, positive market sentiment is found to drive higher levels of underpricing. An increase of one unit in market sentiment corresponds to a 0.9% increase in the level of underpricing. Additionally, launching a token in a more crowded environment, indicated by a one unit rise in Crowdedness, leads to a 0.5% increase in the level of underpricing. This indicates that a greater number of tokens being launched simultaneously is associated with higher levels of underpricing. Lastly, the analysis reveals a substantial impact of token category on underpricing. The transition from releasing a token in the NFT category to the Blockchain service category results in a significant 20% increase in the level of underpricing, while a transition to the social category is associated with a significant 41% decrease in the level of underpricing.

Table 7 Regression results on underpricing for the IDO projects

	(1)	(2)	(3)	(4)	(5)
Total raised			–5.2e-05 (0.2106)	–3.2e-07*** (0.001)	–2.9e-07*** (0.0023)
Volume	2.5e-08*** (<0.0001)	0.0002*** (<0.0001)	0.0002*** (<0.0001)	3.2e-07*** (<0.0001)	3.2e-07*** (<0.0001)
Duration IDO	–0.003** (0.0440)		–0.003* (0.0530)		–0.002 (0.8908)
Duration Launch		–0.003*** (0.0085)	0.0005 (0.7416)		–0.0094 (0.6357)
MCS at Launch	–0.139*** (0.0007)	–0.148*** (<0.0001)	–0.14*** (0.0007)	–1.43e-07*** (<0.0001)	–1.4e-07** (0.0249)
Number of Launchpads			–0.015 (0.5093)		–0.419 (0.1342)
Number of Blockchains			–0.008 (0.859)		–0.69 (0.3103)
FDMC at Launch	–0.142*** (<0.0001)	–0.138*** (<0.0001)	–0.125*** (0.0008)		–1.65e-10 (0.9246)
VC			0.029 (0.73)		–1.42 (0.2655)
Sentiment	0.009*** (<0.0001)	0.006*** (<0.0001)	0.006*** (<0.0001)	0.09*** (<0.0001)	0.1*** (<0.0001)
Crowdedness	0.005*** (<0.0001)	0.004*** (<0.0001)	0.004*** (<0.0001)	0.04*** (<0.0001)	0.04*** (<0.0001)
Blockchain service (1)	0.203** (0.0464)	0.208*** (0.0410)	0.268 (0.1241)		0.309 (0.9201)
DeFi (2)			0.024 (0.8754)	–2.715*** (0.0082)	–2.538 (0.3667)
GameFi (3)			0.116 (0.4382)		0.677 (0.8099)
Social (4)	–0.414*** (0.0011)	–0.289** (0.0108)	–0.22 (0.2292)	–5.137*** (<0.0001)	–4.648 (0.1361)
Blockchain infrastructure (5)			0.101 (0.6391)		–2.323 (0.4548)
CeFi (6)			–0.052 (0.8343)	–3.62*** (0.0076)	–3.22 (0.2906)
Meme (7)			0.246 (0.2378)		–0.848 (0.7837)
Constant	5.134*** (<0.0001)	4.98*** (<0.0001)	4.678 *** (<0.0001)	–0.113 (0.9226)	2.458 (0.4212)
Observations	417	417	417	417	417
Adjusted R^2	0.45	0.53	0.52	0.34	0.34

Note: This table displays the results of a regression analysis examining the relationship between the market adjusted underpricing and various independent variables (Columns 3-5) and the logarithm of market adjusted underpricing and various independent variables (Columns 1-3). The table provides coefficient estimates and associated statistical significance levels for each independent variable across four different models, Robust standard errors are shown in parentheses. Models 1-3 display coefficients of natural logarithms of MCS at Launch and FDMC at Launch. Columns 2-3 display coefficients of square roots of Total raised and Volume. *, **, *** Significant at 10, 5 and 1 percent, respectively

4.3 Multicollinearity

High levels of correlation among independent variables can give rise to issues of multicollinearity within the model. This, in turn, can lead to biased and inconsistent coefficients, potentially distorting the accuracy of my results. Therefore, it is imperative to ensure the validity of my models by addressing the presence of multicollinearity.

The most employed approach is to assess multicollinearity using the variance inflation factor (VIF). By subjecting the initial model, the final model, and all models in between to this test, I can determine the likelihood of multicollinearity problems. The results indicate that none of the presented models exhibit significant issues of multicollinearity. The VIF test reveals a factor range between 1 and 4.5 for the initial model specification (5) and (3), and a factor range between 1 and 1.43 for the reduced model specification (1), (2) and (4). Moreover, none of the models exhibit VIF values higher or equal to 10, which indicates absence of multicollinearity in the models. For a visual representation of the VIF test, please refer to the Appendix A.

CHAPTER 5 Discussion and Limitations

In the previous section I presented my findings from the regression analysis, in this section I aim to present a comprehensive discussion on the mechanisms behind the observed the relationships and their possible causes. Furthermore, I will address and discuss the limitations of this research and propose suggestions for future research in this domain. Lastly, I will introduce potential applications for the findings derived from this study.

5.1 General Discussion

Firstly, in my research I find evidence against the first hypothesis, stating that the level of IDO underpricing is lower than the level of underpricing in ICOs. This finding is surprising as it contradictes intital expectations, it was anticipated that the standardized procedures of listing and external due diligence in IDOs would contribute to a reduced level of underpricing due to decreased information asymmetry. Yet, my analysis unveiled a different reality, challenging this assumption. Moreover, it is possible that IDOs can have larger underpricing levels then ICOs due to the launchpad's deliberate use of aggressive marketing strategies and the implementation of multiple fundraising stages, as explained in the theoretical framework section. These tactics foster inclusivity and intensify competition among investors as well as increased demand in the secondary market, thereby creating an environment conducive to higher levels of underpricing. To further investigate this issue, I conducted a careful examination of the time frames involved in my research, comparing them to the periods analysed in existing scientific papers on ICOs. This exploration led me to consider that the observed disparity in underpricing levels may stem from divergent market conditions prevalent during those particular times. I emphasize the fact that differences in underpricing cannot be solely attributed to the specific characteristics of these fundraising methods. To gain deeper insights into these variations, an analysis of significantly longer time frames would be necessary to ensure robust and conclusive results.

Secondly, in line with my expectations, I have successfully demonstrated that the level of underpricing is significantly influenced by the monetary value of circulating token supply at launch, providing evidence in support of the hypothesis 2a. My hypothesis posited that when a greater number of tokens, resulting in a higher absolute monetary value in USD, enters circulation during the initial stage of trading, it can have a dilutive effect on the token's value. The introduction of a larger MCS at launch can alter the dynamics of supply and demand. In turn, it creates a perception of reduced scarcity, as the overall supply available increases relative to demand. Consequently, this diminishes investor enthusiasm and reduces the willingness to pay a premium for the token after the IDO. Furthermore, larger MCS at launch also contributes to increased liquidity in the secondary market, as more tokens become available for trading. This enhanced liquidity can facilitate easier price discovery and result in reduced volatility, thereby limiting the potential for significant short-term price appreciation.

Thirdly, my analysis has confirmed my initial expectations by revealing a negative relationship between the FDMC at launch and the level of underpricing in IDOs providing evidence in support of the hypothesis 2b. I have considered FDMC at Launch to be a proxy for a project's size, and this finding aligns with similar observations made in the IPO market, as highlighted by Switzer et al. (2022). Their research emphasizes the negative association between firm size and the extent of underpricing in IPOs. I hypothesise the negative effect observed in my study can be attributed to the same factors, commonly observed in the IPO market. Smaller firms often face greater uncertainty in their valuation, which can contribute to higher levels of underpricing. On the contrary, larger firms tend to exhibit reduced information asymmetry, as highlighted by Park et al. (2020). These factors collectively contribute to the negative relationship between underpricing and firm size. I consider it reasonable to believe that similar factors are at play when it comes to underpricing in the context of IDOs.

Finally, when examining the four additional variables of interest, I find that only the Duration of IDO demonstrates a statistically significant, albeit small, negative effect on the level of underpricing. As discussed in the theoretical framework section, the duration of an IDO is predetermined by a smart contract, meaning that investors are aware of the specified duration beforehand. This finding can be interpreted in two ways. Firstly, projects with longer IDO durations may participate in multiple IDOs on different launchpad platforms consecutively. This suggests that these projects might encounter challenges in accumulating the required amount of investment within a single fundraising event. Secondly, it could imply that a project deliberately chooses to engage in an IDO with an extended predetermined duration. This may indicate that project managers anticipate reduced demand and anticipate difficulties in reaching the soft cap, the minimum funding target. It is reasonable to hypothesize that both interpretations mentioned above would lead to a reduced level of underpricing for the project. In both cases, the underlying implication is a decrease in investor demand for the token.

5.2 Limitations and Future Research

While the conducted research remains valid, it is important to acknowledge the limitations inherent in this analysis, as discussed throughout various sections of this paper. In the following section, I will provide an overview of all the limitations considered by the author.

First and foremost, a significant limitation arises from complications in the data collection process and the inherent inaccuracy of data provided by crypto market data aggregators. As a result, I was compelled to only consider IDO observations with an initial market cap equal to or exceeding \$100,000 USD, excluding approximately 60 percent of all observations, thereby reducing the sample's representativeness of the entire population. Moreover, due to the same data collection complications, I was unable to consider the impact of tokenomics, the Twitter score of the project, or other proxies for social media "buzz”, adding to the count of limitations of this research.

For future research, I recommend the development of web scrapers or preferably, parsing data on IDOs directly from the projects' native websites or the launchpads where the IDOs were hosted. This would yield higher-quality data compared to the data used in this research. Additionally, it would enable the inclusion of important variables mentioned above and a much larger sample size, resulting in more precise estimates, reduced biases, and a higher degree of representativeness for the entire population of IDOs.

Secondly, it is important to consider that cryptocurrency, as a market, is still relatively new, while IDOs are a very recent phenomenon, with the first IDO being launched in 2019. To draw robust and statistically valid conclusions, it is recommended to gather more observations and extend the time frame of analysis. I emphasize the significance of longer periods of analysis to yield more conclusive and universally applicable results. I anticipate a wealth of future research being conducted in this domain as it continues to evolve.

5.3 Implications of Results

To the best of the author's knowledge, this scientific paper represents the pioneering analysis of factors contributing to IDO underpricing levels. I firmly believe that this paper will provide valuable insights not only to all parties involved in the IDO process but also to the broader scientific community, fostering further research in this area. Firstly, this research offers practical benefits to investors seeking projects with the highest anticipated underpricing levels. By leveraging the findings outlined in this paper, investors can effectively identify projects exhibiting a greater likelihood of experiencing significant underpricing prior to the IDO launch, based on the characteristics discussed herein. This, in turn, enables speculators to identify projects with heightened potential for gains in the initial trading phase and engage in pump and dump schemes accordingly.

Furthermore, this research has significant practical implications for projects aiming to issue their tokens with minimized underpricing, attracting a larger influx of capital. Project managers can strategically leverage the influential characteristics identified in this study to make targeted modifications, effectively limiting underpricing levels. Alternatively, they can explore the option of setting a higher issue price based on favourable market conditions and the token characteristics discussed in this paper. This approach would allow them to attract the necessary number of investors for efficient and effective capital raising while minimizing underpricing. By employing these insights, project managers can enhance their fundraising strategies, striking a balance between reducing underpricing and maximizing capital attraction. Simultaneously, this research offers valuable insights for launchpads providing advisory services to various projects regarding their pre-launch strategies and token characteristics. Launchpads can leverage this knowledge to consistently guide projects in a manner that generates higher levels of underpricing for their issued tokens. Consequently, this increases the average return on investment (ROI) for tokens launched through these launchpads, enhancing their reputation among investors. As a result, launchpads can attract a larger pool of loyal investors who perceive them as reliable and trustworthy.

Lastly, this research serves as a valuable foundation for academics to build upon when conducting further research in this evolving domain. As the interest in this field is expected to grow significantly in the near future, this study provides a solid starting point for future investigations. Academics can leverage the insights, methodologies, and findings presented in this research to expand the body of knowledge on this topic. By building upon this research, scholars can contribute to the collective understanding of the subject, paving the way for a more comprehensive and informed understanding of the dynamics surrounding underpricing in Initial Decentralised Token Offerings.

CHAPTER 6 Conclusion

This research paper presents a thorough investigation into the factors and token characteristics associated with underpricing in IDOs, making it a pioneering contribution in this domain of study. My primary goal was to deepen the understanding of underpricing in decentralized token offerings while providing practical insights for investors, project managers, and academics. Before delving into the empirical analysis, I provided a comprehensive overview of the theoretical framework that underlies blockchain technology and initial token issuance. Firstly, I observed significant underpricing in IDOs based on evidence from 439 observations, equating to 790%, with a median value of 356%. Using these findings, I show a significant positive difference in underpricing levels between IDOs and ICOs, documented by Momtaz (2018) and Felix, T. H., & von Eije, H. (2019), during the examined time period, providing evidence against my initial hypothesis. Secondly, my regression analysis demonstrated a clear negative and highly significant relationship between the monetary value of circulating token supply at launch and underpricing in IDOs. Thirdly, the analysis showed that FDMC at launch also exhibits a negative association with the level of underpricing in IDOs, providing evidence in support of the hypothesis 2. Lastly, I uncovered a negative correlation between the Duration of IDO measured in days and the level of underpricing. These empirically validated insights contribute to the scientific literature on underpricing in decentralized token offerings, providing valuable guidance for researchers, industry professionals, and investors to make informed decisions. By deepening our understanding of the factors influencing underpricing, this research equips stakeholders with actionable knowledge to optimize investment strategies, project planning, and further scholarly investigations in this rapidly evolving field.

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APPENDIX A TABLES

List of tables:

Table 1 White's test for heteroskedasticity for all models

White's test	P – value	Test statistic	Unadjusted R-squared	Number of observations
Model (5)	0.002	201.850***	0.484	417
Model (4)	<0.0001	85.436***	0.205	417
Model (3)	<0.0001	236.854***	0.568	417
Model (2)	<0.0001	107.639***	0.258	417
Model (1)	<0.0001	138.670***	0.333	417

Note: This table displays the results of White's test for heteroskedasticity for all five models. The test statistics and p-values indicate the presence of heteroskedasticity in all models. The unadjusted R-squared values and the number of observations are also reported. *, **, *** Significant at 10, 5 and 1 percent, respectively

Table 2 Variance inflation factors test for multicollinearity model (5)

Variable	VIF
Totalraised	1.514
Volume	1.097
DurationIDO	1.264
DurationLaunch	1.116
NumberofLaunchpads	1.281
NumberofBlockchains	1.066
VC	1.146
Sentiment	1.223
Crowdness	1.186
MCSatLaunch	3.389
FDMCatLaunch	2.677
DCategory_1	2.899
DCategory_2	4.432
DCategory_3	4.357
DCategory_4	1.759
DCategory_5	1.628
DCategory_6	1.385
DCategory_7	1.050

Note: The table presents the results of the variance inflation factors (VIF) test for multicollinearity in Model (5). VIF values greater than 5 indicate the presence of multicollinearity.

Table 3 Variance inflation factors test for multicollinearity model (4)

Variable	VIF
Totalraised	1.428
Volume	1.070
Sentiment	1.133
Crowdness	1.068
MCSatLaunch	1.401
DCategory_2	1.066
DCategory_4	1.042
DCategory_6	1.022

Note: The table presents the results of the variance inflation factors (VIF) test for multicollinearity in Model (4). VIF values greater than 5 indicate the presence of multicollinearity.

Table 4 Variance inflation factors test for multicollinearity model (3)

Variable	VIF
Sentiment	1.244
Crowdness	1.202
VC	1.201
DCategory_1	2.959
DCategory_2	4.500
DCategory_3	4.404
DCategory_4	1.775
DCategory_5	1.657
DCategory_6	1.395
DCategory_7	1.059
l_MCSatLaunch	1.501
l_FDMCatLaunch	1.624
sqrtTotalraised	1.421
sqrtVolume	1.167
DurationIDO	1.269
DurationLaunch	1.142
NumberofLaunchpads	1.293
NumberofBlockchains	1.061

Note: The table presents the results of the variance inflation factors (VIF) test for multicollinearity in Model (3). VIF values greater than 5 indicate the presence of multicollinearity.

Table 5 Variance Inflation Factors Test for multicollinearity model (2)

Variable	VIF
Sentiment	1.147
Crowdness	1.102
DCategory_1	1.040
DCategory_4	1.044
l_MCSatLaunch	1.359
l_FDMCatLaunch	1.384
sqrtVolume	1.096
DurationIDO	1.046

Note: The table presents the results of the variance inflation factors (VIF) test for multicollinearity in Model (2). VIF values greater than 5 indicate the presence of multicollinearity.

Table 6 Variance Inflation Factors Test for multicollinearity model (1)

Variable	VIF
Sentiment	1.109
Crowdness	1.098
DCategory_1	1.040
DCategory_4	1.037
l_MCSatLaunch	1.357
l_FDMCatLaunch	1.390
DurationIDO	1.045
Volume	1.059

Note: The table presents the results of the variance inflation factors (VIF) test for multicollinearity in Model (1). VIF values greater than 5 indicate the presence of multicollinearity.

APPENDIX B FIGURES

List of figures:

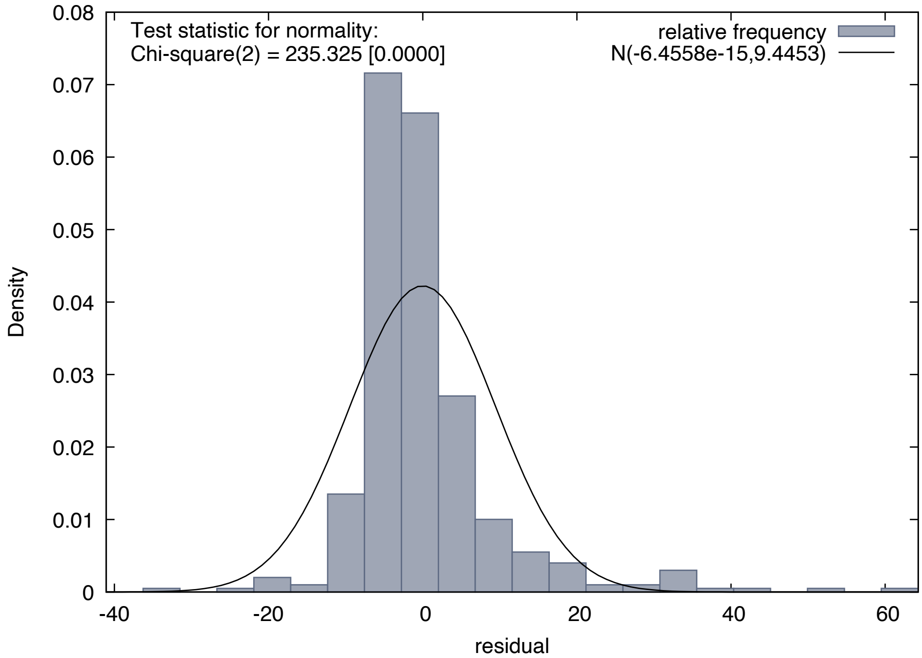


Figure 1 Test for normal distribution of residuals model (5)

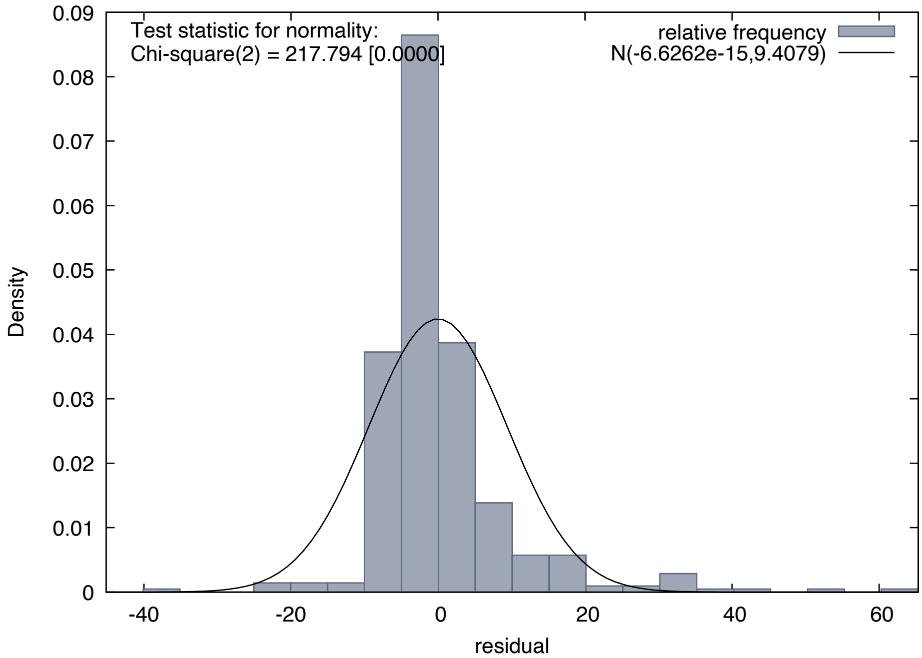


Figure 2 Test for normal distribution of residuals model (4)

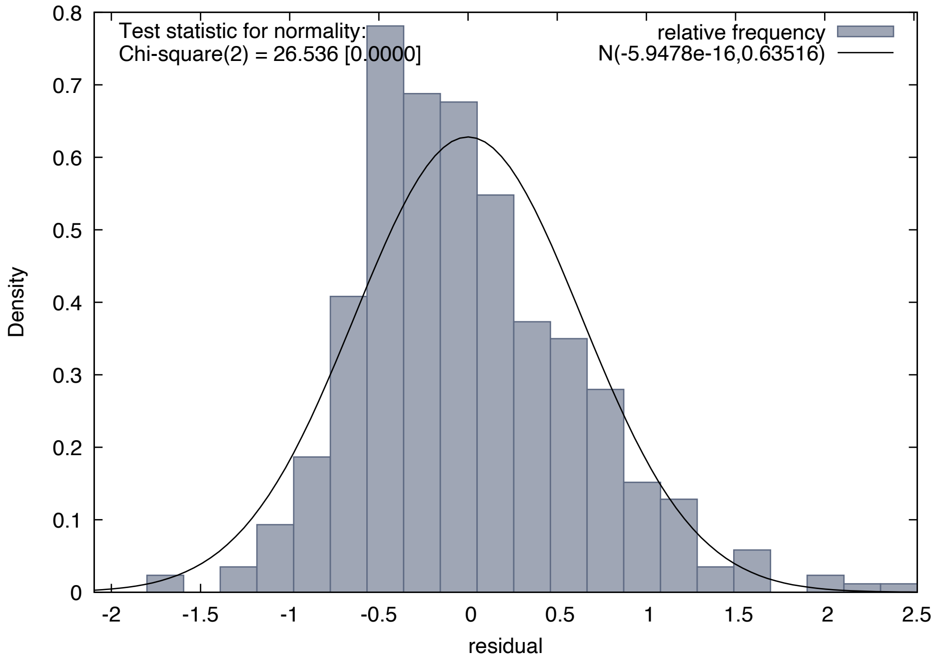
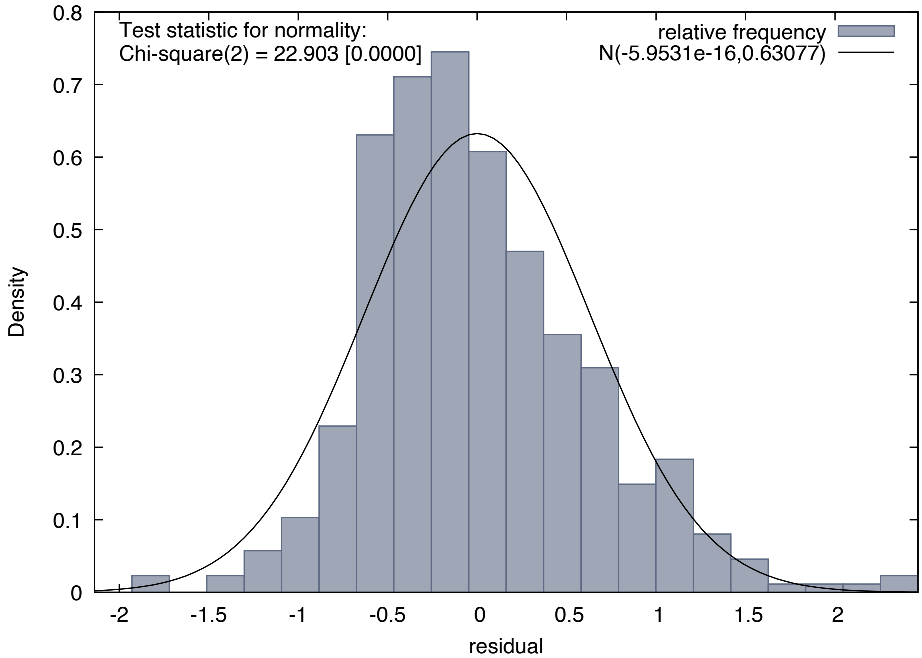


Figure 3 Test for normal distribution of residuals model (3)



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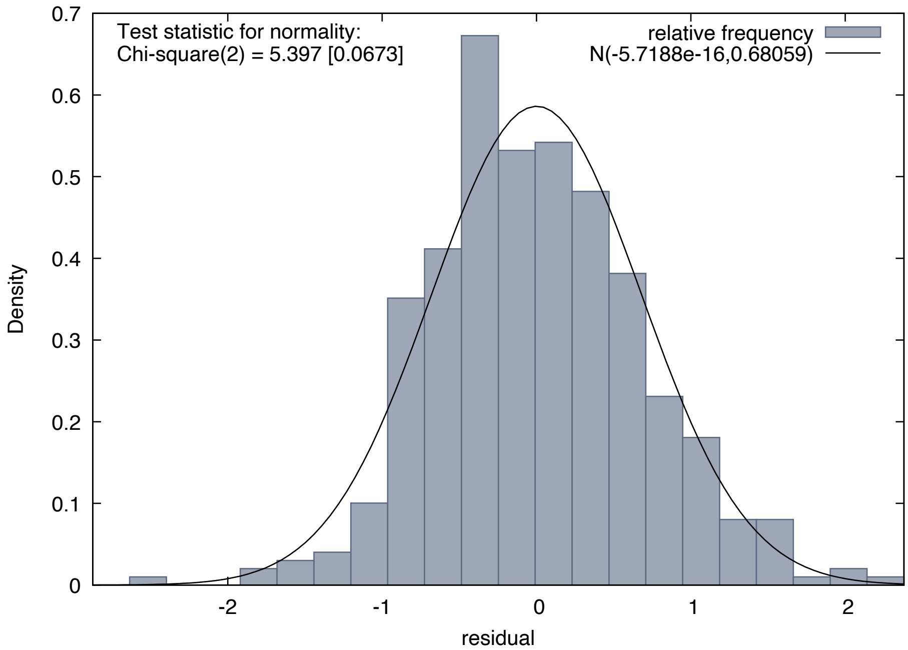

Figure 5 Test for normal distribution of residuals model (1)

APPENDIX C ABBREVIATIONS

Initial Decentralised Offering (IDO)

Initial Coin Offering (ICO)

Initial Public Offering (IPO)

Decentralized Exchange (DEX)

Fully Diluted Market Cap (FDMC)

Monetary Value of Circulating Token Supply (MCS)

Token Generation Event (TGE)