Initial Exchange Offerings (IEOs) and Initial DEX Offerings (IDOs)

A New Hope for Blockchain Fundraising?

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Abstract

Cryptocurrency has been the talk of the town the for the last decade. Initial coin offerings (ICOs) are a new financing method whereby blockchain-related ventures raise external capital in exchange for newly issued cryptocurrency tokens. ICO activity boomed in 2017, and exhibited both astounding returns for investors, and unparalleled funding in comparison to any other early-stage financing method. However, within the span of just a few years, ICOs evolved from a prospering market that offered entrepreneurial firms a new advantageous financing vehicle to becoming associated with scams, regulatory issues, speculation, and risk. In response to this development, two new alternative methods that intend solve some of the inherent problems with ICOs have emerged – initial exchange offerings (IEOs) and initial DEX offerings (IDOs). Today, IDOs account for over 85 percent of the market activity, and the number of IEOs are slightly above to that of ICOs. Despite this, there is little to no academic research on these new alternative methods. We argue that the success of IEOs and IDOs are explained by the fact they have solved some of the inherent problems with ICOs, and that this reduces the risk surrounding the offering. Drawing on IPO literature, we suggest that this should be reflected in the level of underpricing. We investigate this using multiple statistical tests on a data set consisting of 745 token offerings conducted between July 2020 and December 2021. The findings reveal an average underpricing of 1,090 percent across all methods, although with insufficient evidence of significant differences between the groups. However, the observed trend in line with our hypothesized relationship is interpreted as an indication that IDOs and IEOs have taken a step in reducing the risks associated with ICOs, and therefore we suggest that future studies explore other factors that may better reflect the risk differences. In particular, we recommend examining ex-post performance on a longer time horizon.

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1. Introduction

1.1 Background

Bitcoin? Cryptocurrencies? Blockchain? NFTs? Many of us have probably captured bits and pieces from the media or friends, or maybe listened to a speech from your enthusiastic cousin at a Christmas dinner. There is no doubt a lot of buzz about Bitcoin and cryptocurrencies. Optimists assert that cryptocurrencies will radically change payments, economics, and even politics around the world, while pessimists assert that cryptocurrencies are inherently broken and will face an inevitable and dramatic collapse (Narayan et al., 2016). The fact that these innovations challenge the fundamentals of the financial sector that has generated wealth and success for many has led prominent figures to be vocal with their disbelief, for example, Warren Buffett (cited in Bove, 2022) has deemed cryptocurrencies to be “rat poison” with “no unique value at all”. In the advent of disruptive technologies there will always be critics, whether they like it or not – the facts speak for themselves. Over the last decade, cryptocurrencies have evolved from visionary ideas shared and developed in underground cypherpunk communities, to a global phenomenon with a market capitalization that would rank fifth as a country measured by GDP, and that would be considered the most valuable corporation in the world (Statista, 2022a).[1] Today, cryptocurrencies are widely accepted as means of payment (Adhami et al., 2018), and Bitcoin even serves as a legal tender in El Salvador.

Blockchain, the underlying technology to cryptocurrencies, gained traction alongside Bitcoin and nowadays extends well beyond the boundaries of cryptocurrencies, with economically significant uses in virtually every industry (Pilkington, 2018; Amsden & Schweizer, 2019). A blockchain is essentially a decentralized database distributed across a peer-to-peer network where transactions are recorded and arranged chronologically into sequential blocks that are linked and secured by cryptography, forming an immutable ledger (Antonopoulos, 2017). This technology enables radical new decentralized, or ownerless, business models, and replaces the need for trusted intermediaries (Amsden & Schweizer, 2019), which has the potential to disrupt

[1] Based on the all-time high of $3.048 trillion in November 2021, the market cap as of March 31, 2022, is $2.245 trillion.

status quo in numerous traditional industries, forcing incumbent actors to adapt (McFadden, 2019; Hoffmeister Lose & Shaho Skou Poshtara, 2020)

Like for any other venture, blockchain entrepreneurs are in dire need of capital to get their projects off the ground. Many startups suffer from financing constraints at early stages, personal resources or funds available from the 3Fs (friends, family, and fools) may be limited, and obtaining external capital through established sources (e.g., angel investors and venture capital) can prove challenging without a solid track record and prior backing (Leach & Melicher, 2021). Over the last decades, crowdfunding has gained popularity as an early stage alternative due to the ease of access provided by online platforms like Kickstarter and Indiegogo (Zhao et al., 2019). Crowdfunding was initially offered in exchange for future rewards or products, and lately even for securities (equity crowdfunding) (Benedetti & Kostovetsky, 2021). More recently, initial coin offerings (ICOs), or initial token offerings, a hybrid form of crowdfunding, have emerged as a way for blockchain-related ventures to external capital by issuing newly minted digital tokens in exchange for legal tender or other cryptocurrencies (Momtaz, 2020).[2] These tokens are dynamic and can be designed to represent a variety of rights, ranging from financial rights – such as ownership, voting, and cash flow rights – to utility or consumptive rights, such as the right to redeem the token for a future product or service provided by the issuer or to use them as payment in a future marketplace (Ofir & Sadeh, 2019; Howell et al., 2020). Upon completion of the fundraising, the issued tokens are usually listed on a cryptocurrency exchange, enabling trading on the secondary market.

ICOs offer several comparative advantages over conventional financing methods, making them attractive for both issuers and investors (Kaal, 2018). From an issuer's perspective, ICOs may provide funding at any stage of a venture and their digital nature enables a global investor outreach with a perceived lack of regulation (Momtaz, 2020; Amsden & Schweizer, 2019). Issuers also have full autonomy over the fundraising, allowing them to lower transaction costs by avoiding intermediaries (crowdfunding platforms) and dilution of equity and control (angel investors and venture capital).[3] Moreover, the token mechanism enables issuers to build a user base and leverage network effects while still in development (Adhami et al., 2018). From an

[2] The term cryptocurrency encompasses both coins and tokens. However, the vast majority of token offerings involve the issuance of tokens. See section 2.3 for the distinction between cryptocurrency types.
[3] Tokens may represent equity, but it is uncommon.

investor's perspective, ICOs offer more rapid exit options (in contrast to conventional equity-based, lending-based or reward-based contracts) on liquid cryptocurrency exchanges that operate 24/7 (Momtaz, 2020). Thus, investors may benefit not only from the financial right or utility a token conveys, but also from potential token price appreciation (Cong et al., 2020). As a result of their dynamic nature and ability to resemble established financing forms, ICOs have also attracted significant interest from academics fascinated about the potential of the technology. Momtaz (2020) states that an ICO can theoretically be designed to replace all other funding methods by mimicking their distinct characteristics with the use of smart contracts at near zero transaction cost.

Despite being a new phenomenon, the scope of ICOs has rapidly expanded beyond financing blockchain developers, and the market volume has already reached astounding levels, with some ICOs being comparable in size to the largest IPOs, where EOS represents the largest raise to date with $4.1 billion raised in 2018 (Drobetz et al., 2019; Howell et al., 2020; Amsden and Schweizer, 2019). Although the first ICO occured in 2013, it took until 2016 for the new funding method to gain traction. Shortly thereafter, in 2017, ICO activity boomed in terms of both numbers and size, and fortune-seeking issuers and investors flooded the market (Bellavitis et al., 2021; Zetzsche et al., 2018). Investors were attracted by unparalleled returns, with some ROIs exceeding 50,000 percent for early investors, and entrepreneurs envisioned replicating success stories like Tezos, which aimed to raise $10 million in their ICO, but collected over $232 million (ICO Listing Online, 2022; Ofir & Sadeh, 2019; Zetzsche et al., 2018). In the ICO market, over 4,000 firms raised a total of about $7.1 billion and $19.7 billion in 2017 and 2018, respectively (Bellavitis et al., 2021). As a result, ICO funding had surpassed other financing methods in just a matter of years, if not months, whereas Kickstarter raised about $3.3 billion from its inception until April 2018, and venture capital raised $3.6 billion for blockchain projects in 2017 (Amsden & Schweizer, 2019).

However, neither cryptocurrencies in large, nor token offerings are without drawbacks. Cryptocurrencies are highly volatile and exhibit bubble-like behavior, and they are widely used for tax evasion, money laundering, and financing illegal activities due to the anonymity they provide (Shanaev, 2020). Virtually all ICOs in the early stages of the boom were held without any kind of regulation, external audit, or filings normally required for traditional public financing events. The regulatory void left investors vulnerable to a broad range of fraud schemes (Zetzsche et al., 2018; Mendelson, 2019). In addition to the risk for scams, many ICOs in the midst of the boom failed to list their coin or token on an exchange (issuers are required to apply for listing themselves at a cost), thus leaving investors unable to sell their holdings (Zetzsche et al., 2018). Morris (2018) finds that nearly half of the ICOs in 2017 had already failed at the time of his report, while other findings indicate that at least 5 percent of ICOs are outright fraudulent, and that up to 25 percent can be considered scams (Catalini & Gans, 2019). In contrast, a study by Satis Group (2018) claims that 80 percent of ICOs are scams and that only 8 percent get listed on an exchange. The estimates vary considerably as there is an absence of a standard definition of a "scam" or failure. As a result, the ICO activity took a steep downturn in late 2018 and the amount raised fell from $19.7 billion to $4.1 billion between 2018 and 2019 (Bellavitis et al., 2020). However, as a response to this development, new alternative token offering methods with the intent to solve some of the inherent features of ICOs that enable scams and misconduct emerged – initial exchange offerings (IEOs) and Initial DEX offerings (IDOs).

The first IEO and IDO were held in 2017 and 2019, respectively. While IEOs gained traction as an alternative to ICOs in 2018, IDO activity remained low at first, but skyrocketed in late 2020, whereas ICO activity remained at considerably low levels in comparison to the boom period. Today, the number of IEOs stands slightly above that of ICOs, whereas IDOs account for over 85 percent of all token offerings (see Figure 3 in section 3.3.1). IEOs and IDOs share the same fundamentals with ICOs, however, with the principal distinction that the token sale is administered by a centralized cryptocurrency exchange (IEOs) or decentralized launchpad (IDOs) rather than by issuers themselves.[4] Prospective projects are vetted either by the exchange itself (IEOs) or community (IDOs), and once the sale is completed, the tokens are listed at the respective centralized (IEOs) or decentralized (IDOs) exchange. This due diligence layer, guaranteed token listing, and the reputation risk that the exchange or launchpad bears offers investors an additional level of trust, which in turn reduces the risk associated with the issuance (Anson, 2021; Momtaz, 2021). By introducing an intermediary, IEOs and IDOs mitigate the main problems associated with issuers administrating the token offerings themselves, while retaining the advantages that ICOs offer over conventional financing

[4] A launchpad is a third-party platform connected to a decentralized exchange via smart contracts. A smart contract, like any other contract, establishes the terms of an agreement. However, unlike traditional contracts, the terms are written as code into a computer program recorded on a blockchain and are irreversible once the contract is deployed and autonomously executed when certain predetermined conditions are met. Smart contracts are an integral part of the present-day cryptocurrency and blockchain landscape and perform numerous important functions without third-party involvement (Zheng et al., 2020).

methods (Anson, 2021).[5] However, in parallel with the ICO boom fading, attention from scholars and other actors outside of the crypto sphere also waned, and thus these new alternatives have gone slightly under the radar in academic literature. Even with their growing popularity, IDOs are yet to be explored, and there are only a handful of studies that have examined IEOs.[6]

1.2 Problem Statement and Research Question

Given the absence of a governing body and industry standards, and the fact that many ICOs are not subject to specific regulatory requirements, ICOs are characterized by opaqueness and information that are unaudited and inconsistent (Zetzsche et al., 2018; Adhami et al., 2018). Therefore, scholars highlight that ICOs are associated with substantial information asymmetry and uncertainty and taking the prevalence of scams and misconduct into account, investors are exposed to significant risk. In the literature on initial public offerings (IPOs), underpricing is well-documented and considered to be a risk premium to compensate investors for the uncertainty caused by asymmetric information, and several scholars have observed astounding levels of underpricing in ICOs (e.g., Felix & von Eije, 2019; Momtaz, 2020; Adhami et al., 2018). This paper argues that the design of IEOs and IDOs mitigates several of the inherent problems of ICOs, which thereby should reduce the information asymmetry and uncertainty surrounding the issue, and in turn the risk for investors.

Studies covering all facets of ICOs – from legal to technical to financial – have emerged quickly and formed a rather large body of research, although not exhaustive and still in its infancy compared to the literature on traditional entrepreneurial finance. In light of the recent development, there is a need to bridge the gap between ICO literature and these new alternative token offering methods that dominate the market today. There are many potential research questions that would contribute to the nascent literature on IEOs and IDOs, however, we argue that the risk reduction represents the principal advantage of IEOs and IDOs that explain their success. This renders the following research question:

What are the differences between the token offering methods in terms of risk?

[5] Anson (2021) provides this argument for IEOs, given their similarities this should hold for IDOs as well.

[6] To our knowledge, there is only one academic paper that examines IDOs and does so by identifying the success factors involved. However, the paper is only published in Persian, see Chitsaz & Bigdeli (2021). Apart from this, there are only a few papers that mention the existence of IDOs, but without any further elaboration.

Nonetheless, we do provide insight beyond differences in risk. Cryptocurrencies and blockchain are highly complex technologies and may be unfamiliar to many. Thus, we devote a considerable effort to provide a comprehensive introduction to these concepts, and to ICOs, from both a theoretical and practical perspective. Considering the nascent literature, we also provide a background on IEOs and IDOs, outlining how the market has evolved toward these methods and exploring their unique characteristics and advantages.

1.3 Delimitations

The scope of this paper is to explore the differences between ICOs, IEOs, and IDOs, particularly in terms of risk. There are other new alternative token offering methods that have been excluded because they are either fundamentally different in purpose or represent a very small percentage of the overall market activity. Considering our reliance on Cryptorank.io alone for obtaining the list of token offerings, we cannot rule out that there could be potentially significant observations outside of the sample. Thorough arguments for these decisions are presented in section *3.3.2 The shift towards IEOs and IDOs* and *4.2 Data collection*, respectively. We have deliberately explained fundamental concepts on a reader friendly level, and even when we provide more in-depth technical details, it is still a simplification of the reality. We acknowledge that this may not fully reflect the capabilities of these technologies. Nevertheless, providing such a comprehensive portrait of technical aspects lies beyond the scope of this paper, and there are numerous exceptional publications on this matter (see for instance Narayan et al., 2016).

1.4 Structure of the Paper

This paper is structured in 7 chapters. Chapter 2, *Introduction to cryptocurrencies and blockchain*, introduces the reader to the crypto and blockchain landscape, and covers concepts fundamental to this paper. Chapter 3, *Literature Review and Hypotheses*, begins with an overview of conventional financing methods, and then provides a review of the literature on token offerings, describing ICOs in detail, highlighting their benefits and process, followed by a comparison between ICOs and conventional financing methods. Thereafter, we explore IEOs and IDOs, outlining the market development, as well as the differences between them and ICOs. The latter part of the chapter consists of an overview of IPO underpricing theories and a summary of relevant ICO literature to form a theoretical framework for the analysis, and lastly, two hypotheses based upon this are presented. In Chapter 4, *Methodology*, we describe our data collection process and sample, the statistical tests used in the analysis, and the actions performed to fulfill the assumption of the respective tests. In Chapter 5, *Results and Analysis*, the results are presented and then analyzed in accordance with the hypotheses. Chapter 6, *Discussion*, first discusses the findings in comparison to previous research, from both a theoretical and practical perspective, and then the implications of the findings, potential limitations, and finally provides suggestions for future research. Lastly, Chapter 7, *Conclusion*, provides a summary of key aspects and learnings, together with our final conclusions.

2. Introduction to Cryptocurrencies and Blockchain

The purpose of the following chapter is to introduce the reader to the crypto and blockchain landscape in order to establish an understanding of fundamental concepts. In section 2.2, the origins and development of cryptocurrencies are explained, followed by a description of the different cryptocurrency types and their purposes in section 2.3. Section 2.4 provides an in-depth description of blockchain technology by portraying how a cryptocurrency transaction takes place. Lastly, section 2.5 provides a brief overview of the modern cryptocurrency landscape and the key elements important to this paper.

2.2 Cryptocurrency Background

Much has happened since the presumed pseudonymous Satoshi Nakamoto released the Bitcoin whitepaper in 2008. Cryptocurrencies and blockchain date further back in time, but Bitcoin is the starting point of cryptocurrencies as we know them today, and what popularized blockchain technology. In the whitepaper, Nakamoto proposed a peer-to-peer electronic cash system relying on a hash-based proof-of-work network (Nakamoto, 2008). The 2008 financial crisis had caused Nakamoto to distrust traditional banks, and thus his intention was to challenge the prevailing trust-based model for digital transactions, which heavily relied on financial institutions to serve as trusted third parties. Bitcoin as a digital currency offered a model based on cryptographic proof rather than trust to prevent double spending, eliminating the need for intermediaries, reducing the fraud risk, and increasing privacy.

As aforementioned, Bitcoin was neither the first attempt to introduce a digital currency, nor the first usage of blockchain technology. The efforts and research on cryptocurrencies and blockchain are related in many aspects as blockchain is a fundamental underlying technology in cryptocurrency systems. Blockchain research dates back to Chaum (1983), in his dissertation he outlined a vault system which embodied many of the elements of modern blockchain systems. However, the idea of immutably chaining blocks of information first appears in Merkle (1979), and the idea of a distributed ledger goes a few centuries further back (Sherman et. al, 2019). In 1992, Haber, Stornetta, and Bayer incorporated *Merkle trees* in the design of a blockchaineqsue timestamp system for digital documents.[7] Merkle trees allowed several

[7] A non-linear data structure that allows more efficient data storage in contrast to linear data structures. See Merkle (1979) for further explanation.

documents to be collected in each block, and blockchain as a way to verify the authenticity of the timestamps. Haber and Stornetta later started the company Surety in 1994 and put their ideas into practice, creating the first ever blockchain (Narayanan et. al, 2016). The emergence of cryptocurrency research is also to be attributed to Chaum, in his 1983 paper he used his 1982 work to outline the first digital currency system, eCash (Lansky, 2018). In the subsequent centuries, several other attempts were made, including B-money, DigiCash, MagicMoney, and Bitgold. However, all of them eventually failed, or never made it past the whitepaper. The proof-of-work concept, a cornerstone of the Bitcoin system to overcome the double-spending problem without the need of a trusted third party, sprung from Back's (2002) Hashcash, originally developed as a system for preventing email communication against spam. Despite not receiving attention at the time, remaining at a conceptual stage, or being discontinued, these technological ideas are important to mention because they laid the groundwork for Bitcoin and provided key elements of its technology.

Although many of Bitcoin's underlying technologies had arisen many years earlier, Nakamoto's (2008) application and design was unique and eventually proved to be a revolutionary innovation. On 3 January 2009, Nakamoto mined the starting block of the chain, thereby initiating the Bitcoin network and creating the first decentralized blockchain (Narayanan et. al, 2016). However, Bitcoin was not an instant success, during the first years early adopters mainly consisted of cypherpunk supporters, for example Wei Dai, the creator of b-money (Wallace, 2011). The first known commercial transaction took place in 2010 when programmer Laszlo Hanyecz purchased two Papa John's pizzas for ₿10,000 (more than $400 million at today's exchange rate) (Statista, 2022b).[8] Nakamoto kept working on and writing about Bitcoin in the early years. In late 2010, when Bitcoin had yet to reach $1, he handed over the source code to other developers and disappeared (Narayanan et. al, 2016). Nakamoto's identity remains unknown to this day.

In 2011, the first altcoin appeared[9] – Namecoin, and Litecoin shortly thereafter. Early altcoins were very similar to Bitcoin, often directly forking its code base or else adopting much of the code (Narayanan et. al, 2016). Most of these did not launch through an ICO, but rather like Bitcoin; without a coin supply and initiated by mining the starting block, using a proof-of-work

[8] As of 2022-02-18 ($40,829).

[9] The term altcoin has no explicit definition but is commonly referred to as all cryptocurrency other than Bitcoin.

protocol with an initial steep inflation curve. The rate of altcoin launches increased rapidly in 2013 and 2014, reaching almost 300 by the end of 2015 (Narayanan et. al, 2016; Wei, 2018). By then, Bitcoin had reached a market cap of $6.47 billion and the overall cryptomarket $7.01 billion (Statista, 2022a, 2022b). Following the boom, several cryptocurrency exchanges were started, such as Mt.Gox and BitPay (Yadav et al., 2020). During this period more sophisticated cryptocurrencies with innovative and technologically advanced protocols and alternative applications also emerged. A few examples include Peercoin, which uses the energy-efficient proof-of-stake as its consensus mechanism, Stellar, which uses a decentralized protocol to allow transfers between digital currencies and fiat currency, and Ripple, which serves as an intermediary mechanism of exchange between two currencies or networks, much like the SWIFT system for international bank transfers (Frankenfield, 2021; Bisnoff, 2022).[10]

The first ICO occurred in 2013 when Software developer J.R. Willett organized a crowdsale of Mastercoins in exchange for Bitcoin. More notably, the ICO of Ethereum's native token, Ether, took place in 2014, raising $18.3 million. Ethereum was initially outlined in a whitepaper published in 2013 by the programmer Vitalik Buterin (Ethereum, 2022). In the Ethereum project, Buterin envisioned bringing blockchain technology beyond the realm of digital money. Even though some altcoins already had alternative applications, like Namecoin's decentralized domain name registry database, the majority utilized Bitcoin's technology or were built as protocols on top of its blockchain (Buterin, 2014). In the whitepaper, Buterin argued that Bitcoin's technology is not optimized to facilitate protocols to be built on top of its blockchain, thus impeding the development of new projects. On the other hand, building an independent blockchain gives you complete freedom, but most applications are too small to warrant their own blockchain (Narayanan et. al, 2016). With this dilemma at its core, Ethereum is designed to facilitate decentralized applications (DApps), often with a dedicated token, built on top of its blockchain using smart contracts. Ethereum turned out to be a groundbreaking success, becoming the second most valuable cryptocurrency in 2018, and an integral part of the crypto and blockchain landscape today (Dannen, 2017; Gemini, 2021; Statista, 2022b). The Ethereum network facilitates thousands of interconnected DApps and enables a wide range of purposes, such as creating tokens, raising money via crowdfunding (ICOs), decentralized finance applications, creating and exchanging Non-fungible tokens (NFTs), and offer enterprise solutions for supply chain management (Gemini, 2021).

[10] Proof-of-stake is energy-efficient relative to proof-of-work, for example see Zhang and Chan (2020).

The crypto market has experienced severe volatility and crashes throughout the years. In 2017, the crypto market soared, and by mid-December Bitcoin reached an all-time high of $19,783, an increase of almost 1800 percent since the year began (Godbole, 2017). Some scholars point to this development as a major driving force behind the ICO boom (Bellavitis et al., 2021; Myalo & Glukhov, 2019). The major backlash came in 2018, from the peak in December to February 2018, Bitcoin fell approximately 65 percent and by September it had dropped 80 percent, worse than the 78 percent dot-com bubble collapse. Although 2019 and 2020 were relatively quiet years in terms of price development, notable events occurred such as the launch of the Solana and Binance Smart Chain network, as well as the rise of IEOs and IDOs. Price soared again in the first half of 2021, and Bitcoin reached a peak of $63,503 in April before a crash caused Bitcoin to lose roughly half of its value (Statista, 2022b). However, prices bounced back and reached current all-time high levels in November; Bitcoin at $68,789 and Ether at $4,891 whereas the total crypto market topped $3.048 trillion, higher than the GDP of the UK in 2020 (Statista, 2022a, 2022b; World Bank, n.d.).

2.3 Cryptocurrencies as Digital Assets

Cryptocurrencies are essentially digital assets. A common misconception is that all cryptocurrencies are intended as mediums of exchange, i.e., currencies or money, like Bitcoin. In fact, cryptocurrencies can have a variety of characteristics and functions, which also are the premises upon which they are classified. There are numerous definitions and classifications used in practice, academic literature and by authorities for legislative purposes (for a taxonomy overview see Fokri et al., 2021 or Brave New Coin, 2018). For the purpose of this paper, we adopt a classification that is widely used in ICO literature (e.g., Howell et al., 2018; Howell et al., 2020; Momtaz, 2020; Felix & von Eije, 2019), which is based on the classification used by the U.S. Securities and Exchange Commission (SEC) (Clayton, 2017). First, cryptocurrencies are divided into *coins* and *tokens*.[11] Coins function as a medium of exchange, or a store of value that is often perceived as a hedge against inflation and geopolitical instability, and operate on their own independent blockchain (e.g., Bitcoin and Ethereum) (Choi & Shin, 2021). Coins can serve as means of payment for both external (Bitcoin is accepted as a payment method by hundreds of large companies worldwide, including Amazon, Bloomberg, Microsoft, and PayPal (Adhami et al., 2018), and internal matters (Ether is used for fees associated with

[11] Coins are sometimes referred to as payment tokens, exchange tokens or cryptocurrency tokens.

transactions and creating smart contracts within the Ethereum network). Tokens, on the other hand, are built upon other blockchains using smart contracts and serve different purposes. Second, tokens are divided into *security tokens* and *utility tokens*. A security token derives its value from an external asset; the underlying assets may range from commodities to currencies to debt instruments and even to corporate equity or real estate. In addition, security tokens usually convey ownership rights, access to dividend streams, and/or entitlement to a share in future profits or cash flows. Considering their resemblance to conventional financial instruments, security tokens are subject to securities regulations in most countries (Momtaz, 2020). Utility tokens are used in a wide range of contexts; in their most primitive form they simply function as a coupon for a future product or service provided by the issuer, although they may also be used as stake for gambling, loan collateral, or most commonly, as means of payment in a marketplace (Howell et al., 2020). As an example, Filecoin allows token holders to store and retrieve data in their cloud-based storage network, where the tokens represent the only form of payment accepted for these services. Howell et al. (2018) provides a great analogy for utility tokens:

> While a platform may need a native token for a variety of reasons, one justification is not unlike that for concert tickets, food stamps, or stock certificates. Each has value tied to access to a specific good or service, with limited use elsewhere, creating a degree of customer commitment. Buying a utility token before network launch is also akin to buying the rights to a stadium seat before a sports venue is built, if those rights could be easily traded and if the stadium's games were to be played by people in the grandstands; that is, the analogy requires the value of the stadium to come from the participation of spectators. (p. 2-3)

However, the classifications are not mutually exclusive. Cryptocurrencies that fall into more than one category are often referred to as *hybrid tokens*. It is worth mentioning that as per some definitions, the term cryptocurrency does not necessarily encompass both coins and tokens. Deloitte (2019) and Maxson et al., (2019) suggest using the term *crypto assets* as it covers all aforementioned types and extends to other assets such as non-fungible tokens (NFTs). However, in practice and ICO literature, these terms are often used interchangeably, therefore we also use them as synonyms in the running text, although we will reference them by their specific term when appropriate (e.g., Amsden & Schweizer, 2019; Momtaz, 2019).

The value of cryptocurrencies is in large part determined by supply and demand, like any other asset (Ofir & Sadeh, 2019). In addition to supply and demand, a coin's value is generally determined by its acceptance as a form of payment (Hazlett & Luther, 2020), whereas security tokens, as aforementioned, derive their value from the external asset they represent, while the price of utility tokens are determined by the value of consumptive rights they convey, as well as the size of the platform or network (Howell et al., 2020).[12]

2.4 Blockchain and Other Underlying Technologies

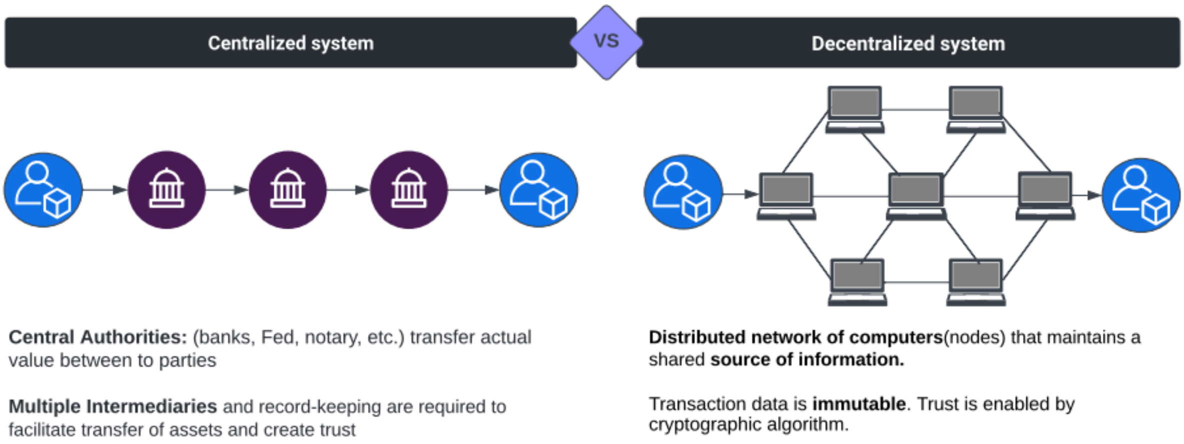
Besides being purely digital, cryptocurrencies differ from fiat currency and conventional assets in numerous aspects. Centralization versus decentralization is at the heart of the differences. Traditional systems, i.e., fiat transactions, are centralized and rely on financial institutions, often a bank, to serve as trusted intermediaries in order to prevent double spending (Swan, 2015). For example, in a peer-to-peer situation, user X sends money to users Y and Z and the intermediary checks whether user X has sufficient funds to transfer the money to both users Y and Z (Felix & von Eije, 2019). Cryptocurrency systems, however, are decentralized and do not require intermediaries.[13] In order to create, verify, and secure transactions, they use blockchain technology.

[12] Perceived value if the token represents a future consumptive right.

[13] It is somewhat disputed to which degree cryptocurrencies are decentralized; Some cryptocurrencies use blockchain that are, in relation to Bitcoin, more hierarchical or centralized (see Tasca, Thanabalasingham, and Tessone, 2017, for further information on this matter).

Figure 1

Centralized vs. Decentralized System

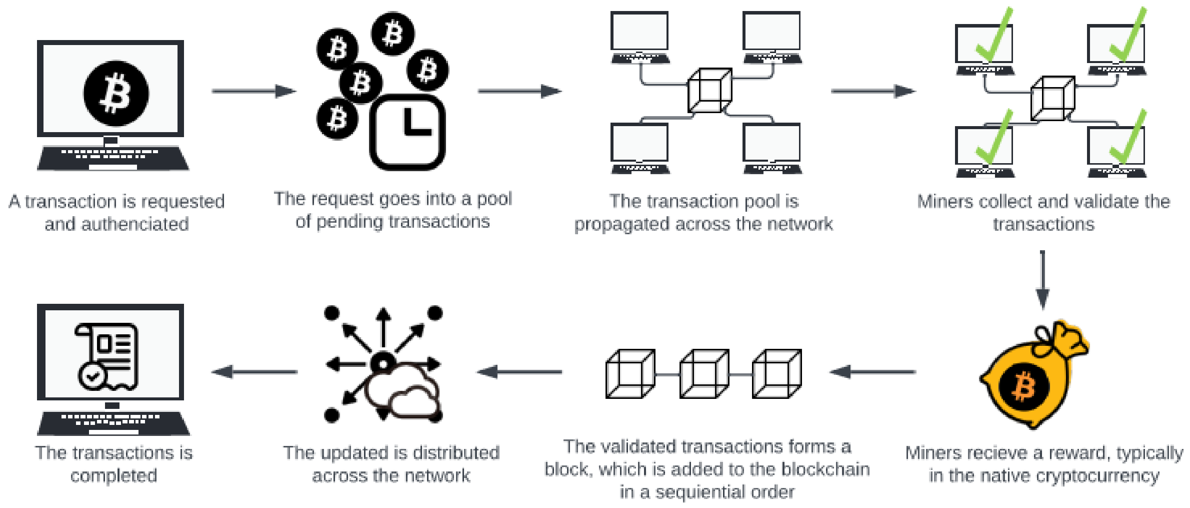


Note. This figure illustrates how transactions take place in the respective systems. Adapted from Deloitte (2019).

As aforementioned, blockchain is a set of technologies and came into light with the release of Bitcoin, although there had been previous attempts, Bitcoin was the first blockchain that proved to be sufficiently robust both conceptually and technologically (Deloitte, 2019). In order to give a better idea of how blockchains function and how particular technologies are used at different stages, we outline and describe the process of a cryptocurrency transaction (see Figure 2).

Figure 2

Bitcoin Transaction



Note. This figure illustrates the main elements of a Bitcoin transaction. Own creation.

Suppose user X wants to send user Y some Bitcoin. Every user needs a wallet to send, receive, and store their funds (Meadows, 2019). Wallets contain a public key that represents an address, and a private key that represents a signature. To initiate the transaction, user X enters the desired amount of bitcoin and user Y's public key, then confirms the transactions by signing it with her private key. This information along with a timestamp and a hash of the previous transaction are fed into a signature algorithm that uses a cryptographic hash function to generate a random 256-bit number.[14] This number, or hash, is the publicly visible signature of the transaction (Nakamoto, 2008). A hash function is deterministic, i.e., a given input value will always generate the same output. The slightest change in the input, like swapping out a letter or simply changing its case, will generate a completely different output. Given the sheer number of possible outcomes, the likelihood of creating a duplicate can be dismissed (Meadows, 2019). The hash function ensures that the data is correct and has not been tampered with and allows other people to verify that the signature was created by the user in question (user X), and that it applies to the specific transaction.

[14] Bitcoin uses Elliptic Curve Digital Signature Algorithm (ECDSA), and a SHA256 algorithm, hence a 256-bit number. However, there are also other types of hash function.

First, the receiver automatically verifies the transaction against a checklist of criteria, ensuring that only valid transactions are propagated across the entire Bitcoin network (Antonopoulos, 2017). The transaction is then distributed to all computers (nodes) in the network and goes into a pool of pending transactions. Blockchain networks are built using distributed ledger technology (DLT). In essence, a distributed ledger is a database that exists across multiple locations, allowing all participants of its network to access, record, and validate data simultaneously (Deloitte, 2019). DLT networks are designed so that they remain accurate regardless of whether one node is compromised, or dishonest, since nodes are incentivized to diligently maintain the network (Amsden & Schweizer, 2018). Cryptocurrencies use what are known as public or permissionless ledgers, i.e., open to anyone who wishes to participate and keep identical copies of the ledger.[15] This essentially means that anyone can use the public key of a user to check the balance of their wallet, although considerable anonymity remains since only the public key is displayed rather than personal identity details. The openness, however, imposes potentially fraudulent activity. Although it is possible to verify the chain of ownership as each signed transaction contains a hash of the previous transaction, one cannot verify that a previous owner did not double-spend the coin (Nakamoto, 2008). In a traditional centralized system, the trusted intermediary can easily check which transaction arrived first and thus prevent double-spending. In order for blockchain systems to avoid double-spending, the network must collectively agree on a single history of the order in which the transactions were received. This is where the process known as mining comes in (Decker & Wattenhofer, 2013).

Miners collect pending transactions from the aforementioned pool and use the timestamps to determine their chronological order, forming blocks of validated transactions.[16] A Bitcoin block essentially consists of two parts: a header, and a transaction list. The header includes software information, a timestamp, the hash used in the previous block, the Merkle Root hash, the nonce, and the target hash (Nasdaq, 2021). As with transactions, the header information is hashed, but in addition, a nonce is appended to the end of the hash.[17] These two elements are then jointly hashed yet again. Miners use computational power to repeatedly hash the block

[15] A DLT platform can also be permissioned or private and/or be centralized, although the vast majority of cryptocurrencies, including Bitcoin, use permissionless ledgers.
[16] A miner may be a single individual, although miners usually combine their computational power and work together in what is known as mining pools. In the early days of Bitcoin, the computational power consisted of only CPU power, but nowadays GPUs or Application-Specific Integrated Circuit (ASIC) equipment is predominately used for mining.
[17] Nonce, or number used only once, is a random number between 0 and 2^{32}.

header and changing the nonce (usually just incrementing it by one) until the combined hash satisfies the requirements of the target hash (Antonopoulos, 2017).[18] Quite commonly, this process is sweepingly referred to as a computational puzzle that miners must solve, but in fact, it is rather a trial-and-error quest of guessing a valid nonce. Once a valid hash is found a new block is added to the blockchain and the miner is rewarded with newly minted Bitcoin. However, this process is also a competition. Multiple miners run this process simultaneously, but it is only the first miner to find the correct hash that gets rewarded for adding the new block to the blockchain. A new block is added approximately every 10 minutes and the current reward for each block is 6.25 BTC (George, 2022).[19] Initially, the reward was 50 BTC per block but it is halved approximately every four years (or precisely every 210,000 blocks) (Antonopoulos, 2017). Bitcoin has a finite supply of coins (20.99999998 million), and eventually (approximately 2140) no additional Bitcoins will be issued, making it a deflationary currency over time.[20] Miners will then only be rewarded in form of transaction fees. However, before a new block is added to the blockchain, every node independently validates the block against a checklist of criteria, ensuring that only blocks from honest miners get accepted. Once accepted, the block is distributed to the network and the ledger is updated. The validated transactions in the new block are considered confirmed, which allows the new owners to spend their received Bitcoins (Antonopoulos, 2017). In our example, this means that user Y receives the Bitcoin sent from user X. It should be noted that you are not required to actively participate in validation and keep a copy of the ledger if you are simply sending someone some Bitcoin. Participants who run the Bitcoin software protocol and take part in validating blocks and transactions often also keep a copy of the ledger and are referred to as full nodes, whereas those who only use a wallet to send and receive their own transactions are referred to as lightweight nodes. Miners are known as mining nodes (Antonopoulos, 2017).

In sum, all transactions are time stamped and arranged chronologically into sequential blocks that are recorded in a public ledger distributed to all computers (nodes) within the network.

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[18] The target hash is a number that the combined hashed must be less than or equal to. The function is used to ensure that it takes 10 minutes to generate a new block and does so by adjusting the input difficulty, i.e., how much computational power (based on statistical probability) is needed to find a valid hash. The difficulty is determined by the network's hash rate (aggregate computational power of all miners) and with additional miners joining the network the difficulty is increased (a lower target hash number).

[19] Compared to other cryptocurrencies, 10 minutes is rather slow. Many newer altcoins distinguish themselves by offering faster transactions. Hence, Bitcoin has evolved to become a store of value rather than a medium of exchange.

[20] While many cryptocurrencies have finite supplies, it is also common to use an infinite supply as Ethereum does.

Each block has a hash that includes the hash of the preceding block. Tampering with the data in any block will invalidate the hash of that block and all subsequent blocks. This forms an immutable chain of blocks, hence the name *blockchain*. However, it is also important to mention how the network agrees on this single history of transactions and why miners are required to expend processing power to find a valid hash. The consensus mechanism is at heart for blockchains to achieve decentralization (Meadows, 2019).[21] Without a central authority that holds the right to validate transactions and maintain account balances, a majority of the nodes have to agree on these matters to deter fraudulent conduct. Bitcoin uses proof-of-work as its consensus mechanism.[22] The miner with the most computational power, or highest hash rate, stands the best chance of achieving a valid block first and thus reap the reward. For this reason, successful miners have had to invest a substantial amount in technology and expend a significant amount of electricity to operate it, which should make them more trustworthy (Meadows, 2019). As all new blocks are independently validated by every node, any anomaly that fails the criteria results in the block getting rejected, meaning that the investment by the miner to process the block was made in vain, hence deterring dishonest nodes. Sometimes new blocks are received by nodes at different times, causing the blockchain to fork into two separate chains. In this situation, miners "vote" with their computational power by choosing which chain to extend and they attach the next block to the longest chain associated as more cumulative proof-of-work increases the credibility of the system (Antonopoulos, 2017).[23] Proof-of-work blockchains are theoretically vulnerable to malicious attacks (Meadows, 2019). However, blockchain technology draws on game theory by incentivizing honest nodes and disincentivizing dishonest nodes as described above (Amsden & Schweizer, 2019). In the event of what is called a 51 percent attack, any dishonest attacker must assemble more computational power than all honest nodes together. In 2018, it was estimated that the total cost of successfully performing such an attack would be at least $1.4 billion (Moos, 2018). As highlighted by Nakamoto (2008), any perpetrator who has gathered the required computational power should

[21] Consensus mechanism is sometimes referred to as a consensus protocol or consensus algorithm.

[22] There are several alternatives, or combinations thereof, to Proof-of-Work used in different cryptocurrency or blockchain systems. The second most used, and more energy efficient, protocol is Proof-of-Stake. In this system, validator nodes are the equivalent of mining nodes. A validator is required to stake an amount of the currency in question onto the blockchain as a deposit. For each new block, a random validator node is selected to perform the task. Upon completion, the validator is rewarded with the transaction fees associated with the block. The staked amount is held for an additional period and if any fraudulent transaction is discovered by the network the validator faces the risk of losing the staked amount, hence deterring dishonest conduct (Saleh, 2020).

[23] In the case of equal length chains, the miners choose the chain associated with the most cumulative Proof-of-Work.

find that the use of his power to mine new coins will result in greater wealth than defrauding people. The attack would also undermine the validity of the system and thus the legitimacy of his own stolen wealth.

2.5 The Modern Cryptocurrency Landscape

In the early days, the cryptocurrency landscape mainly consisted of enthusiastic cypherpunks that ran the protocols on their own personal computers and maintained the networks as a hobby. Today, cryptocurrencies are widely used, and retail investors do not need to make much more effort to invest in, or use, cryptocurrencies than conventional assets. The first step for an investor is to convert fiat currency to cryptocurrency, usually through a credit card transaction or bank transfer on a cryptocurrency exchange. There are two main types of exchanges: centralized and decentralized, whereas the former accounts for most of the trading volume in the crypto market (Tepper & Schmidt, 2021). Centralized exchanges (CEX) offer fiat-to-crypto transactions, while decentralized exchanges (DEX) do not (Coinbase, 2022).[24] Popular CEXs include: Binance, Kraken, Crypto.com, and Coinbase. A CEX establishes prices and clears/facilitates all transactions itself via an internal order book, the same way that stock exchanges like Nasdaq do, quite the contrary to the underlying idea of cryptocurrencies, albeit convenient. They also tend to offer more advanced trading functionalities and supplementary services; however, KYC and other verification is often required, i.e., less anonymity. Nevertheless, CEXs are not immune to technical difficulties. Several CEXs, such as Kraken, have repeatedly suspended deposits and withdrawals without warning (Hall, 2022).

DEXs, on the other hand, consists of a set of smart contracts that enable peer-to-peer transactions between users, and thus avoids the single point of failure of CEXs (Hsieh, 2018). Transactions are directly settled on the blockchain using an automated market maker and liquidity pools, in which investors can lock their funds and earn interest-like rewards (Coinbase, 2022). While some DEXs only allow trades for cryptocurrencies based on a certain blockchain, others facilitate transactions on multiple blockchains, and some even enable cross-chain transactions. Popular DEXs include: Uniswap, Pancakeswap, and SushiSwap. Whereas a CEX acts as a trusted third party in holding the funds for their users, a DEX enables users to

[24] Recently, some firms have released whitepapers and/or attempted to introduce decentralized exchanges that offer fiat-to-crypto transactions. But the feasibility and degree of decentralization is questioned. See for example Orionprotocol.io.

remain in control of their funds. To use a DEX, you need an external wallet. There are several alternatives available, like a DEX, some operate on one blockchain and some on multiple. Popular wallets include: MetaMask, Phantom, and Exodus.[25] The elements described above can be seen as the backbone of the crypto landscape, nevertheless, there are numerous additional important elements, but it lies beyond the scope of this paper to provide such a comprehensive portrait.

2.6 Legal Aspects of Cryptocurrencies

In both academic literature and government policies, there is a lack of consensus on the legal and regulatory aspects of cryptocurrencies (Shanaev, 2020). Bitcoin did not generate much media or investor interest until a few years after its launch, but since then, cryptocurrencies have been under scrutiny of legislative authorities. The fact that cryptocurrency and the underlying blockchain technology bring a lot of positives can hardly be disputed, however, there are aspects and uses of the technology that authorities perceive as potential threats to society, thus driving legislative prohibitions and restrictions (Chohan, 2020).

Drawing on Chohan (2020) and Auer & Claessens (2018), these threats can be classified into three categories. First, as a result of the anonymity offered by these decentralized networks, cryptocurrencies have been identified as being used for illicit purposes, such as tax evasion (Slattery, 2014), money laundering (Bryans, 2014), and financing of illegal activities (Foley et al., 2019). Second, the substantial volatility and bubble-like behavior present a risk to investors and possibly to the entire financial system (Shanaev, 2020), and widespread acceptance of cryptocurrencies could place much of the economy beyond the locus of control of national banks (Yadav et al., 2020; Chen & Bellavitis, 2020). Third, the energy-intensive mining process associated with proof-of-work cryptocurrencies is a negative externality with potentially adverse environmental impact (Truby, 2018).

Authorities have several regulatory and legislative tools at hand to target different elements of the cryptocurrency ecosystem (Auer & Claessens, 2018). Responding to illicit activities can be accomplished by targeting firms that give access to cryptocurrency. Most cryptocurrency holdings are not held directly through hardware wallets or other physical means; instead, they

[25] These are digital wallets, there are also hardware wallets like Ledger Nano X that look much like a usb-memory.

are held through digital wallets and other intermediaries who hold claims on customers behalf. Regulatory programs already in place, such as anti-money laundering (AML) and counter financing of terrorism (CFT) are often possible to enforce to these firms, for instance, in the form of mandatory know-your-customer (KYC) procedures. On the other hand, responses could also be targeted at regulated financial entities that serve as intermediaries in cryptocurrency-to-fiat exchanges and vice versa, such as commercial banks, credit card companies, and exchanges. Regulatory frameworks can determine whether, and how these entities are permitted to deal with cryptocurrency-related assets and transactions for their customers, or on their own behalf. Furthermore, authorities can also define the legal status of cryptocurrencies, or elements thereof. Thus, with this approach, it is possible to ban or allow, for instance, trading, while on the other hand, mining could still be permitted. By clarifying the legal status of crypto-related activities is clarified, certain issues become transparent, such as which customer protection policies apply, to what extent, and who may engage in crypto-related activities, and if so, under what circumstances, and what the tax implications are. Another consideration, in addition to the legal status question, is how cryptocurrencies are classified from a financial perspective, i.e., whether they are treated as securities or generic assets, and therefore subject to strict or modest regulations and oversight.

The regulatory and legislative responses vary significantly across national jurisdictions, the diversity indicates a perplexity of the perceived possibilities of cryptocurrencies and a balance between promoting innovation and enhancing accountability (Chohan, 2020). In one end of the spectrum is a total ban from start, as per Bolivia in 2014 (Law Library of Congress, 2018), while in the other end is El Salvador, which made Bitcoin a legal tender in 2021 (Asamblea Legislativa, 2021). Geopolitical giants like the United States and China (PRC) have had different responses that have evolved in different directions over time. In China, financial institutions were prohibited to handle Bitcoin transactions in 2013 (Bloomberg, 2013), authorities shut down all cryptocurrency exchanges and trading platforms in 2018 and announced mining would be illegal in the near future (Law Library of Congress, 2018; Jia & Xiaojin, 2018), and a ban on all cryptocurrency activities was subsequently imposed in 2021 (John, Shen, & Wilson, 2021). U.S. authorities, on the other hand, have had a more postive legal approach toward cryptocurrencies, although not without regulations. The U.S. Treasury recognized Bitcoin as a convertible virtual currency in 2013 (FinCEN, 2013), the Commodity Futures Trading Commission (CFTC) classified Bitcoin as a commodity in 2013 (Chohan, 2020), and the Internal Revenue Service (IRS) regards cryptocurrencies as taxable property which means that it is taxed like any another conventional asset (IRS, 2014). Nevertheless, at heart for the U.S. policy is the legal classifications of cryptocurrencies into coins, utility tokens and security tokens. This came as a result of the 21A investigative report (the "DAO Report") issued by SEC in July 2017 and affects both initial sales and secondary market trading, i.e., cryptocurrencies in general and ICOs (Mendelson, 2019; SEC, 2017). Tokens that are deemed to be a security token, and exchanges that facilitate the trading of security tokens, are required to register with the SEC and to adhere to conventional securities regulations. Recently, the Infrastructure Investment and Jobs Act, signed by President Biden in November 2021, imposed stricter reporting requirements for tax purposes on both cryptocurrency exchanges and investors, as well as requirements for all firms engaging in crypto-related business to comply with AML and CFT regulations. Even though the U.S. policy is rather supportive in comparison to other countries, it has still deterred a lot of crypto activity and businesses. Most cryptocurrency exchanges prohibit U.S. citizens from accessing their services as they fear that U.S. regulations is too costly or pose a risk for their business (Osipovich, 2021). Exchanges that operate in the U.S. (e.g., Kraken.com) typically only offer spot trading, and no derivatives or leverage options. Some exchanges, like Binance, have a specific branch (Binance.us) in the U.S. market with less trading functions to comply with regulations. For a comprehensive and recent overview of regulations see Law Library of Congress (2021).

3. Literature Review and Hypotheses

The following chapter provides a literature review on the financing methods relevant to this paper, including both conventional and token offerings, and IPO underpricing theories, as well as evidence for underpricing in ICOs. Section 3.1 provides a brief overview of conventional financing methods. Section 3.2 is a deep dive into ICOs, in which their background and benefits are presented, followed by a description of the ICO process and a comparison to conventional financing methods. The section is concluded with an overview of the legal aspects of ICOs. In section 3.3, the chapter turns to IEOs and IDOs and attempts to understand their background and the development towards the current market situation using the scarce available literature, followed by a comparison between the three token offering methods. In section 3.4, we provide an overview of IPO underpricing theories to form a theoretical basis for the hypotheses. Section 3.5 presents empirical evidence of underpricing in the ICO literature. Lastly, section 3.6 presents two hypotheses derived on the basis of the earlier sections, and the variables used in the analysis as explanations for underpricing.

3.1 Conventional Financing Methods

As mentioned in the introduction, early-stage financing is primarily provided by angel investors, venture capital, and crowdfunding (Li & Mann, 2021). Typically, entrepreneurial finance is categorized into four stages of finance, and in chronological order: pre-seed, seed, and series A, B and C funding. As the firm progresses, capital requirements tend to increase, and the funding involved becomes more sophisticated and complex (Leach & Melicher, 2021). Once the firm is mature enough, and when cash flows are positive and predictable, an IPO typically becomes the primary method of raising external capital, which is also used as an exit strategy. While the name is reminiscent of IPO, an ICO is rather an alternative to early-stage financing methods. However, the process of an ICO is more similar that of an IPO than other financing methods, and as most of the theories that ICO scholars use, which are also used in the theoretical framework in this paper, are derived from IPO literature, we focus more on IPOs.

Crowdfunding has gained traction over the last decades, and despite a slight downturn in 2017, it constitutes a significant amount of early-stage funding today (Moxotó et al., 2021). There are two types of crowdfunding: equity-based and reward-based. In equity crowdfunding, firms offer equity in exchange for capital, and in reward-based crowdfunding, investors receive non-financial rewards in the future, such as a product or service, in exchange for capital. Crowdfunding enables entrepreneurs to raise funds while the project is still in the idea or prototype phase, and to reach a large audience through online platforms, available to all types of investors.

In addition to bank financing and bootstrapping, angel investors and venture capital are a part of the traditional, or conventional, financing methods (Leach & Melicher, 2021). Angel investors are high-net-worth individuals that can provide capital and business expertise in exchange for equity or convertible debt, and typically invests in an early stage in firms with long-term growth potential. Venture capital firms are similar to angel investors, although usually with access to a larger pool of capital, and therefore their investments tend to be larger, and also at later stages. Both types of investors target riskier and innovative firms to generate abnormal returns on a long-term horizon, often between 25 and 35 percent per year, or above (Zyder, 1998; Gompers & Lerner, 2004).

The fundamental concept of an IPO stems back to 1602, when the Dutch East India Company offered shares to the public that later could be traded (Sur, 2017). IPOs were an integral part of the infamous dot-com bubble in the late nineties, where the prospects of internet-based companies were highly overestimated and received astounding amounts of capital from the public. When the speculative bubble burst, the IPO market took a steep downturn, but managed to recover over the years, despite suffering another setback during the 2008 financial crisis (Grosh et al, 2006; Li et al., 2018). Today, the IPO market is flourishing, where a total of 2,388 firms raised $453.3 billion globally, an average of $189.8 million in gross proceeds, in 2021 (EY, 2021). As IPOs gained popularity in the 20th century, more and more academic scholars sought to understand their ways of working from a theoretical perspective, creating an extensive body of research on IPOs. Scholars were particularly intrigued by the observed phenomenon that IPO shares on average rose above their offer price at the end of the first trading day, which contrasted the efficient market hypothesis that was one of the cornerstones of financial theory. Major works include Ibbotson & Jaffe (1975), Rock (1986), Ritter & Beatty (1986), and Welch (1992).

An IPO is the process of offering shares of a private firm to the public in a new stock issuance, where the shares could be newly issued, existing, or a combination thereof (Daily et al. 2003).

The transition from privately to publicly owned enables private investors to realize their investments as the shares become tradable on a stock exchange. The process of an IPO is lengthy and complex, with several important steps involved. Firms usually employ an underwriter to lead the process (often an investment bank), and the process is started as proposals from different underwriters are evaluated. Once an underwriter is selected, the underwriter and the firm together outline legal aspects and assemble a core team to work on the remainder of the process. This usually involves extensive paperwork, including an IPO prospectus that serves as the basis of subsequent marketing efforts, which involves a roadshow. During the roadshow, the core team holds presentations at events in major cities and meets with important institutional investors (Daily et al, 2003). Aside from marketing, the underwriter initiates a book building process during the roadshow, where bids are collected from various investors to gauge demand and determine the offer price of the IPO (Sherman, 2000). The final price is set according to a valuation performed by the underwriter based on multiple financial metrics, and the insights from the book building. Lastly, the shares are offered to the public on an IPO date, in return the firm receives funds that are recorded as stockholders' equity on the balance sheet. After the IPO, the shares are listed on a stock exchange, early investors and insiders may be subject to lock-up agreement in order to prevent negative price impacts caused by large quantities of shares being sold immediately after the listing.

3.2 Initial Coin Offerings

3.2.1 Background

In 2012, software developer J.R. Willett published "The Second Bitcoin Whitepaper" (see Willett, 2012) in which he proposed a crowdfunding-like method for people to raise funds using blockchain technology. Shortly thereafter, he held an engaging speech at the 2013 Bitcoin: The Future of Payments conference:

> ... you could do it without going to a bunch of venture capitalists… you're familiar with Kickstarter I assume? Most of you? You can actually say, okay, here’s my pitch, here’s my group of developers…We’re going to make a new protocol layer. It’s going to have new features X, Y and Z on top of Bitcoin, and here’s who we are and here’s our plan, and here’s our Bitcoin address, and anybody who sends coins to this address owns a

> piece of our new protocol. Anybody could do that! And I've been telling people this for at least a year now because I want to invest in it… Does anybody in this room want my bitcoins? (Digital Magus, 2013, 4:19)

Willet took the matter in his own hands, and less than four months later he organized the first ever ICO in conjunction with the launch of his cryptocurrency project Mastercoin (Amsden & Schweizer, 2019). The ICO boom of 2017 and 2018 drew the attention from scholars, investors, media, regulators, and entrepreneurs. Despite the reports of scams and risks, as well as being denounced by several influential figures in the finance industry, investors continued participating in token sales, hoping to win the lottery. Liu (2019) found that the main factors that motivated investors were overconfidence bias, as well as herd behavior and fear of missing out bias. One group of investors believed that they had the skills and abilities to identify high quality ICOs that would yield high returns, while the second group saw other investors making large profits and feared to miss out on these opportunities. The academic attention rendered a rather substantial body of research, which serves as the basis for the upcoming sections.

3.2.2 What are ICOs and their benefits?

As aforementioned, ICOs are essentially a way for blockchain-related ventures to raise public capital by issuing tokens or coins in exchange for legal tender or another cryptocurrency. The ventures typically involve the launch of a startup, but they can also be associated with a project within an existing organization. Regardless of the setting, most ventures are still in the idea or prototype stage at the time of the ICO and intend to launch the project within 1 to 2 years thereafter (EY, 2017). [26] ICOs encompass issuance of all cryptocurrency types (coins, utility tokens, and security tokens), although the vast majority involve venture related utility tokens with a majority being based on the Ethereum blockchain, typically using the ERC-20 token standard (Momtaz, 2020). While in their most basic form, utility tokens simply function as coupons for the issuer's product or service, however, in most ICOs the token upholds as a means of payment in a new marketplace (Howell et al., 2020). Following the ICO, the issued tokens can generally be traded in the secondary market on one or more exchange platforms. The issuer and other insiders, and sometimes the ICO investors as well, are usually subject to

[26] EY (2017) finds that only 5 percent of the ventures had running projects, 11 percent had prototypes, and 84 percent were simply ideas.

lock-up agreements. Since the value of a token largely depends on supply and demand and the size of its network, any pre-ICO valuation attempt is highly speculative (Zetzsche et al., 2018). In addition, given the paucity of information generally available to investors prior to the ICO, there is substantial information asymmetry between issuers and investors, rendering the investment decision to be a gamble rather than an outcome of a rational calculus (Zetzsche et al., 2018). The investors are thus exposed to significant risk.

Despite the speculative nature and risk, there are nevertheless beneficial aspects for investors. Empirical evidence displays average returns substantially higher than those traditionally seen in IPOs (see Table 3). In many cases, however, the median values are relatively low, which can be explained by the astronomical returns of a few highly successful ICOs, yielding ROIs in the hundreds of thousands for early investors (ICOlistingonline, 2022). By being digital and global in nature, ICOs offer investors the opportunity to invest in international ventures to which they might not otherwise have access. Moreover, the secondary market for cryptocurrencies is characterized by liquid exchanges with 24/7 access.

From an issuer's perspective, ICOs offer several benefits. First, as aforementioned, utility tokens are used as a means of payment on a platform or grants the right to redeem the token for a venture-related product or service provided by the issuing company. Given that tokens convey benefits beyond its market value, token holders become users rather than simply investors, which in turn facilitates engagement in the project (Ofir & Sadeh, 2019). Since ICOs are typically held at an early stage of the venture, in most cases the issued utility tokens give the right to a *future* product. Thus, an ICO provides the issuer with the opportunity to build a user base while still at the idea or prototype stage (Howell et al., 2020). In addition, the ICO also provides the issuer with an early indication of consumer demand, giving the ample time for the future product to be adjusted accordingly (Ofir & Sadeh, 2019).

Second, by virtue of its decentralized nature, the value and gains from a blockchain network accrue to its token holders, rather than to financial intermediaries, as in conventional financing methods (Momtaz, 2020). Thus, aligning the incentives of the developers, users, and miners. [27] ICOs can therefore spur innovation by compensating both creators and later contributors without giving any party more control than necessary (Howell et al., 2020). This may also

[27] Mining is only performed when the cryptocurrency operates on its own blockchain, i.e., coins not tokens.

stimulate prevalent open-source business models that currently rely heavily on volunteer work (e.g., Wikipedia) (Popper, 2016).

Third, a tokenized business model can help propel network effects, which is pivotal to the marketplace, or platform, issuers often intend to build (Howell et al., 2020). Despite constituting a challenge in a pre-ICO valuation, the fact that a token's value is largely determined by its network size fosters network effects, highlighting a token's dynamic nature. Drawing on the theoretical model of Cong et al. (2018), users join the platform not only to enjoy its utility, but also to benefit from expected token price appreciation. Given that the platform productivity (the productivity prospect if the platform is yet to be released) is adequate, it is likely that it will attract some users only based on its utility. Thus, the network size increases, and consequently the price appreciates, which in turn attracts investors driven by both motives, and those with a solely speculative interest. Therefore, issuers have an incentive to attract as many users as possible, while investors have an incentive to participate in the ICO to benefit from the price appreciation (Ofir & Sadeh, 2019). This touches upon both previous points in aligning incentives and increasing user engagement in the project.

Fourth, an ICO offers the opportunity to raise external capital without diluting equity. [28] Tokens are dynamic in the sense of rights and obligations and can be designed to fit a specific objective of any venture and circumvent most regulation if representing utility-like rights only (Howell et al., 2020).

Fifth, ICO issuers benefit from global reach and low transaction costs. As aforementioned, ICOs can attract investors worldwide with the only requirement of an internet connection. Thanks to the ERC-20 token standard, anyone can easily create a token on the Ethereum platform without much technical expertise (Momtaz, 2020). The code can be downloaded from Ethereum’s website, and it is designed so potential issuers can adjust parameters like the total amount of tokens, how fast a block is produced, and lock-up agreements.

[28] Except for security tokens that represent equity.

Finally, the liquidity that can be accessed through cryptocurrencies are unparalleled to all other financing methods, except IPOs, which makes ICOs attractive as an exit strategy at an early stage of the venture (Momtaz, 2020).

3.2.3 The ICO process

Pre-ICO

The rather self-explanatory first step of every ICO is to assemble a core team and define the vision of the project. Marketing starts shortly thereafter (Momtaz, 2020). It is typically initiated with an announcement of the project and its vision in order to generate interest and obtain feedback (Ofir & Sadeh, 2019). The announcement is usually made online in cryptocurrency forums or ICO listing platforms. Early marketing activities tend to focus on social media presence, and the core team generally creates accounts on multiple platforms (e.g., Twitter, Telegram, and Discord) (Momtaz, 2020). Aside from the announcement, much of the early communication is conducted directly with potential investors on these platforms. Potential investors are incentivized early on to participate in the project via airdrops and/or bounty programs in exchange for performing certain tasks, such as inviting other people to the social media channels or finding bugs in the code (Ofir & Sadeh, 2019). [29]

Once the project has progressed a bit, and some code has been written, a whitepaper is usually published. The whitepaper is a disclosure document that is similar in spirit to an IPO prospectus (Howell et al., 2020). While the content of whitepapers is very inconsistent, they generally include information to some extent about: (1) the business model; (2) the project's developing team, issuing entity, and their backers; (3) contact information; (4) the token supply, allocation, and distribution; (5) the tokens and the embodied rights and obligations; (6) technical features, the source code, and the potential use and benefits thereof; (7) the applicable law and regulatory situation; (8) the date of the ICO, duration, hard and soft cap, vesting schedules, and accepted currencies; (9) how the funds will be used (10) a roadmap of the projects course of development (Ofir & Sadeh, 2019; AMF, 2018; Zetzsche et al., 2018). However, unlike an IPO prospectus, the whitepaper is voluntary and not subject to any regulations regarding the disclosed information (Ofir & Sadeh, 2019). Hence, the information tends to be unaudited and opaque (Zetzsche et al., 2018). Most whitepapers fail to disclose information about several of these

[29] An Airdrop is an unsolicited distribution of tokens or coins to numerous wallet addresses performed to increase the network size. Allowing potential investors to find bugs in the code is only possible if it is an open-source project.

points; typically, they reveal very little about the developers, issuing entities, and their backers, and lack any contact details other than social media accounts (Zetzsche et al., 2018). In addition, the findings of Zetzsche et al., (2018) reveal that 82.69 percent of whitepapers fail to mention the legal and regulatory status of the ICO, indicating that the issues have designed the ICO to avoid any legislation or relies on regulatory gray areas. A technical description of the underlying technology for which funding is sought, along with some explanation of its expected use and benefits, tend to be the only consistent elements. Cohney et al. (2019) note that there are often discrepancies between the actual ICO code and what is reported in the whitepaper, which they consider problematic in a financial ecosystem where code is seen as the final guarantee of performance.

After the whitepaper has been published, the core team can attend crypto roadshows to meet with potential investors, or intensify their social media marketing (Momtaz, 2020). Moreover, it is important for the project to perform the *Howey Test* prior to the ICO (or pre-ICO) to determine whether their token falls under the legal definition of a security, and thus is subject to conventional securities regulation. [30] Some projects opt to conduct a pre-ICO to target early adopters and followers on social media by offering the token at a discount in comparison to the subsequent ICO (Momtaz, 2020). [31] The rationale behind a presale is twofold. The raised funds can be used to cover the costs associated with the ICO and other expenses associated with marketing, strategic hires, or roadshows. The pre-ICO also serves as an instrument to gauge the market demand and provides an indication of the token's fair value, as well as the amount of funding that is possible to raise in the ICO, which to some extent resembles the book-building process in IPOs. In addition, a successful pre-ICO increases the network size which is, as aforementioned, vital to the success of a market platform. Furthermore, many projects disclose their source code via an online code repository (usually GitHub) to signal transparency and confidence in the quality of code, as well as allow potential investors to assess the code prior to the ICO (Ofir & Sadeh, 2019).

[30] The Howey Test is a product of the SEC v. W.J. Howey Co U.S. Supreme Court case in 1946 and lays down criteria to determine whether a financial product qualifies as an “investment contract”. The four main criteria are: (1) there is an investment of money, (2) in a common enterprise, (3) with an expectation of profit, (4) to be derived solely from the efforts of others. If the financial product passes the test it is classified as a security and thus subject to securities regulation. Cryptocurrencies that pass the test are classified as security tokens, rather than a coin or utility token. See for example Sykes (2018) for further information.

[31] A pre-ICO can be either public or private. A private presale has restricted access and investors typically must be included in a whitelist to participate. The entry requirements are like those of bounty programs and airdrops.

ICO

To launch an ICO, the issuer administers a public sale of its token on their website for a predetermined period, ranging anywhere from a few hours to over a year in some cases (Momtaz, 2020; Li & Mann, 2021). The actual mechanics is very uncomplicated, the issuer simply creates a wallet address to which investors send their funds (other cryptocurrencies or sometimes fiat), and any investor that wants to participate sends their funds to that address. Once the ICO has ended, the tokens are created and investors receive the newly minted tokens in return to their respective wallet addresses in accordance with a predetermined exchange rate (e.g., 10,000 tokens for 1 BTC) (Momtaz, 2020). The tokens are usually sold on a first-come, first-served basis, either at a fixed price, or in accordance with a predetermined price schedule, which often involves that the price increases over time or when a certain number of tokens are sold (Li & Mann, 2021).

Besides the pricing mechanism, many of the characteristics and properties of an ICO can be adjusted in accordance with the issuer preferences. The design choices are written in the token contract prior to the ICO and entails decisions that involve tradeoffs among a set of economic variables (Howell et al., 2020). [32] An important and distinctive feature of the ICO process is the fact the token contract is usually immutable, meaning that once it is deployed the details within cannot be changed (Li & Mann, 2021).[33] Thus, the credible commitments issuers make to matters like token scarcity and governance strengthens the credibility of the project (Howell et al., 2020). In the token contract, issuers must decide how many tokens to issue and what portion of the total amount that fraction should represent. Usually, issuers reserve a portion of the tokens for the founding team and employees, as well as for future bounty programs or to reward users taking part in further platform development. Moreover, most issuers specify the fundraising minimum and maximum goal using a soft and hard cap. The soft cap is similar to an "all-or-nothing" clause commonly included in crowdfunding events (Amsden & Schweizer, 2019). ICOs with a soft cap reduces uncertainty and investor risk since all contributions are returned if the issuer is not able to raise sufficient funds to reach the specified minimum. A

[32] How the above design choices are incorporated into the code differs depending on if it is a coin or token, and what network is used (if it is a token). As an example, if the issuer issues a utility token based on the Ethereum blockchain and uses the ERC-20 token standard (as the majority is and does), most of these details are included in the token contract. The ERC-20 token contract is a smart contract that keeps track of the properties during the ICO (such as soft and hard cap) and automatically executes the ex-ante determined actions once the ICO has ended. After the ICO, the token contract constitutes the token registry and automatically updates the balances after each transaction. For coins, the details are generally written directly into the source code of the network.

[33] The immutability depends on the network used, any token contract on Ethereum is immutable.

hard cap limits the number of tokens that can be sold and represents the maximum amount of funds the issuer aims to raise in exchange for their tokens. This helps investors to track the progress and measure success of the ICO (Amsden & Schweizer, 2019). Another question is whether to use a lock-up agreement or not, and if so, how much of the token supply that it applies to. Lock-up agreements can either apply to insiders or ICO participants, or both, and are used to reduce short-term volatility and to align developer incentives with those of the token buyers (Amsden & Schweizer, 2019; Howell et al., 2020).

In addition to the ICO design, many of the characteristics and properties of the future platform or network are also ex-ante decisions. The issuance of a coin involves the creation of an independent blockchain, meaning that the issuer is faced with multiple decisions regarding the underlying technologies such as consensus protocol, validation algorithm, and block creation time (Lesavre et al., 2021). Token issuers on the other hand, are not faced with these decisions as tokens are built upon other blockchains. However, both issuers must determine the governance structure, which in the case of tokens refers to how and who decides on issues outside the boundaries of the immutable token contract. The governance is generally either off-chain (typically the issuing entity) or network based, or some type of hybrid thereof (Lesavre et al., 2021). As an example, many decentralized finance (DeFi) platforms use governance tokens (a type of utility token) whereby each token represents a vote, and a majority of the token holders must agree on any changes regarding the platform.

Post-ICO

Once the token sale has ended, the tokens are minted and distributed to the investors. Listing the token on an exchange following the ICO is a crucial undertaking for every issuer (Momtaz, 2020). The listing represents a significant milestone for the project as it enables the token to be traded freely on the secondary market, and the ensuing liquidity attracts new investors, laying the foundation for the token's purpose and its platform. In addition, getting listed on a major exchange is often viewed as an important marker of success (Amsden & Schweizer, 2018; Li & Mann, 2021). In order to get listed, issuers must manually submit applications to exchange platforms. Hence, not all tokens get listed, either because the issuer chooses not to pursue listing, fails to meet the criteria of the exchange platform, or simply disappear with investors' funds as in the case of a rug pull scam. Benedetti & Kostovetsky (2018) find that tokens were listed in only 26 percent of ICOs, whereas Amsden & Schweizer (2018) and Lyandres et al. (2020) report 42 and 41 percent, respectively. There are numerous exchanges, and the listing criteria varies accordingly, but it is generally significantly less rigorous than the eligibility criteria for an IPO. [34] Exchanges tend to charge listing fees, although there is a trend among major exchanges to remove listing fees (e.g., Bitfinex and OKX). During the ICO boom, it was not uncommon for exchanges to charge listing fees ranging as high as $1-3 million (Howell et al, 2020). While the listing process typically lasts for 1-3 months after the ICO, it is preferable to get listed sooner rather than later (Drobetz et al., 2019). However, there are multiple factors that influence the decision when to list a coin. Drobetz et al. (2019) suggests that issuers consider investor sentiment, competing ICOs, and market liquidity in finding the right timing for listing, and similarly, Adhami et al. (2020) suggests that the listing decision entails market sentiment and other strategic considerations. While a token may not get listed on an exchange, it can still be exchanged via normal transactions between the buyers' and sellers' wallet addresses. Nonetheless, listing a token on an exchange greatly facilitates trading and acts as a quality signal for the long-term value (Amsden & Schweizer, 2019).

3.2.4 Comparison of ICO and conventional financing methods

Even though the name implies a resemblance to an IPO, a direct comparison is misleading since the two methods have significant differences (Li & Mann, 2021). ICOs also differ from other forms of corporate and entrepreneurial financing, but offer several distinct advantages, including near-zero transaction costs, immediate liquidity, and light regulation (Drobetz et al., 2019). Nonetheless, there are also similarities in some respects, however, in ICO literature, scholars mainly examine ICOs in comparison to IPOs since most theories and concepts emanate from IPO literature. The overview provided in Table 1 below displays a comparison of ICOs to several conventional financing methods, while the following text will mainly focus on ICOs in relation to IPOs.

By the time a firm decides to go public, it is usually already relatively large and profitable, or at least revenue-generating (Li & Mann, 2021). Hence, the IPO issuer can be considered mature in some senses, and usually also well-known to the public. The typical firm has also received other forms of funding prior to the IPO, which tends to be held after late-stage funding (Momtaz, 2020). IPOs have traditionally attracted more sophisticated and institutional investors, generally within the country of issue, that are primarily driven by financial motives

[34] For an example see Coinbase (2021).

(Momtaz, 2020). Moreover, an IPO involves the sale of a specific security, usually common equity, and must adhere to strict regulations.

An ICO, on the other hand, is typically associated with a new startup or the launch of a venture within an established organization (Li & Mann, 2021). Consequently, the ICO issuer tends to be less known to the public. While an ICO usually takes place in an early stage, it can theoretically be conducted at any funding stage (Momtaz, 2020). Moreover, the choice of ICO as a financing method does not necessarily exclude other sources of capital, and it is fairly common that the issuing firm has received funding prior to the ICO, usually in the form of venture capital (Benedetti & Kostovetsky, 2021; Howell et al., 2020). There are some large ICOs in the large-cap segment, although entrepreneurial firms still dominate the ICO scene (Momtaz, 2020).

The digital nature of ICOs gives them global reach and allows to theoretically be accessible to any investors.[35] On a similar note, while IPOs and other financing methods tend to draw a specific type of investor, ICOs are suitable to attract all types of investors (Momtaz, 2020). As aforementioned, in the early days, the crypto community was composed of dedicated enthusiasts who participated in the networks out of personal interest. This devotion remains true today to some degree, reflected by the fact that ICO investors are often equally driven by financial and non-financial motives (altruism, a sense of community, product interests, etc.) (Momtaz, 2020).

IPOs involve the issuance of securities in the form of common or preferred stock representing a claim of the firm's profits. While ICOs encompass all cryptocurrency types, the vast majority of ICOs involve venture related utility tokens based on the Ethereum blockchain (Momtaz, 2020). In terms of size, the observed mean and median gross proceeds vary across ICO literature since the numbers are dependent on sample design details (Li & Mann, 2021). Momtaz (2020) exhibits a mean (median) of $15.057 million ($5.8 million), which is similar to the findings of Howell et al. (2020), $15.8 million ($6.62 million), whereas Benedetti and Kostovetsky (2020) finds a mean (median) of $11.5 million ($3.8 million). The skewness in the samples can be attributed to the fact that the aggregate funding is concentrated around a

[35] Some countries prohibit investing in ICOs, even for ICOs launched in other jurisdictions. Consequently, it is becoming more common for ICO issuers to exclude investors with IP addresses from certain jurisdictions to avoid potential legal problems.

small number of highly successful ICOs. As an example, 37 percent of the total funding in 2017 came from only 20 ICOs (Momtaz, 2020). As a comparison, the average gross proceeds in the global IPO market 2021 was $189.8 million (EY, 2021). IPOs are required to adhere to securities laws, and additional IPO specific regulations. The legal aspects of ICOs are somewhat ambiguous where regulations are evolving and uncertain, however, many ICOs are issued in jurisdictions with light to no regulations (Kaal, 2018).

ICOs and IPOs are rather similar in terms of after-market liquidity because both methods allow the issued assets to be traded on the secondary market. However, as an early funding stage alternative, the after-market liquidity offered by an ICO is a major advantage as no other method can provide similar levels of liquidity (Momtaz, 2020). This liquidity also allows ICOs to provide the earliest exit option of all methods; the issuer may exit even before a product or service is developed, thereby delegating the development of a platform to a decentralized network of developers (Momtaz, 2020). However, there may be a dark side to this if the ability of issuers to cash out quickly undermines their incentive to build a successful business (Howell et al., 2020).

Table 1

Comparison of Financing Methods

	Initial Coin Offerings	Reward Crowdfunding	Equity crowdfunding	Venture Capital	Initial Public Offerings
			Panel A: Start-up or Firm Characteristics		
Funding stage	Theoretically all stages	Before seed stage	Early stage	Balanced stage	After later stage
Issuance	Utility tokens, coins, or security tokens	Products (vouchers)	Equity-like instruments	Equity shares	Equity shares
			Panel B: Investor Characteristics		
Investors	All types	Early adopters	Angel Investors	Limited partners	Public
Motivation	Financial and non-financial	Financial and non-financial	Financial and non-financial	Financial	Financial
			Panel C: Deal Characteristics		
Average funding	$11-16m	$20-50k	$250-350k	$15-$30m	$150-200m
Transaction cost	Low	Low	Low	Medium	High
Information basis	Whitepaper	Project description	Business plan and pitch deck	Business plan and pitch deck	IPO prospectus
Degree of regulation	Low	Low	Low	Medium	High
Liquidity	High (if listed)	Low	Low	Low	High
Voting rights	Yes or no, depending on the project and token.	No	No	Yes	Yes
Exit options	ICO, open market	IPO, acquisition	IPO, acquisition	IPO, acquisition	IPO, acquisition

Note. This table shows a comparison between ICOs and conventional financing methods. Adapted from Momtaz (2020).

3.2.5 Legal aspects of ICOs

In a similar vein as for cryptocurrencies in large, the legal situation for ICOs is rather ambiguous. Following the boom in 2017, authorities found themselves faced with a similar situation to that with cryptocurrencies previously, albeit in a new and even more rapidly evolving context (Zetzsche et al., 2018; Mendelson, 2019). In 2017, The U.S. Securities and Exchange Commission (SEC), published an investor alert warning investors about the risks of participating in ICOs. Tech giants such as Facebook, Twitter, Google and Mailchimp banned ICO advertising in 2018, but it has since been allowed again (Sunny, 2018; Leathern, 2018). In line with the response to cryptocurrencies, some countries, like South Korea and China, have outright banned ICOs, while others, like Estonia and Singapore, have taken a more positive approach (Bellavitis et al., 2021). At the time of publication, Kaal (2018) reports that an overwhelming majority of the 25 most important jurisdictions by market capitalization allow ICOs with light to no regulation. However, in contrast to the gradual development of cryptocurrency regulation, ICO regulation spread exceptionally fast. In the second quarter of 2017 only two countries had implemented ICO specific regulation, and by Q2 2018, the number of countries had grown to 64 (Bellavitis et al., 2021). The amount raised in ICOs fell from $19.7 billion to $4.1 billion between 2018 and 2019, indicating an impact of initial ICO regulations and policies (Bellavitis et al., 2020). Bellavitis et al. (2020) find that the bans on ICOs in China and South Korea, both in 2017, affected both quantity and quality of ICOs in the global market; the quantity decreased, while quality increased. [36] Morover, Bellavitis et al. (2021) further emphasize the relationship between regulations and ICOs, highlighting that ICO quantity has continued to decline at the same time as more countries introduce regulations to protect investors. In addition, the findings of Bellavitis et al. (2020) indicate a trend towards ICOs being launched more frequently in countries with supportive legislation (e.g., Singapore) and less frequently in countries with restrictive legislation (e.g., the U.S.). Contrary to Bellavitis et al. (2020), Karpenko et al. (2021) describe the U.S. as an ICO-friendly country despite the regulations, considering its legislative transparency, highly developed financial markets with large pools of liquid investors, and the digitalization of their economy and legal system. Nevertheless, in many jurisdictions, regulations are continuously updated or still under development, and the China/South Korea ICO ban has raised concerns about stricter legislation in the future, which have caused a regulatory uncertainty (Bellavitis et al., 2021).

3.3 Initial Exchange Offerings and Initial DEX Offerings

3.3.1 Background

The ICO boom was undeniably characterized by a market frenzy that sent a shock wave beyond the crypto sphere. Fortune seeking investors were lured into the market by the prospect of astronomical returns, while some hit the jackpot, others fell victim to speculative bubbles and market manipulation. Malicious issuers took advantage of the irrational exuberance to perpetrate a wide range of scams and purveying worthless tokens. The rapidly emerging phenomenon quickly drew the attention of academic scholars and legislative authorities. Legal

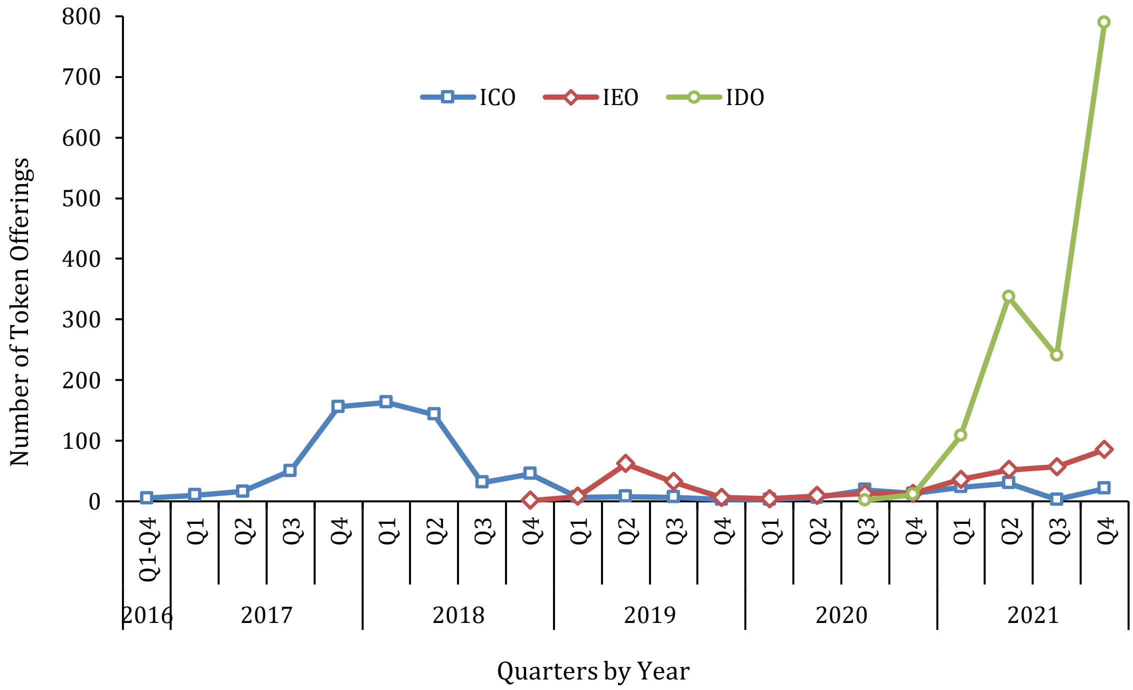
[36] Bellavitis et al. (2020) defines quality as the rating of an ICO given by ICObench.com

and regulatory responses varied across jurisdictions, whereas some authorities extended existing securities regulations or AML and CFT procedures, others targeted cryptocurrency in general, and a few introduced ICO specific regulation, ranging from an outright ban to supportive regulation that aims to attract blockchain ventures and ICOs (Bellavitis et al., 2021). Nevertheless, in many jurisdictions, regulations are continuously updated or still under development and the China/South Korea ICO ban raised concerns about stricter legislation in the future, causing regulatory uncertainty.

Figure 3 below illustrates the evolution of the token offering market. In 2017, the ICO market continued to flourish despite new regulations and the ICO activity peaked in early 2018. However, from this peak, the development took another direction and began to decline. By the end of 2019, both the number of ICOs and amount raised had fallen drastically (Bellavitis et al., 2021). The downward trend has continued after 2019, albeit not as drastic, but the ICO activity remains at remarkably low levels compared to the boom years. ICOs evolved from being a prospering market that offered entrepreneurial firms a new advantageous financing vehicle for blockchain-related ventures to becoming associated with scams, regulatory issues, manipulation, and speculation (Anson, 2021). As a response to this development, the crypto community developed alternative token offerings methods (Binance, 2022). The most notable are STOs, IEOs, and IDOs, all of which have been dubbed ICO successors at some point. STOs are inherently different from ICOs and therefore not to be viewed as a successor, or a direct alternative. IEOs and IDOs, on the other hand, share the same fundamental function and purpose with ICOs, and the recent development in which they have become the predominant fundraising methods demonstrates their position as ICO successors. By introducing an intermediary in the form of a centralized exchange or decentralized launchpad, IEOs and IDOs mitigate the issues associated with issuers administrating the token offering themselves. The due diligence, guaranteed token listing, and the reputational risk that the platform bears add an additional level of trust. More recently, the number of IDOs has skyrocketed, and today they account for over 85 percent of the market activity. Despite this, there has been little academic research on this development, whereas the dramatic surge in IDO activity has not been covered at all. Academic literature and publications from non-crypto sources tend to focus more on regulatory aspects and STOs, or security tokens, as ways to adhere to regulations. We perceive this as a rationale in which regulations are viewed as the cause of the decline in ICO activity, as well as the solution to the problems, arguably over-estimating the impact of regulations to the crypto market. In our view, the success of IEOs and IDOs contradicts this rationale. We do not disregard the impact of regulations on the ICO market; however, we rather view the widespread prevalence of scams and misconduct that affects both investors and issuers as the principal factor behind the development. In the design of IEOs and IDOs, the inherent dysfunctionalities of ICOs that facilitate scams and misconduct are addressed. The fact that IEOs and particularly IDOs have grown in number, while ICO activity has remained at a low level, suggests that the design has been successful, and in turn that scams and misconduct are key factors behind the decline of ICOs. Moreover, these arguments are further strengthened considering that the same regulations apply to ICOs, IEOs, and IDOs on a fundamental level, and by the fact that STO activity and security tokens in large are still scarce. [37]

Figure 3

Evolution of the Number of Token Offerings



Note. This figure shows the evolution of the token offering market per quarter. Own creation, data retrieved from https://cryptorank.io/ico.

[37] The legal aspects of IEOs and IDOs are further explained in section 3.6.3

The success of IEOs and IDOs arguably demonstrates that the crypto community has managed to develop new token offering methods that mitigates the main problem of ICOs, while preserving their advantages. In the following section we review the (limited) literature on the decline of ICOs and the shift towards IEOs and IDO to provide a better understanding of the factors involved.

3.3.2 The shift towards IEOs and IDOs

Drawing on institutional theory, Bellavitis et al. (2020) attribute the post boom crash to regulatory spillovers from the China/South Korea ban in September 2017. In the short-term, issuers (particularly those of low quality ICOs) rushed to the market with expectations of a closing window of opportunity and launched ICOs in other countries, which explains that the ICO activity continued to increase until the peak in 2018. In the longer-term, Bellavitis et al. (2020) argue that the ban affected market dynamics and entrepreneurship in other jurisdictions, resulting in the decline. Bellavitis et al. (2021) extend to this and offer additional explanations of the decline in 2018 and 2019. Bitcoin prices plummeted concurrently with ICO activity in 2018, which suggests that the decline in ICOs was fueled by the movement in Bitcoin prices. Bellavitis et al. (2021) argues that the regulatory changes (not only the China/South Korea ban as proposed in Bellavitis et al. (2020)) played a vital role in the ICO development. The fact that many ICO regulations were introduced in 2017 as ICO activity continued to grow may seem contrary; however, it can be explained by the fact that Bellavitis et al. (2021) find a delay between governments announcing their regulatory intentions and when the regulations are enacted.

Besides the above papers, the crash in ICO activity is largely overlooked in the academic literature. Although much of the ICO literature is published in 2018 and 2019, even more recent studies overlook it. There are some scholars who mention it briefly in passing (e.g., Masiak et al., 2020), others who elaborate briefly but only provide rather ungenerous explanations (e.g., Lyandres et al. 2022) and some who fail to acknowledge it entirely (e.g., Karpenko et al., 2021; Fahlenbrach & Fatarolli, 2021). To our knowledge, only Bellavitis et al. (2020) and (2021) have thoroughly explored the post boom crash and its underlying causes.

Bitcoin prices increased again in 2019, while the ICO activity continued to decline. Despite its importance in explaining the current market structure, this negative long-term development is even more overlooked than the post boom crash. Given its recentness and the nature of academic research, it is perhaps more accurate to say it has not been covered yet rather than overlooked. However, to our knowledge, no study has so far explored this in detail, although some mention it briefly. Bellavitis et al. (2021) believe that the development is due to an increased number of countries implementing regulations to protect investors, as well as an increased number of government warnings that might have cooled investors' interest in ICOs. Lyandres et al. (2022) attribute the decline to regulatory uncertainty starting in 2019, and Ahmad et al. (2021) postulate that the market is suffering from a declining trust of institutional investors not able to distinguish between different quality ICOs. Both Bellavitis et al. (2021) and Lyandres et al. (2022) recognize the emergence and rise of IEOs and STOs and add them as a partial explanation to the continued decline, although stating that ICOs are still predominant in their sample periods. There is academic literature on STOs and IEOs, albeit limited in number.

Security tokens in large have gained quite a lot of attention as potential future (regulated) crypto assets as the regulatory frameworks in many jurisdictions have been developed around extending current securities regulation to cryptocurrencies recognized as securities (Kaal, 2018). Taxonomy and the consequent regulatory uncertainty are frequently discussed in ICO literature, with the current state and future of security tokens being a common topic since most scholars employ the classification used by the SEC (i.e., coins, security tokens, and utility tokens) (e.g., Adhami et al., 2018; Ofir & Sadeh, 2019; Howell at al., 2020; Karpenko et al., 2021). In studies that compare crypto-related fundraising methods, STOs tend to receive more attention than other methods, including IEOs (e.g., Myalo, 2019; Momtaz; 2021). Looking beyond academic literature, there are publications in which STOs are praised and hailed as the successor of ICOs (e.g., Deloitte, 2020; Li, 2019; CMS Law, 2019). This rationale assumes that current securities regulations would solve many of the dysfunctionalities of ICOs, and that having a cryptocurrency backed by an underlying asset would reduce volatility and speculation. However, in recent academic literature on STOs, Lambert et al. (2021) and Momtaz (2021) argue that STOs are fundamentally different from ICOs. While security tokens are tokenized versions of traditional assets (e.g., stocks and bonds) where the token is a digital representation of an investment product recorded on a blockchain, utility tokens aim to support and develop a community-based ecosystem where the token represents consumptive rights to investors, and coins are means of payment in a blockchain-based ecosystem (Lambert et al., 2021). In essence, STOs only utilize blockchain for recording, whereas blockchain is an integral part of the future ecosystem in ICO issues (and IEOs and IDOs). Furthermore, more and more established institutions, such as government authorities and banks, are using STOs to conduct corporate direct issuances of tokenized bonds and loans (PwC, 2020). In contrast, issuers of ICOs (and IEOs and IDOs) are typically entrepreneurial firms that seek to raise capital for a blockchain-related venture. Some scholars view STOs as an alternative to IPOs rather than to ICOs (Chew & Speigl, 2021). Moreover, STOs are generally targeted towards accredited investors rather than the general public as in ICOs (and IEOs and IDOs) (Lambert et al., 2021). Thus, we argue that STOs serve a different purpose than ICOs (and IEOs and IDOs) and are therefore not to be seen as a successor, or direct alternative, to ICOs. This argument is further strengthened by the fact that security tokens are rarely traded on the secondary market on cryptocurrency exchanges (Cryptorank.io is an aggregator platform that provides data from over 90 exchanges, and they have a mere 12 out 9860 listed on their website[38]). If a cryptocurrency exchange (or any exchange) wishes to offer trading on security tokens they are subject to securities regulations, if applicable, in the jurisdictions they are active, therefore most cryptocurrency exchanges do not list security tokens (Momtaz, 2021). There are a few regulated exchanges that exclusively focus on security tokens exclusively (e.g., U.S.-based tZERO), however with limited functionality and only a few tokens listed. Operating a security token exchange on a global scale would be practically impossible as securities regulations differ in each jurisdiction, therefore, it would be very time consuming and difficult to be approved in every country.

IEOs gained popularity as an alternative to ICOs in 2018, although its origins can be traced back to Binance's ICO in July 2017 where $100 million was raised through the issuance of the native Binance Coin (BNB), which subsequently was listed on the Binance exchange (Anson, 2021). As illustrated in Figure 3, IEO activity surpassed that of ICOs in mid-2018, despite a downturn shortly thereafter, the activity recovered and surpassed that of ICOs again in early 2020. The handful of studies on IEOs have been published to date recognize the decline of ICOs and that IEO activity increased as the ICO boom ebbed away, although without thoroughly exploring its underlying causes (Anson, 2021; Myalo, 2019; Miglo, 2020; Takahashi, 2020; Momtaz, 2021). Most only mention the increasing regulatory scrutiny and uncertainty, as well as the prevalence of scams and fraud. Nonetheless, these studies focus on

[38] There are possibly more cryptocurrencies that could in fact be considered securities and vice versa as the classification is contested and inconsistent. For example, in their initial sample of 280 security tokens, Lambert et al. (2021) finds that 86 tokens were utility tokens and coins disguised as security tokens due to concerns over potential regulatory consequences. In addition, SEC chairman Gary Gensler has said he believes that a vast majority cryptocurrencies and ICOs violate U.S. securities laws (De, 2021).

comparing financing methods and the evidence (both empirical and theoretical) indicates that IEOs have several distinct advantages over ICOs that affect the token offering process in several aspects, whereas a reduced risk of scams and fraud is emphasized by the scholars. Considering our argument proposed in the previous section, this is a logical explanation for the shift towards IEOs (and subsequently to IDOs). The advantages of IEOs (and IDOs) in relation to ICOs will be outlined in the upcoming section. Although several aspects have improved, the underlying risk of token offers and cryptocurrencies in general remain, and the advantages of IEOs are not without their drawbacks (Anson, 2021). The additional level of trust exchanges offer as an intermediary also imposes a higher barrier of entry. Exchanges typically charge high fees for IEOs (generally higher than listing fees associated with ICOs (Myalo, 2019)) as they manage much of the process, including marketing of the project, firms at an early stage or with inexperienced team members may not pass the due diligence, and investors must register with the exchange which may exclude investors from certain countries. Although AML and CFT regulations vary by jurisdiction, centralized exchanges generally use KYC verification as a compliance measure to avoid potential sanctions. Moreover, the exchanges behind IEOs are exclusively centralized, which conflicts with the fundamental ethos of cryptocurrencies as decentralized networks.

The first ever IDO took place in June 2019, when Raven Protocol listed RAVEN on Binance DEX, but it was not until late 2020 that the concept gained traction, and since then the number of IDOs has skyrocketed. The initial idea of an IDO in theory provided several benefits, however, the first few offerings encountered complications that stalled the new fundraising method's success (Georgiev, 2022). In these first offerings, the issuer simply listed the on a DEX at a fixed price and investors could buy it until the hard cap was reached. This meant open and fair fundraising, fast trading, and immediate liquidity. However, the absence of oversight or any individual caps led tokens to be sold out in a matter of seconds, leaving average investors empty handed and with a notion that they had been tricked by insiders and bots (Georgiev, 2022). In order to satisfy critics and to meet the growing demand for alternatives to ICOs, the crypto community had to adapt. In 2019, decentralized exchanges were still nascent and not designed to facilitate token offerings, lacking the ability to set limits for individual allocation and other key capabilities. This led to the emergence of launchpads, a third-party platform that is connected to the DEX via a smart contract and manages the IDO, vetting projects and enabling allocations limits and other design choices. Launchpads were integral to the evolution of the IDO concept, once again attracting investor attention, and thus reinvigorating IDO activity in late 2020 (Georgiev, 2022). Today, IDOs account for over 85 percent of all token offerings, and their current and most popular form bears little resemblance to the original idea. The success has a two-fold explanation: the crypto community has adapted to the early challenges and developed IDOs into a robust financing method, and the economics of IDOs entail a lower entry barrier in comparison to IEOs. In addition, IDOs represent decentralized fundraising, in line with Nakamoto's vision for cryptocurrencies. In our view, IDOs retain the advantages of IEOs hold in relation to ICOs, while preserving the benefits of ICOs better than IEOs.

In hindsight, the decline of ICOs, combined with the rise of IEOs and IDOs, arguably demonstrates that the crypto community is the driving force behind the development and that has managed to solve the problems inherent in ICOs, rather than any regulatory bodies or other external entities. In our view, the focus on regulation and security tokens reflects that academic scholars and legal institutions view token offerings through the lens of traditional finance and economics, failing to acknowledge the unique nature of the cryptocurrency landscape and its origin as a revolt against the banking system.

3.3.3 Legal aspects of IEOs and IDOs

The legal situation of IEOs and IDOs further illustrates the regulatory uncertainty associated with ICOs and the challenges authorities face in keeping up with a dynamic and fast-evolving market. ICO and cryptocurrency regulations are constantly evolving, and since they vary by jurisdiction, there is no clear consensus as to which exact regulations apply. Due to the novelty of IEOs and IDOs, the legal and regulatory situation is even more uncertain. The lack of academic and government publications regarding IEOs and IDOs makes it a difficult task to decipher the legal situation. While there are some academic papers and government publications regarding IEOs, such as the investor alert published by the SEC (2020) there are almost none regarding IDOs, and other sources available often contradict each other. However, at a fundamental level these methods are all token offerings and therefore should regulation regarding ICOs, and cryptocurrencies in large, apply to all methods. For instance, issuing security tokens using any of these methods requires compliance with securities regulation (Agathangelou, 2021). The decentralization, i.e., having no central authority, of a DEX poses some regulatory issues, however, the initiator(s) of the platform may still be held responsible for legal and regulatory noncompliance (Auffenberg, 2021). As mentioned in section 2.6, the

Infrastructure Investment and Jobs Act, imposed AML and CFT regulations to cryptocurrency exchanges. Even before this, many exchanges had already implemented KYC procedures (a part of AML and CFT regulation) due to requirements in other jurisdictions or concerns over potential regulatory consequences. Despite this, many sources (e.g., Derymova, 2021; Ideasoft, 2021; Binance, 2022; Cryptorobin, 2021; Cointelegraph, n.d.) postulates that IDOs are largely unregulated and that launchpads do not perform KYC on participants. To remedy this conflict, our initial intent was to obtain the KYC requirements for each token offering in our analysis, however, this proved to be difficult as this type of information is not typically available for past token offerings, only for ongoing or upcoming ones. Nonetheless, we observed that (as of March 2022) the two largest launchpads by market capitalization (DAO maker and Polkastarter) require participants to go through a KYC process, while other launchpads leave the decision to the issuer. This misconception may be explained by the fact that DEXs have been under less scrutiny than CEXs due to the difficulties associated with decentralization, despite that they appear to be subject to the same regulation. However, the SEC insists that centralization or decentralization does not matter in terms of legal obligations (Michaels & Kiernan, 2021). Moreover, the U.S Financial Action Task Force (FATF) recently published a draft statement in March 2021 wherein they consider DEXs as Virtual Asset Service Provider (VASP), thus formalizing that both types are governed by the same regulations (FATF, 2021).

DEXs, and by extension IDOs, were likely less regulated initially, and that the above-mentioned sources fail to provide up-to-date information. Hence, one could argue that our argument that the reduced risk for scams and misconduct explains the success of IEOs and IDOs does not hold up, and that it in fact was the regulatory void caused their increase in numbers (particularly IDOs). However, the newly enacted regulations, and clarifications, combined with the fact that many launchpads employ KYC procedures, while IDO activity continue to increase, contradict such an argument.

3.3.4 Comparison of IEOs, IDOs and ICOs

The above-mentioned situation is not limited to legal and regulatory matters. Considering the shortage of literature, we are forced to mainly rely on non-academic sources, particularly regarding IDOs. These sources provide conflicting information in several instances and aspects, likely because the concept of an IDO has changed significantly since its inception, making it difficult to decipher the situation. However, we have cross-checked the material between several sources, and double-checked specific aspects with up-to-date information from firsthand sources, such as the websites of launchpads. Also, it is important to mention that there is no standard definition of an IEO or IDO, and their ways of working may differ between platforms. In the following paragraphs, we compare IEOs to IDOs on a high level of generalization and highlight their differences with ICOs when relevant. Table 2 below provides an overview of the comparison between all three types.

The use of an intermediary is what primarily distinguishes IEOs and IDOs from ICOs. In an IEO, a centralized exchange (CEX) act as an intermediary, whereas this role is taken by a decentralized exchange (DEX) or launchpad platform in an IDO. Although launchpads and DEXs perform many of the functions typically performed by intermediaries, they are not the same as intermediaries in traditional centralized systems (Lisher, 2022). These platforms rely on self-executing smart contracts and are decentralized organizations run by community governance within their network of token holders. Also, they operate with full transparency since all activities within the network is settled directly on the blockchain which is open for anyone to view. As such, no single entity or human possess the authority to hold or control the funds raised in an IDO, or to verify transactions on the platform. Investor funds are directly transferred to the issuer via the smart contracts created by the platform, and the distinction between these decentralized intermediaries is further highlighted by the fact that they neither investors, nor issuers are subject to any intermediary fees apart from gas fees.[39] An IDO can be launched either directly at the DEX or via a launchpad, although most IDOs is held on laundpad platforms (see Cryptorank, n.d.a). As aforementioned, all IDOs were initially held directly at a DEX platform without any form of intermediary functions, but now either the third-party launchpad or DEX performs these functions. CEXs, on the other hand, are highly centralized and governed similar to any other traditional corporation, and act as a traditional intermediary in IEOs. In an IEO, the CEX store and control all investor funds. There is no intermediary at all in ICOs and issuers are solely responsible for the whole process which makes them highly centralized as well.

Intermediaries play an important role in IEOs and IDOs since projects are vetted before being approved to launch at the platforms, thereby avoiding potential scams or junk projects. In the

[39] Fees for transactions, smart contract creation and execution, and other functions on all blockchains. Typically, below 0.3% (Murali, 2021). Note that the gas fees vary between blockchain networks.

due diligence process, the CEX or launchpad evaluate the whitepaper and source code, screen its team members, and ensure that the project goals are realistic and attainable (Anson, 2021; Szczęsny, 2020). Although it varies across platforms, the due diligence tends to be more rigorous for IEOs (Binance, 2022; Craig, 2022). Projects are typically vetted by a small, specialized team at the CEX, and bears resemblance to the due diligence performed in IPOs. Since launchpads are decentralized, their projects are usually vetted by their community members who vote on their approval (Scaleswap, n.d.). Some launchpads, like Polkastarter, use a council to vet projects, where projects having greater than 60 percent of the council's vote are approved for launch (Polkastarter, 2021). The council is an independent group of industry experts, and the seats rotate once per quarter.[40] Although most sources report that the due diligence is more rigorous at a CEX, Polkastarter describes their process as thorough and rigorous. (Polkastarter, 2021). The reputational risk that the CEX or launchpad bears also offers investors an additional level of trust (Anson, 2021). In the case of launching a scam or junk project, the potential reputational damage is arguably greater for a CEX than a launchpad, where the damage accrues to the entity behind the CEX rather than to a large, decentralized community, where there is less at stake per member. In an ICO, there is no due diligence which leaves it up to investors themselves to evaluate the legitimacy of projects themselves, and the fact that issuers repeatedly fail to reveal the identities of their team members, makes the reputational risk negligible (Zetzsche et al., 2018).

Nevertheless, the due diligence also imposes a higher barrier of entry than for ICOs. CEXs charge a high fee (approximately $100,000-1,000,000) for an IEO and investors typically required to go through a KYC process and charged taker and maker fees —approximately $5 to $10 (Prosvirkin, 2019; Anson, 2021). Even though some of the largest launchpads require investors to go through KYC processes, the prevalence of KYC procedures is likely higher for CEXs given the new AML and CTF requirements introduced with the Infrastructure Investment and Jobs Act in 2021, and the fact that it is easier for authorities to target the entities behind CEXs rather than the "ownerless" decentralized networks. IDOs, on the other hand, have changed the economics of token offerings; transaction costs for issuers are near-zero since neither the launchpad nor the DEX charge fees for IDOs (Murali, 2021). Instead, investors are typically required to purchase the launchpad's native token and lock it into a liquidity pool in

[40] For more information see Polkastarter (2021)

return for allocation in the IDO.[41] Thus, the launchpad benefits from the network effects associated with a growing user base, and since the DEX facilitates the secondary market trading of the IDO on its platform, they generate revenue from gas fees. However, one could argue that IDOs that the technical knowledge required to participate in the offering constitutes for a higher barrier of entry in relation to IEOs (Cointelegraph, n.d.). Participants in an IDO are required to have a crypto wallet, and sometimes they must transfer funds to the launchpad's blockchain through multiple steps depending on the wallet's interoperability. In an IEO, participants are only required to create an account at the CEX, similar to investing in conventional stocks.

Nonetheless, as part of the IEO fee, a number of services provided by CEX are included for issuers. Although much of the marketing is conducted through social media channels and communities for all token offerings, additional market activities are organized and covered by the CEX (Szczęsny, 2020). The token contract is also managed by the CEX. Even though the CEX writes the code, they usually have a standard contract that specifies certain requirements regarding design choices, such as the minimum number of tokens issued in relation to the total supply. In IDOs, both these elements are a collaboration between the issuer and the launchpad. Thus, IDO issuers tend to have a large marketing budget, and spend more time and resources on marketing activities in comparison to IEO issuers (Szczęsny, 2020). In IDOs, token contracts also follow certain requirements, but there is more room for project-specific adjustments, and in accordance with transparent nature of decentralization, all token contracts for ongoing and past offerings are publicly available. ICO issuers are responsible for creating the token contract and the cost of development can reach above $10,000 (Prosvirkin, 2019).

The principal advantage of IEOs and IDOs in relation to ICOs is perhaps the guaranteed token listing, and the ensuing liquidity. As aforementioned, many ICOs fail to list their tokens on exchanges since they lack the funds to pay the high listing fees, or they fail to meet the listing criteria, leaving investors without the ability efficiently sell their holdings (Zetzsche et al., 2018). In an IEO, the token is guaranteed to be listed at the CEX where the token offering occurs, whereas in an IDO, the token is listed immediately after the fundraising concludes on the DEX the launchpad collaborates with. DEXs are governed by numerous smart contracts and facilitates trading using liquidity pools where trades are executed using an automated

[41] The allocation can be either guaranteed or lottery based where the chances increase with the number of tokens investors lock into the liquidity pools.

market maker that determines the exchange rate of the pairs based on market conditions (Krishnamachari et al. 2021). The issued tokens are traded in pair with stablecoins or major cryptocurrencies (e.g., Bitcoin and Ethereum) that makes up the liquidity in these pools.[42] Thus, liquidity is provided at all levels, even for smaller altcoins without high trading volumes, although the amount of liquidity available varies between platforms.[43] The liquidity on these platforms is provided by individuals who lock in their funds for interest like rewards (Coinbase, 2022). CEXs, on the other hand, use order books similar to stock exchanges, in which liquidity may be limited when there are not enough buyers or sellers, although CEXs generally have a higher overall liquidity level (Jensen, 2022). ICO issuers can pursue listing on either type of exchange.

Given the above-mentioned characteristics, the different token offering types tend to attract specific projects. The near-zero transaction costs in IDOs makes them attractive at an early stage of the venture and for projects without significant resources, thus IDO firms tend to be young and tend to raise low amounts (John, 2021; Georgiev, 2022). Consequently, IEOs are appropriate to somewhat mature projects that can pass rigorous due diligence and afford the high listing fees, whereby the high levels of liquidity, reputation, and reach of major CEX can prove fruitful for the project. Thus, IEOs also typically raise substantially higher amounts. In contrast, ICO projects vary considerably, ranging from small, dubious projects to multibillion-dollar offerings by well-established multinational firms, comparable in size to the largest IPO offerings.

[42] Stablecoins are cryptocurrencies that are pegged to fiat currencies or exchange-traded commodities, typically U.S dollar or gold. Stablecoins are designed to be less volatile and stable over time and are frequently used as means of payment in cross-chain transactions, or as one of the cryptocurrencies in a liquidity pair in the liquidity pools of DEXs. USD/BTC is an example of a liquidity pair.

[43] See Krishnamachari et al. (2021) for further information.

Table 2

Comparison of Token Offering Types

	ICO	IEO	IDO
Fundraising is conducted at	The issuer's website	The platform of the CEX	Launchpad platform/DEX
Crowdsale Counterparty	The issuer	The CEX	The issuer via smart contracts
Token contract managed by	The issuer	The CEX	Collaboration between the issuer and launchpad platform
Model	Highly centralized	Highly centralized	Decentralized
Intermediary fees	None	High	None
AML/KYC	Sometimes	Mostly	Sometimes
Marketing budget	High – organized by the issuer	Low – organized by the CEX	Medium – collaboration between the issuer and launchpad platform
Due diligence	None	Rigorous	Yes – although the rigorousity varies
Guaranteed listing	No – the startup must reach out to exchange to list its tokens	Yes– at the CEX where the IEO is conducted	Yes – almost immediately on a DEX

Note. This table shows a comparison between ICOs, IEOs, and IDOs. Own creation based on the sources used in the above paragraphs.

3.4 IPO Underpricing Theories

IPO underpricing represents the relative difference between the offer price and the closing price at the end of the first trading day and is one of the most well-documented market anomalies that contradicts the efficient market hypothesis (Alvarez-Otero & González-Méndez, 2006). From 1980 through 2021, the average underpricing in the U.S. IPOs were 18.9 percent, and globally underpricing ranges from 3.3 percent (Russia) to 270.1 percent (United Arab Emirates) (Loughran, 2022). Ibbotson and Jeff (1975) were the first to observe what they called a "mystery", namely that IPO shares were systematically priced below their fundamental value, rendering abnormal first day returns for investors. This led to the emergence of numerous papers aiming to provide theoretical explanations of the phenomenon, and despite the substantial body of research formed over the years, there is no clear consensus on the reasons behind underpricing. Nevertheless, on a fundamental level, the degree of underpricing reflects the risk investors are exposed to in IPO participation (Ritter, 1984). The theories developed thus far are neither mutually exclusive nor individually exhaustive (Loughan & Ritter, 2004). However, there are a handful of theories, or models, that remain cornerstones of IPO literature, and upon which many new theories are based. These include ex-ante uncertainty model, signaling model, and the winner's curse.

Most theories on IPO underpricing are based on the asymmetric information between the different parties involved in the process. All theories on information asymmetry can be traced back to Akerlof (1970), in his paper “Market of Lemons”, he describes how an adverse selection problem in the secondary market for cars arises due to information asymmetry between sellers and buyers. More recently, several theories derived from behavioral finance have emerged as additional explanations of underpricing.

3.4.1 Winner's curse

In his 1986 paper, Rock proposed the famous winner's curse model, whereby he demonstrates that Akerlof's theory also holds for IPOs. In the model, IPO investors are divided into two groups: informed and uninformed investors. Informed investors have the resources required to obtain superior knowledge which helps them to identify promising offerings, resulting in a higher participation rate in these offerings. Uninformed are not able to determine whether an offering is promising or not and are left with a winner's curse: they receive an unproportionally high allocation in overpriced IPOs since informed investors refrain from subscribing to these offerings. Therefore, Rock (1986) suggests that issuers underprice their offerings to compensate uninformed investors to keep them in the market despite the uneven allocation caused by the asymmetric information.

Winner's curse is one of the most well-known models of IPO underpricing, and it serves as the basis for virtually all other models with asymmetric information. There is substantial empirical evidence for the model. Falconieri et al., 2009 and Miller & Reilly (1987) finds significant support for the theory using trading volume as a proxy, implying that when investors are uncertain about the price, the after-market trading volume is high. Chowdhry & Sherman (1996) argues that underpriced IPOs are subject to information leakage about demand, whereas informed investors obtain private information about the demand. Based on the information leakage, informed investors will subscribe to underpriced offerings, resulting in oversubscription. Thus, Chowdhry & Sherman (1996) use shares sold ratio as a proxy for the information asymmetry between investors, and postulate that offerings with more oversubscription are subject to more information asymmetry.

3.4.2 Ex-Ante uncertainty model

In the ex-ante uncertainty model, Beatty & Ritter (1986) draws on the winner's curse model and suggests that there is asymmetric information between issuers and investors in addition to that between investors. This information asymmetry causes ex-ante uncertainty about the after-market equilibrium price, and in turn underpricing arises as a risk premium to investors for the uncertainty. The main reason behind this rationale is that investors are faced with a difficult task in estimating the future value of IPO shares since there is a lack of historical information available about the issuing company. To test their hypothesis, Beatty & Ritter (1986) use gross proceeds as a proxy for ex-ante uncertainty since they suggest that there is less information available on smaller and less known firms, and they find significant support for this. There are numerous scholars that have tested the model using different approaches and consequently there is empirical evidence on several proxies, such as, firm age (Loughran & Ritter, 2004; Habib & Ljungqvist, 2001), trading volume (Miller & Reilly, 1987), and industry (Megginson & Weiss, 1991)

3.4.3 Signaling theory

Signaling theory dates to Spence (1973), where he discusses how job seekers can use certain signals of quality towards potential employers. Ibbotson & Jaffe (1975) suggest that IPO issuers can do the same towards potential investors. Welch (1989) and Allen & Faulhaber (1989) argue that issuers of high-quality IPOs underprice their offerings to distinguish them from low quality IPOs, and thus attract investors. The cost of such a signal would be too high for low quality firms, and thus it is only high-quality firms that can use underpricing as a signal of quality. Welch (1996) suggest that high quality firms are prepared to sacrifice short-term gains in favor of being able to raise more capital in future seasonal equity offerings (SEO). If investors are satisfied with their outcome in the underpriced IPO, the likelihood increases that they will invest in future SEOs (at a higher price).

In addition to underpricing, issuers can signal quality in multiple other ways. Grinblatt & Hwang (1989) suggest that issuers can retain a large fraction of shares as a sign of confidence in future cash flows, this signal attracts investors, leading to oversubscription and a high demand in the secondary market which drives up the price. They find a significant relationship between fraction sold and underpricing in their analysis. Ibbotson & Ritter (1995) suggests that a lock-up period for insiders represents a similar signal, whereas Mohan & Chen (2001) find empirical evidence for this relationship.

3.4.4 Behavioral theories

Many scholars have suggested theories which relate underpricing to investor behavior in an attempt to understand the phenomenon in its entirety since the above theories fail to capture its full effect (Ljungqvist, 2007). The Information Cascade theory is among the most well-cited behavioral theories. Welch (1992) argues that investors are often irrational, basing their investment decisions on trends rather than an estimate of fundamental values. Therefore, if an IPO outperforms (underperforms) an investor's estimate, the investor will adjust his estimation based on other investors' actions and disregard his own. Also, later investors purchase shares above their estimated prices due to that they assume that earlier investors hold information superior to their own. This causes a snowball effect, or an *Information Cascade,* whereas bids early in the after-market serve as a basis for future bids, leading to a cumulative increase in price for well-forming IPOs. This type of investor behavior also touches upon herd behavior theories. Welch (1992) postulates that issuers can boost early performance in the after-market by underpricing their offerings since it will attract many early investors that increases the likelihood of information cascades.

Ibbotson and Jaffe (1975) observed that IPO markets experienced periods of abnormally high and low returns, and that it could be traced back to the number of issues during these periods, whereas a period with a high volume of IPOs is referred to as a hot market. Ritter (1984) suggest that the competition during hot markets leads issuers to underprice their offerings to attract investors, and the cost of such a signal is lower since the overall market receive more attention in these periods. In addition, investors are overly optimistic and accept more risk in hot markets, which drives up first-day returns. The findings of Helwege & Liang (2009) suggest that irrational investors are the principal factor behind the high level of underpricing in hot markets, rather than issuers of high-quality firms underpricing their issues as a signal. Loughran et al. (1994) suggests that issuers time their offerings in periods when market sentiment and valuations are high, rendering investor return to be low in the long run.

Ljungqvist et al. (2006) suggests that there are two types of IPO investors: unsophisticated and sophisticated. Unsophisticated investors are mainly driven by emotions and affected by cognitive biases and are therefore prone to sentiment and treat all information equally relevant, including noise that is irrelevant to the fundamental values of IPOs. Sophisticated investors, on the other hand, interpret information rationally and therefore make unbiased estimates. Ljungqvist et al. (2006) states that in a hot market period, unsophisticated investors are optimistic and will invest in IPOs that trade above their fundamental value in the secondary market, thus leading to high first day returns for early investors. On the contrary, sophisticated investors only invest in underpriced IPOs, and wait until the market turns cold to invest in those IPOs trading above their fundamental value.

3.5 Evidence on ICO Underpricing

Despite being a new phenomenon, there has been considerable research on many facets of ICOs, from both empirical and theoretical perspectives. The theoretical research primarily focuses on the economic benefits ICOs can offer with the use of tokenized business models and network effects, whereas empirical papers tend to focus on financial or legal aspects. Many empirical papers explore the determinants of ICO success, whereas the measures of success include employee growth (Howell et al., 2020), reaching the hard or soft cap (Adhami et al., 2018; Ahmad et al., 2021; Blaseg, 2018), listing on an exchange (Amsden & Schwiezer, 2018, Blaseg, 2018; Benedetti & Kostovetsky, 2018), amount raised (Fisch, 2018; de Jong et al., 2018; Amsden & Schwiezer, 2018), and ex-post performance (Lyandres et al., 2022). Aside from ICO success, there are several scholars that examine, and find evidence of, underpricing in ICOs.

Table 3 presents an overview of the mean and median underpricing observed in ICO literature. The average underpricing is substantially higher than in most IPO markets, which scholars attribute to the fact that ICOs are associated with a greater degree of risk and uncertainty. Considering the inconsistency and paucity of information available to investors prior the ICO, there is substantial information asymmetry between issuers and investors (Zetzsche et al., 2018). Drawing on Habib and Ljungqvist (2001) and Loughran and Ritter, (2004), the fact that ICO firms tend to be younger and smaller than IPO firms further contributes to this situation of asymmetric information. Also, whitepapers tend to be rather technical in nature, which leads to information asymmetry between investors of different technical knowledge (Li & Mann, 2021). Furthermore, the absence of formal requirements and external audits leaves ICOs vulnerable to a wide range of scams and dishonest issuers, which pose a great risk to investors. In addition, the legal uncertainty of ICOs pose a risk for both issuers and investors (Ahmad et al., 2021, Bellavitis et al., 2020).

there is no mechanism to prevent fraud, and investors are left to determine the legitimacy of the project for themselves. Thus, the asymmetric information and heightened risk for fraud associated with the absence of transparency and due diligence in ICOs poses a risk for both issuers and investors.

Table 3

Empirical Evidence on ICO Underpricing

Academic paper	Underpricing measure	Mean	Median	n
Ahmadi et al. (2018)	Offer price to price at closing of the cryptocurrency exchange	919.9%	24.7%	140
Bellativis (2018)	Log opening price to closing price	14%	6%	659
	Log offering price to closing price	39%	40%	300
Benedetti & Kostovetsky (2020)	Offer price to opening price first trading day. Equal weighted return.	179%	-	416
Charson et al. (2018)	Offer price to 5th day closing price	111%	42.5%	95
Drobetz et al. (2018)	Offer price to price at closing of the cryptocurrency exchange	14.8%	0.1%	1403
Felix & Von Eije (2018)	Offer price to price after the first 24 hours of trading.	102%	26%	255
Lyandres et al. (2021)	Offer price to opening price first day	384.39%	46.6%	1007
	Opening price to closing price	9.7%	1.62%	1170
Lee et al. (2018)	Offering price to closing price	158.2%	24.4%	432
Momtaz (2020)	Opening price and closing price after	8.2%	2.6%	302

Note. This table shows a summary of the findings from selected academic papers that examine ICO underpricing.

3.6 Hypotheses

In the design of IEOs and IDOs, several of the problems associated with ICOs are addressed, and the recent development of the ICO market suggests that these changes should be considered successful. We thus argue that these changes reduce the risk surrounding the offering. IPO underpricing is one of the most well-documented phenomena in finance literature, and recent empirical evidence shows that underpricing exists in ICOs as well. Although there are numerous explanations of underpricing, many reflect the risks investors are faced with due the uncertainty and information asymmetry between the different parties in the process. The bottom line is that riskier issues will be more underpriced than less risky issues (Ritter, 1984). We therefore expect that the differences between ICOs, IEOs and IDOs will be reflected in the level of underpricing.

We argue that IEOs and IDOs hold three major inherent advantages in relation to ICOs that reduce the risk associated with the offering. In the following paragraphs, we present these advantages briefly while accentuating the respective dysfunctional aspects of ICOs. [44]

First, *token listing* is guaranteed and occurs shortly after the issuance, ensuring essential liquidity. The listing process for ICOs, on the other hand, lies in the hands of the issuer, and they must manually apply to an exchange (or multiple exchanges) to get listed. The issuers must fulfill the listing criteria of the respective exchanges in order to be accepted and are typically faced with significant listing fees. Empirical evidence from ICO literature shows that issuers encounter difficulty getting listed, either resulting in a long delay or a failure to list the token at all (Benedetti & Kostovetsky, 2018; Amsden & Schweizer, 2018; Lyandres et al., 2022). This can have severe consequences as it jeopardizes the future of the project and leaves investors unable to (efficiently) realize their investments. Moreover, the lack of guaranteed listing renders ICOs vulnerable to scams like rug pulls, where the issuer disappears after the ICO with all the funds without ever trying to list the token. Thus, the uncertainty associated with the listing process for ICOs poses a risk for investors.

[44] See section 3.6.4 for an overview of the characteristics of the different token offering types.

Second, the exchange or launchpad performs *due diligence* on projects before approval to launch on their platform. In contrast, an ICO is solely organized by the issuer and conducted on their website. The lack of any third-party involvement or formal requirements leads to a process characterized by opaqueness and unaudited information (Adhami et al., 2018). Issuers typically disclose a very limited set of information, with the whitepaper generally being the main element. Empirical evidence suggests that the content of whitepapers is inconsistent, misleading, and unaudited, and typically reveal little information besides a brief description of the project and its underlying technology (Adhami et al., 2018; Zetzsche et al., 2018). In addition, it has been observed that there are often mismatches between the actual code and promises in the whitepaper (Cohney et al., 2019). It is reasonable to argue that the inadequate nature of disclosure documents leads to investor distrust that affects all ICOs, including high quality offerings. Furthermore, whitepapers tend to be rather technical in nature, making it difficult for investors who lack fundamental technical knowledge to assess a project's quality (Li & Mann, 2021). This leads to severe information asymmetry between issuers and investors, as well as between investors of different technical knowledge levels. Moreover, without formal requirements and external audits, there is no mechanism to prevent fraud, and investors are left to determine the legitimacy of the project for themselves. Thus, the asymmetric information and heightened risk for scams associated with the absence of transparency and due diligence in ICOs poses a risk for investors.

Third, when investing in an IEO or IDO you deal with a *trusted counterpart* that has a verifiable track record. By all means, IEOs and IDOs are not guarantees for success and there is still the possibility of scams, albeit at a lower risk than in ICOs. As aforementioned, an ICO is organized by the issuer alone, meaning that they are the only counterpart for investors and are responsible for all aspects of the process. This includes key activities such as handling investor funds, source code and token contract creation, and allocation of the raised funds. Although the ERC-20 token standard simplifies much of this for Ethereum based tokens, there is still room for error and misconduct. As an example, while in an IEO the funds are usually divided into tranches (i.e., certain amounts are allocated for specific objectives within the project) controlled by the exchange (Musienko, 2019), and a portion of the funds in an IDO is locked into liquidity pools (Binance, 2022), an ICO issuer possess full control over the funds raised. In addition, Cohney et al. (2019) find several instances where ICO issuers use the funds raised to reward their team members rather than to what was promised in the whitepaper or token contract. While there are examples of high quality ICOs with well-known issuing entities and reputable executives, Zetzsche et al. (2018) finds that more than half of ICO whitepapers do not reveal the identities of the team members and backers or do not provide any contact details to these parties. In addition, there are examples of fraudulent ICOs where the issuer used fake identities (SEC, 2020). As a result, it can be difficult to assess and verify the background, experience, and technical skills of the individuals behind an ICO, resulting in information asymmetry between the issuer and investors. In contrast, at an exchange or launchpad, an investor can access information on past offerings held at the platform, and they typically require issuers to disclose their identities. In this way, an investor can verify, for example, the quality of the smart contract (most platforms use a standard smart contract as a basis for all offerings) (Binance, 2022). This, combined with the reputational risk the platform bears, provides investors with an additional level of trust (Anson, 2021). Thus, the asymmetric information and uncertainty associated with ICO issuers poses a risk for investors.

The above-mentioned effects of the dysfunctional aspects of ICOs touch upon traditional underpricing theories in IPO literature, at least per analogiam. Information asymmetry between issuers and investors causes ex-ante uncertainty, which in turn leads to underpricing as a risk premium (Beatty & Ritter, 1986), drawing on signaling theory, issuers of high-quality offerings underprice to distinguish them from low quality issuers (Ibbotson, 1975; Welch, 1989; Allen & Fallhauber, 1989). Information asymmetry between informed and uninformed investors causes unequal allocation and the issuer must underprice to compensate the uninformed so that they will join the market (Rock, 1986), with greater ex-ante uncertainty, there is more underpricing (Ljungqvist, 2006). Although some studies have found support for these theories in ICOs (e.g., Felix & von Eije, 2019; Benedetti & Kostovetsky, 2021), the evidence is nowhere near as extensive as in IPO literature, thus one should be cautious to claim their validity for ICOs. However, at a fundamental level, riskier issues will be more underpriced than less risky issues (Ritter, 1984). Based on the above discussion, ICOs are riskier than IEOs and IDOs, and therefore should exhibit a higher level of underpricing. Hence, our first hypothesis:

Hypothesis 1: Underpricing is higher in ICOs than in IEOs and IDOs

While there many similarities between IEOs and IDOs, there are nevertheless differences as well as portraited in section 3.3.4. First, in IDOs, the due diligence process tends to be community-driven and less rigorous than in IEOs, and in combination with a lower potential reputational damage, the risk for scam and junk projects should be greater. In addition, the high transaction costs of IEOs (listing fees in particular) should deter malicious issuers and provide greater incentives to build a successful business in the long run. Second, IDOs are associated with more regulatory uncertainty than IEOs. Third, the fact that IDO projects tend to be smaller and younger implies a higher degree of asymmetric information. Thus, we argue that IDOs are riskier for investors than IEOs, and therefore should exhibit a higher level of underpricing. Hence, our second hypothesis:

Hypothesis 2: Underpricing is higher in IDOs than in IEOs

3.6.1 Explanations of underpricing

Besides variables to capture the effect of the different token offering types, our approach to explain underpricing is twofold. First, we use a set of variables from IPO literature to test their relevance for token offerings. These variables are widely used proxies related to asymmetric information and behavioral theories used in the above hypothesis derivation. Second, we use an additional set of variables from ICO literature to control for factors specific to token offerings. These variables represent issue specific factors with proven effects, rather than specific theories, and are important in examining the differences between the token offering types. The following paragraphs outline the theorical and economical arguments behind the predictor variables. See Table X for an overview of the variables and calculations.

Information asymmetry between issuers and investors

Gross proceeds (e.g., Habib & Ljungqvist, 2001; Beatty & Ritter, 1986) and *age* (e.g., Habib & Ljungqvist, 2001; Loughran & Ritter, 2004) are commonly used in IPO literature as proxies for ex-ante uncertainty. The reason for this is that investors generally have more information at their disposal when it comes to larger issues and older firms. Consequently, the lack of information on smaller issues and younger firms renders the investment decision more uncertain and therefore riskier. In line with IPO evidence, Lyandres at al. (2022) and Felix & von Eije (2019) find a significant (negative) relationship between gross proceeds and ICO underpricing.[45] Conversely, Chanson et al. (2018) and Benedetti & Kostovetsky (2021) examine ICO underpricing, and, unlike evidence for IPOs, find that age does not significantly affect underpricing. Nevertheless, given the extensive support in IPO literature, we expect negative signs for both variables.

Issuer retained ratio (e.g., Welch, 1992; Grinblatt & Wang, 1989) is related to signaling theory. Given that issuers know more about the intrinsic value of the company and asset than investors, it is important that they send signals to bridge the information gap. Retained stock and serves as a key signal of quality and intrinsic value. A high ratio of issuer retained shares indicates that the issuer is confident about the long-term performance and expects value appreciation of the issued asset, and thus leading to increased underpricing (Felix & von Eije 2019). In some papers, scholars use *fraction sold* instead of issuer retained ratio, which is simply the inverse, and in that case, the expected sign is the opposite. However, unlike shares in an IPO that typically represent cash flow and/or ownership rights, tokens are dynamic and can represent a wide range of rights and utilities. Tokens can, for example, convey the right to redeem a product or service, or uphold as means of payment in a marketplace. Besides their primary use case, tokens are commonly used for staking rewards, community rewards, community initiatives, or other ex post functions specific to the project. The allocation to these functions is ex-ante the token offering, and the funds are typically held in community-controlled treasury, or reserve (Zhang et al., 2018).[46] *Issuer retained ratio* is typically calculated as the number of shares not offered in the IPO divided by the total number of shares (Felix & von Eije (2019) use the same calculation for ICOs). Considering the ex-ante allocation of tokens to specific functions in the ecosystem, and the fact that the tokens are usually not controlled by the issuer post-offering, we argue that issuer retained ratios in token offerings do not reflect the same signal as in IPOs. Therefore, we use an alternative method to calculate the issuer retained ratio which represents the percentage of the total tokens that is retained by a project's core team and employees. In addition, we use *fraction sold* to account for the (inverse) signal reflected by the traditional calculation of issuer retained ratio in IPO literature. We found low VIF values for issuer retained ratio and fraction sold in the regression models, indicating that the variables are not simply the inverse of each other when using our method. The theoretical model of Gan et al.

[45] Felix & von Eije (2019) use issue size (offer price times the number of tokens offered) instead of gross proceeds (offer price times the number of tokens sold). Both measures are used as proxies for ex-ante uncertainty and are used rather interchangeably in IPO and ICO literature.

[46] Sometimes the funds are controlled by the issuer, but the allocation is still decided ex-ante.

(2021) implies that the more tokens the issuer gives out in the ICO, the fewer tokens it then has left to sell into the secondary market to benefit from future value appreciation. Thus, issuers have less "skin in the game" and are discouraged to invest the ICO proceeds into project development after the token offering, resulting in a lower token price. Lyandres et al. (2022) test this model empirically and find a negative relationship between fraction sold and first-day returns. Thus, we expect a positive sign for is*suer retained ratio* and a negative sign for *fraction sold*.

Lock-up provision (e.g., Mohan & Chen, 2001; Ibbotson & Ritter, 1995) also relates to signaling theory. The expected relationship with underpricing follows the same reasoning as above, namely that issuers who are confident of long-term success install lock-up agreements to signal quality, and hence resulting in increased underpricing. In ICO literature, Bourveau et al. (2018) finds a negative relationship between lock-up provisions and underpricing. We extend the concept by including dummy variables for both public and private lock-up agreements. The first dummy variable represents token offerings where there is a lock-up agreement for the tokens issued in the public token offering, while the second represents token offerings where there is a lock-up agreement for the tokens issued in earlier private offerings (e.g., private, seed, strategic, team). We expect positive signs for both variables.

Information asymmetry among investors

Rock (1986) posits that investors are either informed ex-ante about the after-market equilibrium price or are uninformed about the price. Many scholars draw on this information asymmetry between informed and uninformed investors to explain underpricing. Miller & Reilly (1987) use *trading volume* as proxy for uncertainty among investors about the value of an issue. They argue that underpricing will be greatest for those issues with the greatest uncertainty, and that the level of trading signifies the degree of disagreement among investors. Thus, implying a positive relationship between trading volume and underpricing. This relationship is further strengthened by the findings of Falconieri et al. (2009). In ICO literature, Felix & von Eije (2019) reports a positive relationship between trading volume and underpricing in all five regression models, while Howell et al. (2020) finds higher trading volumes to be associated with ICO success. Therefore, we expect a positive sign.

Underpricing often occurs in oversubscribed IPOs, particularly if there is information leakage about the demand (Chowdhry & Sherman, 1996). Informed investors identify if an offer price is too low and subscribe to the IPO, leading the issue to sell out fast. If the issue reaches the hard cap, uninformed investors in the secondary market may interpret this as a signal that the informed investors are confident in the long-term performance of the project (Felix & von Eije, 2019). In turn, the confidence draws investor interest and more uninformed investors purchase the asset in the secondary market, and therefore underpricing increases. This phenomenon can be further strengthened by behavioral theories, such as information cascade and herd behavior. *Coins sold ratio* is used as an indicator of the long-term performance of the issued asset. Felix & von Eije (2019) find that coins sold ratio has a positive influence on underpricing, but without significance. Despite using a slightly different method, Chanson et al. (2018) draw on the same theory. The authors account for oversubscribed ICOs using a dummy variable and find a significant positive relationship with underpricing. We expect a positive sign for coins sold ratio.

Behavioral theories

Market sentiment is widely used in IPO literature to explain underpricing (e.g., Loughran & Ritter, 2002; Ljungqvist & Wilhelm, 2001; Ljungqvist et al., 2006). During times of high market optimism, investors evaluate the available information on IPOs differently, which may lead to an overestimate of long-term performance of IPO prospects. The most extreme cases of euphoric investor sentiment are usually referred to as irrational exuberance. This reflects an unfounded market optimism, a belief based on psychological factors, such as optimism bias, overconfidence bias, and herd behavior, rather than fundamental valuation. In these situations, irrational investors bid up the price of IPO shares beyond the true value, and thus underpricing increases. Also, issuers tend to not fully capitalize on this optimism which further increases underpricing (Felix & von Eije, 2019). Considering the volatile nature of the cryptocurrency market and the fact that token prices are strongly tied Bitcoin and Ethereum prices (Bellavitis et al., 2020), market sentiment likely plays a significant role in ICO underpricing. Market sentiment, as an exogenous variable, also introduces the effects of external factors into our model, unlike the above variables. There is extensive evidence in ICO literature that market sentiment has a significant effect (positive) on ICO underpricing (e.g., Felix & von Eije, 2019; Momtaz, 2020; Drobetz et al., 2019). Therefore, we expect a positive sign.

Even though an infinite number of combinations between stock price and number of outstanding shares can generate the same valuation, nominal prices have been shown to influence investor behavior in the stock market. Investors tend to overestimate the growth potential of low-priced stocks relative to high-priced stocks, a phenomenon that has been named nominal price illusion (Birru & Wang, 2016). In IPOs, empirical studies have found that nominal *offer prices* are negatively associated with underpricing (Fernando et al., 2004), and it has also been shown to affect pre-listing demands (Sandu & Guhathakurta, 2020). ICO issues tend to have very low offer prices (in dollars $) in comparison to IPO issues. Ofir & Sadeh (2019) suggests that issues use low prices to attract investors, as they may compare tokens to Bitcoin, and therefore buy a large quantity of tokens, hoping they will achieve Bitcoin-like values. Empirical evidence from ICOs indicates that ICO investors also suffer from nominal price illusion (Benedetti & Kostovetsky, 2021). We expect a negative sign for offer price.

Token offering-specific characteristics

Aside from the variables derived from IPO theories, there are several variables that represent characteristics unique to token offerings that are commonly used in ICO literature. These variables do not rely on certain theories but are rather supported by economic argumentation. Considering the explorative nature of this study, these variables may be an important factor in illustrating potential differences between the token offering types. As mentioned in section 2.5.3, many issuers conduct a *pre-sale* prior to the public token offering. A pre-sale is assumed to assist the issuer in setting an appropriate price for the subsequent public sale and provide investors with an indication of the fair token price at the public sale (Momtaz, 2020; Felix & von Eije, 2019). Therefore, the existence of a pre-sale is expected to reduce underpricing. ICOs typically have a *duration* between 25-40 days (Ofir & Sadeh, 2019). The literature on crowdfunding suggests that long durations may signal a lack of confidence in a project (Mollick, 2014), while short durations may encourage potential investors to act quickly (Lukkarinen, 2020). Evidence from the ICO literature indicates that duration is negatively associated with the amount raised (Fisch, 2018; Momtaz, 2020). A *whitepaper* is typically the only disclosure document issued by an issuer in an ICO; they tend to be very simple descriptions of the project and reveal very little about the issuer (Zetzsche et al., 2018). Since whitepapers are not governed by any formal requirements, some issuers opt not to distribute one at all. Scholars in ICO literature view the issuance of a whitepaper as a potential way for issuers to signal quality, however, the effect of this signal is unclear. In most studies, simply disclosing a whitepaper does not seem to have any significant effect, however, several studies have found a significant positive association between whitepaper quality (e.g., number of words, pages, and unique words) and ICO success. Aside from the whitepaper, some projects make their source code available on online code repositories, typically on *Github*, and the effect of the signal follows the same rationale as stated above. Adhami et al., (2018) find that source code disclosure is positively associated with ICO success, while Blaseg (2018) and Fisch (2018) find similar effects with source code quality. However, in our view, disclosure of a whitepaper or source code may also help reduce the information asymmetry between issuers and investors, and thereby reduce underpricing, as opposed to a signal of quality, which would increase underpricing. Thus, we have no prespecified assumptions on the signs for these two variables. ICO studies often include a dummy variable to control for tokens based on the *Ethereum* blockchain. Considering Ethereum's popularity as the most used blockchain for tokens issued in an ICO and given that the ERC-20 token offers investors some trust and quality assurance, scholars assume that Ethereum tokens are positively associated with success and underpricing. Fisch (2018) finds a positive relationship between Ethereum tokens and amount raised, while Momtaz (2020) finds a positive relationship between Ethereum tokens and both amount raised and underpricing. We also extend this by including dummy variables for additional blockchains, such as Binance Smartchain and Solana, although without prespecified assumptions on the signs, since no other studies are yet to do so. Lasty, we control for categories (e.g., gaming, DeFi, NFT, business). Most scholars do not control for this, and those who do use different categories from ours (e.g., Felix & von Eije, 2019). Therefore, we have no prespecified assumptions on the signs for the respective categories either. See Table 6 in section 4.4.3 for an overview of all variables with the respective expected signs.

3.6.2 Excluded explanations of underpricing

In addition to the above variables, there are further explanations that potentially could be important to include in the analysis. ICO and IPO literature contains a wide range of theories and variables, some of which are unsuited for token offerings (e.g., underwriter theories) or for IDOs and IEOs (e.g., ICO ratings and listing dummies), others are developed to answer narrow research questions. ICO ratings, or token ratings, are frequently used as a proxy for project quality in ICO literature, as there are many websites that review and evaluate ICO projects based on metrics such as management team, vision, and ICO profile. Occasionally, exchange platforms provide "analyst" ratings on the IEOs launched through their platforms. Most ICO rating websites rate only ICOs and IEOs, some do offer IDO ratings as well, but to a much lesser extent. Adding ratings to our analysis would therefore result in hundreds of missing data points. Ratings are also subject to bias. There are no industry standard guidelines for how projects should be rated, nor are there any professional standards or quality control systems for the analysts that rate projects (Anson, 2021). Furthermore, issuers must pay a fee to receive a rating, and the rating websites usually offer different levels of promotional packages. Hence, this raises a potential concern that issuers that purchase more premium packages are likely to receive a higher rating. According to a recent report by Swiss firm Alethena, exchange platforms offer higher ratings in exchange for a fee (Anson, 2021). As mentioned in section 3.6.3, we intended to include individual KYC requirements in the analysis, both to provide insight into the current regulatory environment for token offerings, as well as an explanation of underpricing. However, we were forced to exclude this due data unavailability. We also excluded different cryptocurrency types (coins, utility tokens, and security tokens) from the regression analysis since coins and security tokens only accounted for a very small fraction of the total sample. In light of the exploratory nature of this study, apart from the variables designed to capture the effect of the different token offerings types, we consider the above variables adequate to provide a representation of the potential differences between token offerings and to represent the risks we used to formulate our hypotheses.

4. Methodology

The following chapter presents the methodology used in this paper. Section 4.1 is an introduction to the methodology. Section 4.2 describes the data collection process and the problems accompanying this. Section 4.3 presents final sample and the data cleaning performed. In section 4.4, we present the statistical tests used in the analysis, as well as the assumptions behind these tests and how they were tested.

4.1 Introduction

In line with most scholars in the ICO field, we adopt a quantitative approach to explore the underpricing phenomenon and its driving forces. The methodology has been developed largely based on the few studies available that examine ICO underpricing (e.g., Felix & von Eije, 2019; Momtaz, 2018; Adhami et al., 2018; Benedetti & Kostovetsky, 2021), particularly the approach taken by Felix & von Eije (2019). Further inspiration has been drawn from IPO studies that compare the level of underpricing between subgroups (e.g., Kliger et al., 2012; Keef et al., 2015). In order to test our hypotheses, we conduct a univariate analysis using t-tests and an ANOVA test, and a multivariate analysis using several regression models to capture possible explanations of underpricing. The analysis is performed on a final sample of 745 token offerings.

4.2 Data collection

Due to the decentralized and unregulated nature of the crypto market, information is scattered across a multitude of heterogeneous online sources, which means no single source can provide all the data required for this study. Well-regarded databases that are widely used to obtain data for finance studies (e.g., Thomson Reuters and Bloomberg) typically only provide market data on some tens of the largest cryptocurrencies. While some crypto sources offer API solutions for market data (e.g., Coinmarketcap.com and Cryptorank.io), the plans that include the amount of historical data we need are very costly.[47] Therefore, the data collection has relied on hand collecting (against the recommendation of our supervisor) and verifying data across multiple sources, thus making the process very time-consuming and vulnerable to human error.

[47] We reached out to CoinMarketCap to request a customized student plan and were offered their standard plan with an increased historical data window for $375 per month.

The initial set of token offerings was obtained from CryptoRank, a platform that aggregates token offerings and market data from over 90 exchanges, 70 launchpads, and numerous news providers. Scholars within the ICO field have typically used other aggregator platforms as data sources, particularly ICObench.com (see Li & Mann (2021) or Lyandres et al. (2022) for an overview). While we initially intended to use a source that previous studies have used as a sign of good practice, we quickly discovered that these sources are either infrequently updated or simply no longer available. As an example, ICObench.com has not published any new token offerings since June 2021. Aside from this, it is common that aggregator and listing platforms exclude either IDOs or IEOs and IDOs jointly, and that they to some degree depend on issuing firms to request inclusion on the list of upcoming token offerings, whereas the listing criteria tend to differ among the platforms. Hence, the number of token offerings listed vary greatly among platforms. Based on our search for alternative data sources, CryptoRank was found to have by far the most token offerings during the time period in question. We did discover that a few token offerings from other platforms were not included on CryptoRank, however, the majority was token offerings held before 2019. Therefore, we did not attempt to use multiple sources to compile a data set, since the small increase to our already adequate sample size would not justify the additional time and effort required.

In order to construct the variables used in the analysis, all data had to be hand collected except for *market sentiment*, which was calculated using daily OHLCV values obtained as a .csv file from the CCi30 index website. The CCi30 index tracks the 30 largest cryptocurrencies by market capitalization and is widely used ICO literature (e.g., Felix & von Eije, 2019; Momtaz, 2018). In terms of issue-specific data, it is only market data that can be argued to be at the same level of consistency and reliability as the CCi30 index. Even though it is standard practice in ICO studies to use market data from CoinMarketCap, we use CryptoRank as our primary source for market data. CoinMarketCap is generally regarded as the most reliable and comprehensive database for cryptocurrencies, however, in comparison to other aggregator platforms, CoinMarketCap have relatively strict listing criteria for both cryptocurrencies and exchanges (Momtaz, 2020; Felix & von Eije, 2019). [48] Given this, a token may have been traded before it was listed on CoinMarketCap. Amsden & Schweizer (2018) finds that 42 percent of tokens in the sample are traded on an exchange, but only 36 percent are listed as traded on

[48] Some scholars also report that CoinMarketCap requires a token to be listed at two separate exchanges in order to be listed at their platform (e.g., Felix & von Eije, 2019). However, this seems to have been changed. For the current listing criteria, see CoinMarketCap (2022) and CryptoRank (n.d.b)

CoinMarketCap. While evaluating data sources, we found several instances where a token had been traded for several days or even months before it was listed on CoinMarketCap. While there were discrepancies in the first trading day between CoinMarketCap and other sources, the market data was consistent in periods when the token was listed at all sources. However, using an alternative platform is not a guarantee that this will not happen as there is a possibility that tokens are listed on CoinMarketCap before other platforms. Although, it is arguably less likely due to the strict criteria of CoinMarketCap. In our view, the use of market data from CoinMarketCap entails a risk to capture an inaccurate level of underpricing. Upon hand collecting market data, we observed a trend that token prices rose immensely immediately after being listed on an exchange and then declined sharply shortly thereafter. As such, this strengthens the above argument since it is possible to inadvertently misrepresent the true level of underpricing if a later closing price is used. Thus, we argue that measuring underpricing correctly (i.e., the difference between the offer price and the price at the end of the *first* trading day) outweighs the possible concerns of using a source not previously used in ICO literature.

Among the variables, only *age* was collected from a non-crypto related source. Since issuers might not disclose the issuer's legal entity or simply are not a registered business, we follow the approach of Benedetti & Kostovetsky (2021) and use the time between the start date of the token offering and the creation date of the Twitter account associated with the token as a proxy for the age of the issuer. In the few instances where no Twitter account existed, we instead used the creation date of the Telegram channel. The data required to calculate all other variables were collected using this approach:

1. First, we view the information about the token offering available on CryptoRank and cross-check it with icodrops.com. If the information is consistent, the data is accepted and recorded in the data set.
2. If the token offering is not listed at icodrops.com, we use the same procedure but turn to Crypototem.com and/or ICOmarks.com instead. We accept data which is consistent across a majority of websites in the event that there are discrepancies between sources. The observation is excluded if the data is inconsistent between all sources, and if the token offering is only listed at CryptoRank, we accept that data.
3. In the event that data is missing on one or more variables, we follow the same procedure as in step 1 and 2. When none of the secondary sources provide the data, we turn to primary sources. These typically include the respective exchanges or launchpads,

whitepapers, as well as publications on the issuer's Medium page. The observation is excluded if no data can be found.

One could argue that it would be a better choice to rely on primary sources since they are generally considered to be more reliable than their secondary sources (Stock & Watson, 2020). However, Zetzsche et al. (2018) highlight that the unregulated nature of the ICO market means that there are no formal requirements for disclosure documents and that the issuer is not subject to any regulations regarding the disclosed information. As such, whitepapers are voluntary, and the information tends to be unaudited and opaque. In addition, Lyandres et al. (2020) find that 37 percent of the whitepapers in their sample have been updated and that only 8 percent of the whitepapers represent information available to the investors at the time of the ICO. Changes in the whitepapers often concern crucial information, which introduces a potential look-ahead bias. While we collected our data, we found that whitepapers were often updated and as such did not include information about the token offering, and there were several cases where no whitepaper was available because the project had been abandoned, or no whitepaper had been published at all. Also, it was difficult to find data on the outcome of the token offering, possibly because the fundraising goals were not achieved. Data from aggregators is less likely to exhibit a look-ahead bias since the information is published in advance of the token offering, and the aggregator has no incentives to update it thereafter. Moreover, aggregator data are unlikely to suffer from survivorship bias because they retain data on inactive tokens.

The above-described process highlights the lack of consistent and reliable data which emphasizes token offerings as a nascent and imperfect market with severe information asymmetry. Data limitations remain to be the biggest limitation in ICO literature and of this paper. Lyandres et al. (2022) devotes a large section of their paper to data quality, and it is an excellent read for more on this topic.

4.3 Data cleaning and sample

The initial list retrieved from CryptoRank consisted of 1997 token offerings. Given that issuers often conduct multiple token offerings of different types and/or at more than one exchange or launchpad, preliminary data cleaning was necessary. 154 issuances that involved multiple types of token offerings were excluded as such observations would violate the independence assumption of the statistical tests used. In the occurrence of multiple offerings of the same type, we simply removed the duplicates and kept one observation per project. In cases where the offerings were conducted with different prices, we calculated a weighted average offer price based on the number of tokens issued in each offering. As such, a total of 1044 duplicates were excluded. We had to exclude 39 observations for which tokenomics, offer prices, or market information were not available in any primary or secondary source. In four cases, there were no Twitter or Telegram accounts associated with the issued token or the accounts had been deactivated because the project was abandoned. We discovered seven cases in which the offering resembled a seasoned equity offering rather than an initial issuance since the token was already listed prior to the offering. Upon testing the assumptions of the Gauss-Markov theorem, we identified four outliers in the residuals of our regression models. In total, the data cleaning rendered a loss of 1252 observations (see Table 4).

The final sample used in the analysis consists of 745 token offerings with 16 variables and some categorical data across a period of 1.5 years between 15-07-2019 and 31-12-2021. The former date represents the end date of the first IDO with sufficient information available. Regarding ICOs and IEOs, an earlier start date would have provided a larger sample size. However, we argue that a longer time period would not be representative of the current market considering that the introduction of IDOs has changed the dynamics of the token offering market.

Table 4

Data Cleaning and Sample

Process	Observations
Initial sample	1997
Overall loss	-1252
Duplicates	*1044*
Multiple offerings using different methods (ICO, IEO, IDO)	*154*
Missing tokenomics	*15*
Offer price not set	*12*
Missing market data	*12*
Listed prior offering	*7*
Missing information on firm age	*4*
Outliers	*4*
Final sample	745
Initial Coin Offerings (ICOs)	*51*
Initial Exchange offerings (IEOs)	*49*
Initial DEX offerings (IDOs)	*645*

Note. This table shows the initial sample and final sample, as well as the reasons for which observations were excluded

4.4 Hypothesis testing

In this section we present the method and statistical tests performed to test our hypotheses. The tests rely on a set of assumptions that are presented in the running text along with the adjustments to fulfill them. We will devote a longer section to the assumptions of the Gauss-Markov theorem that underlie our regression models. We take a two-pronged approach to test our hypotheses. First, we juxtapose ICOs with IEOs and IDOs jointly in line with our first hypothesis, and then we analyze the offering types separately to test the second hypothesis, and as an alternative for the first hypothesis

4.4.1 Underpricing definition

Underpricing serves as the dependent variable in all tests. In the ICO literature, different indicators are used to measure underpricing (see Ofir & Sadeh (2019) for an overview). We measure underpricing by its classic definition in IPO literature, namely the difference between the offer price and the closing price at the end of the first trading day (in line with e.g., Felix & von Eije (2019) and Adhami et al. (2018)). In IPO studies, the closing price at the end of the first trading day simply represents the stock price at the closure time of the local exchange where the stock is traded. Cryptocurrencies, on the other hand, are traded continuously and therefore no closing time is available. For that reason, we define the closing price as the token price 24 hours after trading began, which is consistent with most ICO studies. In this instance, our method of hand collecting market data actually provides more accurate figures. To our knowledge, all ICO studies gather market data from CoinMarketCap using their API. While it is an effective method, the data provided is in the form of OHLC figures in a 24-hour format. CoinMarketCap uses the same 24-hour time period for all its tracked cryptocurrencies and therefore it is unlikely that the closing times represents a full 24 hours of trading for the respective token offerings. Using hand-collection, we can identify the unique 24-hour time period of each observation and thus accurately record closing prices based on a full 24 hours of trading, with an error margin of no more than a few minutes. Underpricing is given by Equation (1):

$$Underpricing = \frac{P_1 - P_0}{P_0} \quad (1)$$

$P_0 = Offer\ price$
$P_1 = Price\ after\ 24\ hours$

In addition to the above raw measure of underpricing, we also use a market-adjusted underpricing as a robustness test in all three tests due to the volatility of the crypto market.
In line with Felix & von Eije (2019), we adjust the underpricing by subtracting the crypto market return, which corresponds to the 24-hour return of the CCi30 index for the respective listing days. Market-adjusted underpricing is given by Equation (2):

$$Market\ Adjusted\ Underpricing = \frac{P_1 - P_0}{P_0} \tag{2}$$

$P_0 = Offer\ price$
$P_1 = Price\ after\ 24\ hours$
$M_1 = Market\ Opening\ price\ offering\ day$
$M_0 = Market\ price\ 24\ hours\ after\ offering\ day$

4.4.2 Comparison of mean values

We compare the level of underpricing across the different offering types using two-sample Student's t-tests and a one-way ANOVA test. These parametric tests determine if the population from which the samples are drawn is equal in the terms of their mean values. In this way, the tests can be used to determine whether mean differences observed between samples are significant or simply due to random chance (Stock & Watson, 2020). The two-sample Student's t-test is used to compare the means between *two* groups, whereas the one-way ANOVA test is used to compare the means between *several* groups. While it is possible to perform multiple t-tests to compare each group against the other, the risk of committing a Type I error (rejecting the null hypothesis when it is in fact true) increases with each t-test.[49] On the other hand, it is impossible to compare all groups using the same ANOVA test since the observations in the group containing both IEOs and IDOs are the same as in the separate groups, which would violate the independence assumption. Thus, we use both tests.

[49] When α=*5 percent* the risk of committing a Type I error is 5 percent. Performing, for example, three t-tests increases the risk to 14.3 percent.

The two tests are based on the same underlying assumptions, namely that the populations follow a normal distribution, the samples are independent of each other, and the variance of the samples are equal. Given the fact that the distribution of the populations is unknown, this assumption is tested by checking if the residuals of the model are normally distributed.[50]A common misconception, or simplification, is that each sample should be normally distributed. Normality of the overall residuals is a much stronger assumption. However, if the samples follow a normal distribution, it is likely that the residuals are normally distributed (Stock & Watson, 2020). Upon examining the raw data, we found that the level of underpricing was highly (positively) skewed and heavily tailed with outliers in each group. Neither the level of underpricing in the samples nor the residuals of the initial tests using raw data followed a normal distribution. We identified this using QQ-plots, a box plot with outliers, kurtosis and skewness measures, and multiple statistical tests (e.g., Shapiro-Wilk and Jarque-Bera). See Appendix B1 for an overview of the normality tests on the raw data.

T-tests and ANOVA are both sensitive to outliers, as they are given an unproportionally large influence which can cause severe distortions to the estimates and in turn the t- or F-statistic (Stock & Watson, 2020). In order to address this and make the data better fit a normal distribution, we tried several methods proposed by Stock & Watson (2020), including winsorizing and log-transformation, as well as combinations thereof. Since the dataset contained many outliers, we initially intended to winsorize the data as it is a common method for reducing the impact of outliers while keeping the observations. However, winsorizing was attempted at different levels and satisfactory results were obtained first at a 80 percent winsorizing, we consider that a 10 percent modification to each tail risks making the data significantly biased. The best results were obtained using logistic transformation without any winsorizing. We use the adapted natural logarithm given by adding a value of 1 to the underpricing ratio before the transformation. In this way, the log-transformation does not generate missing values for observations with negative underpricing. Despite the transformation, we had to reject the null hypothesis of a normal distribution in some of the normality tests, although with a much smaller margin than before. In the residuals of the t-tests

[50] In theory, it is the error terms rather than the residuals that should follow a normal distribution. An error is the difference between the observed value and the true value, whereas a residual is the difference between the observed value and the predicted value by the model. In a t-test or ANOVA test, residuals are calculated as the difference between the mean and observed value. Error terms is a theoretical concept that can never be observed, the residuals are provided by the model and can be seen as estimates of the error terms. Hence, the residuals are used to test the normality assumption.

and ANOVA tests, there were no outliers, but in the regression models, four outliers were identified[51]. After removing these outliers, all normality tests conclude that both the samples and residuals of the t-tests and ANOVA test follow a normal distribution. Considering the large sample size, we consider that achieving normality justifies the exclusion of these four outliers. The normality tests on the transformed data with the outliers excluded are displayed in Appendix B2.

The independence assumption implies that all samples and observations should be independent of one another. The samples are independent in the sense that no observation is present in multiple groups used in the same test. However, we discovered indications of autocorrelation in the residuals of both tests (see Appendix B3 for a correlogram of the ANOVA). This violates the independence assumptions as there should be no relationship between the observations within the groups. Autocorrelation, or serial correlation, represents the correlation between a time series and a delayed version of itself over successive time intervals (lags) and measures the linear relationship between a variable's current value and its past values (Smith, 2021). The presence of autocorrelation implies that the value of one observation can be in part predicted by the value of the preceding observation and as such introduces a bias to the model and likely leading to overestimated test statistics (Stock & Watson, 2020). Autocorrelation can be either negative or positive and occurs in a time series due to seasonality or other trends. The autocorrelation in our sample is likely since the data is recorded over time and collected in a chronological order. In addition, time series data from the stock market often exhibit autocorrelation since past returns can be used to predict future stock prices (Martin & Xia, 2021). There are several alternative methods to Student's t-test that corrects the standard errors for autocorrelation. Yilmaz & Aktas (2017) use a simulation study to compare the performance of five alternative approaches with respect to their empirical power and Type I error probabilities. They find that when $n > 20$ and the level of autocorrelation is low or moderate, the alternative t-tests yield results similar to Student's t-test. Given these findings and the fact that the correlogram in Appendix B3 indicates a low level of autocorrelation, we use Student's t-test with classic standard errors. In the ANOVA test we use heteroscedasticity and autocorrelation (HAC) robust standard errors, also known as Newey-West standard errors. This approach is derived from the work of Newey & West (1987) in which the authors introduce a weighting scheme to the standard errors in the design matrix of a regression model. The weights

[51] Based on an outlier limit of 2.2 standard deviations.

decrease up to a given lag in order to assign disturbances farther apart less weight. This ensures that the design matrix converges to a finite matrix and that the resulting covariance matrix becomes positive semi-definite (Newey & West, 1987). In this way, Newey & West (1987) creates a robust covariance matrix that handles the common problem of autocorrelation and heteroskedasticity in time series data. The lag length, or number of lags, considered in the model is given by the truncation parameter *m*, we use the rule of thumb ($m = 0.75T^{\frac{1}{3}}$) proposed by Stock & Watson (2020). This formula determines *m* as a function of the sample size and assumes that there is a moderate amount of autocorrelation. In our case, *m* equals 6.799 and is rounded up to 7. Besides the Newey-West standard errors, there are several alternatives (mostly to correct for heteroskedasticity) and it has become standard practice to use robust standard errors in empirical finance research (Felix & von Eije, 2019).

The equal variance, or homogeneity of variances, assumption states, as the name implies, that the variances of the different samples should be equal. We test this assumption by performing Fisher's F-test and Levene's test in conjunction with the t-tests and ANOVA test respectively. We perform three tests in total and cannot reject the null hypothesis that residuals are homoscedastic in any group, thus no further actions are required. We follow the recommendation of Stock & Watson (2020) to use Student's t-test when variances are equal. The alternative Welch's t-test for unequal variances can also be used when variances are equal and will yield similar results to Student's t-test, albeit with less power (Stock & Watson, 2020). Welch's ANOVA is an alternative to the classic one-way ANOVA if the homogeneity of variances assumption is not met; however, even if the variances were unequal, the HAC robust standard errors also correct for heteroskedasticity in addition to autocorrelation. See Table 8 and 9 in section 4.4.2 for the results of the homoscedasticity tests.

Despite not being an assumption, the different sample sizes used in our tests can entail reduced empirical power. Some scholars recommend using Welch's t-test and ANOVA or other non-parametric alternatives when sample sizes are unequal. However, when the above assumptions are met, they should perform similarly. As a robustness test, we tested the Welch alternatives and found that they produced almost identical results to Student's t-test and the one-way ANOVA with HAC robust standard errors.

Given the above assumption validation and adjustments, we begin by conducting two two-sample Student's t-tests in line with our hypotheses. The first test compares ICOs to IEOs and IDOs jointly (H1), and the second test compares IEOs to IDOs (H2). The test is two-sided and assumes in the null hypothesis that there is no difference in means between the samples. The test statistic follows a Student's t-distribution with *v* degrees of freedom when the null hypothesis is true and is given by Equation (3):

$$t = \frac{\underline{x}_1 - \underline{x}_2 - D_0}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \sim T_v \quad (3)$$

$$v = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\left(\frac{s_1^2}{n_1}\right)^2 / (n_1 - 1) + \left(\frac{s_2^2}{n_2}\right)^2 / (n_2 - 1)}$$

$\underline{x}_1 = \text{ Underpricing mean in Group } x$
$\underline{x}_2 = \text{ Underpricing mean}$
$D_0 = \text{Mean difference under the null hypothesis}$
$s_1^2 = \text{Variance in group } x$
$s_2^2 = \text{Variance in group } y$
$n_1 = \text{sample size group } x$
$n_2 = \text{sample size group } y$

Following this, we conduct a one-way ANOVA test on all three groups of offering types separately. We use ANOVA to test both hypotheses since they together imply an order of ICO>IDO>IEO in the level of underpricing. The test is two-sided and assumes in the null hypothesis that there is no difference in means across the samples. The test statistic follows a F-distribution with *df* degrees of freedom when the null hypothesis is true and is given by the equations in Table 5.

Table 5.

ANOVA Equations

Source of variation	Sum of squares	Degrees of freedom	Mean squares	F
Within groups	$SSW = \sum_{j=1}^{k}\sum_{j=1}^{l}\left(X - \bar{X}_j\right)^2$	$df_w = k - 1$	$MSW = \frac{SSW}{df_w}$	$F = \frac{MSB}{MSW}$
Between groups	$SSB = \sum_{j=1}^{k}\left(\bar{X}_j - X\right)^2$	$df_w = n - k$	$MSB = \frac{SSB}{df_b}$	
Total	$SST = \sum_{j=1}^{n}\left(\bar{X}_j - X\right)^2$	$df_t = n - 1$		

Note. This table shows the equations used for ANOVA.

No significant differences were found in neither the t-tests nor the ANOVA test, thus no post hoc tests were performed.

4.4.3 Regression analysis

We conduct five regressions models according to the ordinary least squares (OLS) method in order to examine the relationship between underpricing and the different offering types. The rationale behind this is twofold, first, the use of regression analysis to examine hypotheses related to underpricing is standard practice in IPO and ICO literature (e.g., Felix & von Eije, 2019; Momtaz, 2018; Adhami et al., 2018; Kliger et al., 2012), and second, the Gauss-Markov theorem states that, under certain conditions, the ordinary least squares (OLS) estimator is the best linear unbiased estimate (BLUE). In order to explore underlying factors that drive underpricing, we use a set of 20 predictor variables, divided into independent variables and control variables. The independent variables account for the different token offering types, whereas the control variables represent asymmetric information and behavioral theories that originates from the IPO literature, as well as factors specific to token offerings that are commonly used in ICO studies.

The t-test, ANOVA, and OLS regression are all versions of the general linear model as they can be written as a regression equation (Graham, 2008). As such, the same fundamental assumptions underpin the models, although with some differences. The assumptions presented in the previous section extend to Gauss' theorem (1823), while the assumptions are reduced in the Gauss-Markov theorem following Markov's work (1912). Gauss provided proof for his theorem under the assumptions of normality and independence, while Markov dropped the normality assumption and stated that the error terms only needed to be uncorrelated and not independent. Normality of the error terms is therefore not per se an assumption following the latter work. However, normally distributed error terms generate reliable confidence and prediction intervals and as such allow statistical hypothesis testing (Frost, 2020). Thus, it is common for scholars to test for normality in OLS regression models as well. The standard Gauss-Markov assumptions are given by Equation (4):

$$\begin{aligned}
&1.\quad E[\in_i] = 0 \\
&2.\quad Var(\in_i) = \sigma^2 < \infty, \forall i \\
&3.\quad Cov(\in_i, \in_j) = 0, \forall i \neq j
\end{aligned} \tag{4}$$

The Gauss-Markov theorem (4) states that the error terms of a given linear model should be uncorrelated, have equal variances and a conditional mean of zero in order for the OLS estimator to be the best linear unbiased estimator. What exact assumptions are suggested and used varies, some use the three standard Gauss-Markov assumptions, and there is proof that the assumptions can be relaxed further (Rothman, 2020), while others recommend additional assumptions of other classical linear regression models (e.g., independent and identically distributed random variables (i.i.d)) (e.g., Stock & Watson, 2020; Olsson, 2002). In addition to the three standard Gauss-Markov assumptions, we test for normality and multicollinearity, and discuss the exogeneity and inherent linearity assumption. As noted in the previous section, error terms, or standard errors, are a theoretical concept and unobservable, therefore the residuals of the regression models are used to validate the assumptions. In regression models, residuals are the differences between the observed value and the predicted value of the model, taking all predictor values into account. The addition of predictor variables to the models requires a different approach and validation methods than used for the t-tests and ANOVA.

Although linearity is not explicitly stated as an assumption in Gauss-Markov, it is an implicit assumption in all *linear* regression models. Regression models are linear when all terms in the model are either a constant or a product of parameter and a predictor variable (Stock & Watson, 2020). The relationship between the dependent variable and the predictor variables does not need to be linear, the model only needs to be linear in the parameters. In this way, linear models can exhibit curvature by including log transformed variables or nonlinear variables such as polynomials. Regression models are therefore linear if the equation, or function, is correctly specified in accordance with the above criteria. See Appendix D1 for the equations of all five regression models.

Exogeneity is the condition when all predictor variables are uncorrelated with the error term; when this type of correlation is present, we have endogeneity. This can occur due to simultaneity bias, measurement error in the predictor variables, or omitted variable bias, and can lead to under- or overestimated coefficients (Frost, 2020). Simultaneity bias occurs when the model exhibits causal correlation in two directions at the same time, in other words, that one or more predictor variables are influenced by the dependent variable. Since we use predictor variables used in previous studies, we assume that simultaneity bias is not present. [52] Measurement errors can arise from many sources, and in practice they are likely to some degree (Stock & Watson, 2020). Considering the inconsistent data sources described in section 4.2, we suspect some measurement errors in the predictor variables that could lead to bias in the regression models. Omitted variable bias occurs when one or more important predictor variables are not included in the model (Stock & Watson, 2020). In a new field, there may be additional variables of relevance that have yet to be incorporated, but as in the case for simultaneity bias, we use well-documented variables from IPO and ICO literature to adequately address this. There is, unfortunately, no way to test for omitted variable bias, although some scholars use the Ramsey RESET test, but it is a test for functional form rather than omitted variable bias (Felix & von Eije, 2019; Godfrey & Orme, 1994).

Under the assumption of zero conditional mean, the error term is expected to have a value of zero given any values of the predictor variables (Stock & Watson, 2020). The error term

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[52] We use dummy variables for the blockchains that the tokens are based on, which has not been done before in ICO studies. However, scholars usually include a dummy variable for ERC-20 (Ethereum based) tokens, and this can be considered a similar approach. There is no logical reason why this would entail a reverse causation as the choice of blockchain is decided ex-ante the token offering.

accounts for the variance in the dependent variable that the predictor variables do not explain, and its value should be determined by random chance (Frost, 2020). In order for the regression model to be unbiased, the error term must not exhibit any systematic patterns and have a mean of zero. Any deviation from zero mean means that the model systematically under- or overestimates the observed values. Including a constant (Y intercept) in the regression equation ensures that the mean of the residuals equals zero (Frost, 2020). Thus, the assumption is fulfilled when the regression equation is correctly specified.

Similar to underpricing, raw data for most predictor variables were non-normally distributed and tended to be positively skewed and heavily tailed. As with t-tests and ANOVA, OLS regressions are sensitive to outliers (Stock & Watson, 2020). Thus, we log transformed all variables except *Market sentiment* and *Issuer retained ratio*. As aforementioned, the normality tests still rejected normality and by using a box plot of the residual, we identified four with outliers that were consequently excluded. After removing the outliers, we could not reject the null hypothesis of normality of the residuals using the Shapiro-Wilk test in all models except model (3). Neither log transformation nor winsorizing rendered the variable *Coins sold ratio* to follow a normal distribution, likely because there were few examples of over- or undersubscription in the sample. Nevertheless, excluding the variable from the regression models did not improve the results, therefore we decided to keep it.[53] Appendix C1 displays kurtosis and skewness values, box plots with outliers, QQ-plots, and Shapiro-Wilk tests of the residuals before and after the transformation.[54]

Uncorrelated error terms means that no autocorrelation is present; the error terms should be uncorrelated with each other, and as such, the error term of one observation cannot be used to predict the error term for the next observation (Frost, 2020). As with the ANOVA test, we detected autocorrelation in the residuals of the regression models. We tested for autocorrelation using the Durbin-Watson test, and the null hypothesis of no autocorrelation was rejected in all models except model (4). Therefore, we use HAC robust standard errors in the four regression

[53] We use Coins sold ratio in logarithmic form because it gives better results compared to winsorizing (kurtosis=86,710, skewness=-6.468).

[54] The results of the Shapiro-Wilk tests are presented for all five models, while for the other validation methods only results for model (1) are shown. We performed all validation methods for each model but decided not to add them to the Appendix since they take up space without adding any value. In the case of any discrepancies between the models regarding any assumption we mention it in the running text.

models with autocorrelation. For each model, the truncation parameter is determined by the rule of thumb formula in section 4.4.2. See Appendix C2 for the Durbin-Watson tests.

In addition to autocorrelation, multicollinearity is another type of correlation that might arise from the inclusion of predictor variables in a regression model. Multicollinearity refers to the correlation between predictor variables, and to fulfill the assumption no predictor variable should be a perfect linear function of another predictor variable (Stock & Watson, 2022). Perfect multicollinearity almost never occurs in practice, but even high values can cause inflated standard errors. As a result, the model produces less precise estimates, and the coefficients of the predictor variables can be very misleading. To test for multicollinearity, we calculated Variance inflation factors (VIF) for the predictor values in our regression models. A VIF value quantifies how much the variance of a given variable is inflated due to collinearity with other predictor variables (O'Brien, 2007). In contrast to pairwise correlations, VIF accounts for the correlations between a given variable and all other predictor variables. The square root of a VIF-value represents how many times larger the coefficient of a given predictor variable is than if that variable had 0 correlation with the other predictor variables. Despite being a widely used method, there is no formal threshold defining how high VIF values are acceptable (O'Brien, 2007). Some scholars use a rule of thumb threshold of 10, while others employ a more conservative threshold of 4. We use the latter threshold. In addition to the final 20 predictor variables used in the regression models, we collected data for another few variables. We initially intended to include dummy variables based on token category, such as gaming, DeFi, and business, but they unfortunately caused high VIF values in all models. Four other variables were related to the total amount raised, and they, as suspected, had high VIF values well above even the most acceptable thresholds. Hence, *amount raised private, amount raised total, issue size,* and the category dummies were excluded for all models. In three of the regression models, some of the predictor variables had VIF values above 4 and therefore were excluded in the respective models. The variables included in each model and the respective VIF values are presented in Appendix C3.

The equal variance, or homoscedasticity, assumption in OLS regression states that the error terms should have constant variances. Another way of putting it is that residuals should simply be random fluctuations around the true line, and not show any patterns when plotted against fitted values (Frost, 2020). If this assumption is violated, i.e., the residuals are heteroskedastic, an OLS model remains unbiased, but produces inefficient results (Stock & Watson, 2020).

When error terms are both homoscedastic and uncorrelated, they are referred to as spherical errors, and as such the OLS regression can be proven to be BLUE, given a conditional mean of zero (Huang, 1970). We tested for heteroskedasticity in all five regression models using the White and Breusch-Pagan test. While the null hypothesis of homoscedastic residuals could not be rejected in any of the models under the White test, it was rejected for model (1), (2), and (5) under the Breusch-Pagan test. Thus, the alternative hypothesis of heteroscedastic residuals was accepted in these three models. However, HAC robust standard errors also correct for heteroskedasticity and are used in these models. Therefore, no further actions were taken. See Appendix C4 for the results of the heteroskedasticity tests.

Regression model (1) uses underpricing (log) as the dependent variable and is the main model that tests both hypotheses. We compare the level of underpricing between the token offering types using an approach in which IDOs serves as the base group and where ICOs and IEOs are accounted for using dummy variables. The hypotheses imply a positive coefficient for the ICO dummy and negative coefficient for the IEO dummy. In addition to these key variables of interest, we include a set of 18 control variables (see Table 6 for all predictor variables). This approach is in line with studies that compares underpricing between different groups (e.g., Kliger et al., 2012; Momtaz, 2021).

$$\begin{aligned} UP = {} & \alpha + \beta_1 \times ICO_{dummy} + \beta_2 \times IEO_{dummy} + \beta_3 \times \ln Gross\ proceeds\ public_i + \beta_4 \times \ln age + \beta_5 \times \\ & Issuer\ retained\ ratio_i + \beta_6 \times \ln Fraction\ sold_i + \beta_7 \times \ln trading\ volume_i + \beta_8 \times \\ & \ln Coin\ sold\ ratio_i + \beta_9 \times market\ sentiment_i + \beta_{10} \times \ln Offer\ price_i + \beta_{11} \times \ln Duration_i + \\ & \beta_{12} \times Lockup\ public_{dummy} + \beta_{13} \times Lockup\ private_{dummy} + \beta_{14} \times Presale_{dummy} + \\ & \beta_{15} \times Whitepaper_{dummy} + \beta_{16} \times Github_{dummy} + \varepsilon_i, \end{aligned} \tag{1}$$

Model (2) utilizes the same design except that market adjusted underpricing (log) is used as the dependent variable as a robustness test. Models (3)-(5) use underpricing (log) as the dependent variable and are conducted to explore potential differences in the explanations of underpricing between the token offering types. These models use underpricing (log) as the dependent variable and analyze token offering types separately by including only those observations that pertain to the type in question. The equations for regression models (2)-(5) are presented in Appendix D1.

Table 6

Predictor Variables

Variables	Description	Primary data source	Suppl. data source(s)	Expected sign
	Panel A: Independent Variables			
ICO	Dummy. 1 if ICO, otherwise 0.	[1]	[3]	(+)
IEO	Dummy. 1 if IEO, otherwise 0.	[1]	[3]	(+)
	Panel B: Control Variables			
Gross proceeds public	Log of the total number of tokens issued times the offer price	[1]	[2], [3], [4], [9]	(+)
Age	Log of the time (in years) between issuers creating Twitter account and listing day	[2]	[3], [7], [8], [9] [10], [11]	(-)
Issuer retained ratio	Log of number of tokens retained by team of, divided by total number of tokens	[1]	[4]	(+)
Fraction sold	Total number of tokens offered divided by total number of tokens	[1]	[2]	(+)
Trading volume	Log of trading volume in the first 24 hours.	[1]	[2]	(+)
Coins sold ratio	Log of number of tokens sold divided by total number of tokens issued	[1]	[2], [8]	(+)
Market sentiment	Past 30-day return of the CCI30 index measured at listing day	[12]		(+/-)
Offer Price	Log of offer price set at listing day	[1]	[10]	(+/-)
Duration	Log of number of days from start to end the token offering	[1]	[5]	(+/-)
Lock-up public	Dummy. 1 if lock up requirement for public sale, otherwise 0.	[1]	[9]	(-)
Lock-up private	Dummy. 1 if lock up requirement for private sale investment, otherwise 0.	[1]	[9]	(+)
Pre-sale	Dummy. 1 if pre-sale was held, otherwise 0.	[1]	[9]	(-)
Whitepaper	Dummy. 1 if Whitepaper accessible, otherwise 0.	[1]	[8], [9]	(+)
Github	Dummy. 1 if source code available at GitHub, otherwise 0.	[1]	[9]	(+)
Ethereum	Dummy. 1 if based on Ethereum blockchain, otherwise 0.	[1]	[5]	(+)
Binance	Dummy. 1 if based on Binance Smart Chain, otherwise 0.	[1]	[5], [3]	(+/-)
Polygon	Dummy. 1 if based on Polygon blockchain, otherwise 0.	[1]	[5], [3]	(+/-)
Solana	Dummy. 1 if based on Solana blockchain, otherwise 0.	[1]	[5], [3]	(+/-)

Note. This table shows the calculations, primary and supplementary, as well as expected signs for the independent and control variables used in the regression analysis. [1] Cryptorank.io [2] ICOdrops.com [3] Coingecko.com [4] Cryptototem.com [5] Coinmarketcap.com [6] Twitter [7] Telegram account [8] Medium [9] Issuers Whitepaper [10] Issuers Website [11] Instagram account [12] CCI30 index website

5. Results and analysis

The following chapter presents the results of the statistical tests and analyses this in accordance with the two hypotheses. Section 5.1 presents descriptive statistics for all variables. In section 5.2, the results of the t-test and ANOVA are reported, while the results of the regression models are reported in section 5.3. In both sections, we present the outcomes of the respective hypothesis tests.

5.1 Descriptive statistics

Given the explorative nature of this study, we present descriptive statistics based on raw data, including the removed variables with high VIF-values and outliers, in order to more accurately portray the lunatic crypto market. Table 7 presents descriptive statistics on all variables, except categorical, for ICOs, IEOs, and IDOs separately, as well as in total. Appendix A1 contains the equivalent of Table 7 on the treated data, which serves as the basis for the main statistical analysis. Summary statistics on the categorical variables are presented in Appendix A2. Out of the total 749 observations in Table 7, 51 are ICOs, 50 are IEOs, and 648 are IDOs.

We find a mean (median) underpricing across all token offerings of 1,090.50 percent (323.70 percent), whereas the lowest level of underpricing was -94.67 percent, and the highest 37,700 percent, which represents a range of 37,095 percent. While the minimum (-43.37 percent) and maximum (103.07 percent) return of the CCI30 index on the issue dates indicates that the correction is not trivial, the observed values of the market adjusted underpricing is almost identical to the values of the unadjusted underpricing. Among different token offering types, IDOs are associated with the highest mean underpricing (1,109.78 percent), whereas ICOs and IEOs have a mean underpricing of 1,064.82 percent and 867.20 percent, respectively. However, looking at the treated data in Appendix A1, the mean underpricing across the different types is in line with our hypotheses since all four outliers were IDOs.

ICO issuers raise on average the highest amounts ($11.049 million), while IEO and IDO issuers raise an average of $1.454 million and $1.702 million, respectively. These figures represent 64.67 percent, 81.03 percent, and 47.96 percent of the total amount raised (including previous private sales) respectively. We observe that IDO projects hold their token offerings at an early stage, as indicated by their mean age of 0.90 years, as opposed to ICO and IEO projects, which hold token offerings at an average age of 1.58 and 1.77 years, respectively. While issuers retain an average 12.75 percent of the total token supply, the public token offering on average constitutes 5.06 percent, in which 103.30 percent of the tokens are sold on average. IEOs are associated with the largest trading volumes (M = $152.905 million), followed by ICOs (M = $40.540 million and IDOs (M = $14.055 million). The average market sentiment over the 30 days prior to the token offering is approximately 13 percent for ICOs and IEOs, while IDOs are associated with an average of 6.26 percent. Whereas IEOs last for an average of 5.76 days and have an average offer price of $0.68, ICOs and IDOs have a mean duration and offer price of 4.33 days and $0.38, and 2.84 days and $0.52, respectively. A majority of ICOs and IDOs issuers employ both public and private lock-up agreements and conduct a pre-sale, while lock-up agreements and pre-sales are less common in IEOs (M = 0.16 (public), M = 0.24 (private), and M = 0.4 (pre-sale)). 59.41 percent of all issuers issue a whitepaper, while 26.84 percent publish their source code on Github.

The summary statistics in Appendix A2 reveals that 98.13 percent of all tokens are utility tokens, and that the remaining 2 percent are coins. We observe no security tokens. No coins are issued in an IDO, while 15.69 percent of all ICOs involve coins. 54.47 percent of all tokens are based on Binance Smart Chain, and 50.20 percent on Ethereum[55]. Tokens issued in ICOs and IEOs tend to be based on Ethereum (74.51 and 68 percent respectively) rather than Binance (25.49 and 28 percent respectively), whereas 58.80 and 46.91 percent of the tokens issued in IDOs are based on Ethereum and Binance respectively. DeFi (Decentralized Finance) is the most common category (30.57 percent), followed by Gaming (29.37 percent), Blockchain (12.55 percent), and NFT (7.74 percent). 32.10 percent of all IDOs are in the Gaming category, and 14 and 9.80 percent of IEOs and ICOs respectively.

[55] A token can be based on multiple blockchains simultaneously, therefore the respective cumulative percentage distribution can equal over 100 percent.

Table 7

Descriptive Statistics

Variable	# Obs.	Mean	Median	Minimum	Maximum	SD
Panel A: All Token Offerings						
Underpricing	749	10.91	3.24	-0.95	377.00	28.26
CCI30 return on issue dates	749	0.07	0.02	-0.43	1.03	0.01
Market adjusted underpricing	749	10.90	3.24	-0.97	377.09	28.26
Gross proceeds public (in million)	749	2.32	0.300	0.010	379.26	15.47
Gross proceeds to total raised	749	0.51	0.33	0.00	1.00	0.41
Age	749	1.01	0.39	0.00	12.64	1.80
Issuer retained ratio	749	0.13	0.13	0.00	0.75	0.07
Fraction sold	749	0.05	0.02	0.00	1.00	0.09
Trading volume (in million)	749	25.12	2.23	0.000	2 313.52	148.07
Coins sold ratio	749	1.03	1.00	0.00	10.00	0.55
Market Sentiment	749	0.07	0.02	-0.43	1.03	0.27
Offer Price	749	0.52	0.08	0.00	50.00	2.65
Duration	749	3.14	2.00	1.00	39.00	4.40
Lock-up public	749	0.54	1	0	1	0.50
Lock-up private	749	0.54	1	0	1	0.50
Pre-sale	749	0.63	1	0	1	0.48
Whitepaper	749	0.59	1	0	1	0.49
Github	749	0.27	0	0	1	0.44
Ethereum	749	0.50	1	0	1	0.50
Binance	749	0.54	1	0	1	0.50
Polygon	749	0.10	0	0	1	0.30
Solana	749	0.05	0	0	1	0.22
Panel A: Initial Coin Offerings (ICOs)						
Underpricing	51	10.65	2.62	-0.49	106.00	20.24
CCI30 return on issue dates	51	0.13	0.09	-0.43	0.72	0.29
Market adjusted underpricing	51	10.64	2.58	-0.46	105.99	20.24
Gross proceeds public (in million)	51	11.04	5.50	0.050	65.00	14.41
Gross proceeds to total raised	51	0.65	0.70	0.05	1.00	0.35
Age	51	1.58	0.81	0.81	12.36	2.33
Issuer retained ratio	51	0.13	0.15	0.00	0.30	0.08
Fraction sold	51	0.06	0.05	0.00	0.33	0.06
Trading volume (in million)	51	40.54	7.92	0.015	683.27	106.25
Coins sold ratio	51	1.17	1.00	0.16	6.67	0.97
Market Sentiment	51	0.13	0.09	-0.43	0.72	0.29
Offer Price	51	0.38	0.22	0.00	2.00	0.47
Duration	51	4.33	2.00	1.00	33.00	5.99
Lock-up public	51	0.51	1	0	1	0.50
Lock-up private	51	0.47	0	1	1	0.50
Pre-sale	51	0.47	0	0	1	0.50
Whitepaper	51	0.69	1	0	1	0.47
Github	51	0.53	1	0	1	0.50
Ethereum	51	0.75	1	0	1	0.44
Binance	51	0.25	0	0	1	0.44
Polygon	51	0.04	0	0	1	0.20
Solana	51	0.00	0	0	0	0.00

Variable	# Obs.	Mean	Median	Minimum	Maximum	SD
Panel B: Initial Exchange Offerings (IEOs)						
Underpricing	50	8.67	2.30	-0.90	101.00	17.15
CCI30 return on issue dates	50	0.13	0.11	-0.31	0.80	0.26
Market adjusted underpricing	50	8.67	2.32	-0.90	101.02	17.15
Gross proceeds public (in million)	50	1.454	0.542	0.030	10.33	2.112
Gross proceeds to total raised	50	0.81	1.00	0.00	1.00	0.32
Age	50	1.77	1.12	0.01	9.92	2.01
Issuer retained ratio	50	0.16	0.15	0.00	0.75	0.12
Fraction sold	50	0.09	0.04	0.00	1.00	0.17
Trading volume (in million)	50	152.90	6.085	0.019	1 770.71	390.78
Coins sold ratio	50	1.01	1.00	0.00	4.13	0.50
Market Sentiment	50	0.13	0.11	-0.31	0.80	0.26
Offer Price	50	0.68	0.10	0.00	14.60	2.16
Duration	50	5.76	2.00	1.00	38.00	7.78
Lock-up public	50	0.16	0	0	1	0.37
Lock-up private	50	0.24	0	0	1	0.43
Pre-sale	50	0.40	0	0	1	0.49
Whitepaper	50	0.68	1	0	1	0.47
Github	50	0.28	0	0	1	0.45
Ethereum	50	0.68	0	0	1	0.47
Binance	50	0.28	0	0	1	0.45
Polygon	50	0.04	0	0	1	0.20
Solana	50	0.00	0	0	0	0.00
Panel C: Initial Exchange Offerings (IDO)						
Underpricing	648	11.10	3.41	-0.95	377.00	29.47
CCI30 return on issue dates	648	0.06	0.01	-0.43	1.03	0.26
Market adjusted underpricing	648	11.10	3.38	-0.97	377.09	29.47
Gross proceeds public (in million)	648	1.702	0.286	0.010	379.26	15.93
Gross proceeds to total raised	648	0.48	0.24	0.01	1.00	0.41
Age	648	0.90	0.37	0.00	12.64	1.72
Issuer retained ratio	648	0.13	0.13	0.00	0.45	0.07
Fraction sold	648	0.05	0.02	0.00	0.74	0.08
Trading volume (in million)	648	14.052	1.895	0.000	2 313.52	107.26
Coins sold ratio	648	1.02	1.00	0.02	10.00	0.51
Market Sentiment	648	0.06	0.01	-0.43	1.03	0.26
Offer Price	648	0.52	0.07	0.00	50.00	2.78
Duration	648	2.84	2.00	1.00	39.00	3.79
Lock-up public	648	0.57	1	0	1	0.50
Lock-up private	648	0.57	1	0	1	0.50
Pre-sale	648	0.66	1	0	1	0.48
Whitepaper	648	0.58	1	0	1	0.49
Github	648	0.25	0	0	1	0.43
Ethereum	648	0.47	0	0	1	0.50
Binance	648	0.59	1	0	1	0.49
Polygon	648	0.11	0	0	1	0.31
Solana	648	0.05	0	0	1	0.22

Note. This table shows descriptive statistics on the raw data by token offering type, and includes the number of observations, mean, median, minimum, maximum, and standard deviation values. Gross proceeds public and Trading volume are displayed in million USD.

5.2 T-test and ANOVA

There are four groups used in the analysis (ICO: 51; IEO: 49; IDO: 645; IEO+IDO: 694), which differ slightly from those in the descriptive statistics as a result of excluding the four outliers. Due to the log transformation, geometric means are tested instead of arithmetic means as in normal form. The full results for the t-tests are presented in Table 8 and the ANOVA in Table 9.

H1: Underpricing is higher in ICOs than in IEOs and IDOs

An independent-samples t-test was conducted to compare the level of underpricing for ICOs and IEOs and IDOs together. No significant differences were found (*t* (df) = 743, *p* = 0.598) in the scores for ICOs (*M* = 1.558, *SD* = 1.277) and IEOs and IDOs (*M* = 1.455, *SD* = 1.342). The magnitude of the differences in the means (mean difference = 0.102, 95% *CI*: -0.279 to 0.483) is small. Hence, H1 is not supported.

H2: Underpricing is higher in IDOs than in IEOs

An independent-samples t-test was conducted to compare the level of underpricing for IEOs and IDOs. No significant differences were found (*t* (df) = 692, *p* = 0.437) in the scores for IEOs (*M* = 1.312, *SD* = 1.462) and IDOs (*M* = 1.466, *SD* = 1.333). The magnitude of the differences in the means (mean difference = -0.155, 95% *CI*: -0.545 to 0.236) is small. Hence, H2 is not supported.

Table 8

Student's t-test and Fisher's test

								Fisher's test		*t-test*		
Variable	Group	Obs.	Mean	Std. dev	Mean diff.	Lower	Upper	F	*p*	t	df	*p*
UP	ICO	51	1.558	1.277	0.102	-0.279	0.483	0.905	*0.678*	0.527	743	*0.598*
	IEO+IDO	694	1.455	1.342								
UP_ma	ICO	51	1.553	1.282	0.101	-0.283	0.485	0.897	*0.648*	0.517	743	*0.605*
	IEO+IDO	694	1.452	1.353								
UP	IEO	49	1.312	1.462	-0.155	-0.545	0.236	1.202	*0.341*	-0.777	692	*0.437*
	IDO	645	1.466	1.333								
UP_ma	IEO	49	1.306	1.468	-0.156	-0.55	0.238	1.191	*0.364*	-0.778	692	*0.437*
	IDO	645	1.463	1.345								

Note. This table shows the results of Student's t-test and Fisher's test for equal variances by group and underpricing measure. Lower and Upper represents the limits for a 95 percent confidence interval for the mean differences.

An ANOVA test was conducted to compare the level of underpricing differs across the three groups in line with both hypotheses. As stated in section 4.4.2, the two hypotheses taken together imply an order of ICO>IDO>IEO in the level of underpricing. The ANOVA results suggests that the level of underpricing do not differ significantly across the groups ($F_{2,742}$ = 0.443, p = 0.642). Hence, H1 and H2 are not supported.

Since the analysis revealed insignificant ANOVA results, no post hoc analysis was performed to assess between group differences.

Table 9

ANOVA and Levene's test

				Levene's test		*ANOVA*	
Variable	Groups	Mean	Std. Deviation	F	*p*	F	*p*
UP	ICO	1.558	1.277	0.471	*0.624*	0.443	*0.642*
	IEO	1.312	1.462				
	IDO	1.466	1.333				
UP_m	ICO	1.553	1.282	0.473	*0.623*	0.439	*0.645*
	IEO	1.306	1.483				
	IDO	1.463	1.347				

Note: This table shows the results of the ANOVA and Levene's test for equal variances by group and underpricing measure.

5.3 OLS-Regression

Table 10 presents the results for the five regression models. The table displays coefficients and standard errors for the predictor variables, and the constant, *F*-statistic, R^2, R^2 adjusted, and the number of observations for the respective models. For model (1), we present standardized coefficients and the impact on underpricing of a change in each predictor variable in Appendix A3.

Underpricing (log) is the dependent variable in all models except (2), where market adjusted underpricing (log) is used. In total, there are 20 predictor variables, whereas the two independent variables are used in model (1) and (2) to account for ICOs and IEOs (IDOs serve as the base group), the 18 control variables are used in all models (some categorical dummies are excluded in model (1)-(3) due to multicollinearity) and reflect both IPO underpricing theories and token offering-specific characteristics.

Model (1) serves the main model to test the hypotheses and, as stated in section 4.4.3, the design of the model in relation to the hypotheses implies a positive coefficient for ICO and a negative coefficient for IEO. The dependent variable (underpricing (log)) was regressed on 16 predicting variables as seen in Table 6. The predictor variables significantly predict underpricing, $F_{16,\ 728} =$ 45.797, p = <0.0001, which indicates that the 16 factors have a significant impact on the level of underpricing. Moreover, the R^2= 0.491 depicts that the model explains 49.1 percent of the variance in underpricing.

Additionally, coefficients were further assessed to ascertain the influence of the independent variables. The results suggest that there is no significant relationship between the variable ICO and underpricing. Hence, H1 is not supported. However, the results reveal that the variable IEO has a significant and negative impact on underpricing (β = -0.299, p = 0.057). Hence, H2 is supported at the 10 percent level.

Model (2) yielded similar results to model (1) with a R^2 = 0.493 and the same sign and significance levels for each predictor variable. In model (1) and (2), all predictor variables except Duration, Whitepaper, Github have a significant impact on underpricing, whereas Trading volume is the most influential factor based on the standardized coefficients. Considering that the regression models contain a log-transformed dependent variable, together with log-transformed, normal and dummy predictor variables, interpreting and comparing the estimates of the coefficients can prove challenging. The coefficients of the log-transformed variables represent the elasticity of the Y variable with respect to the given X variable, and the coefficients of the normal variables represent a multiplicative change in the Y variable with respect to a linear change in the given X variable (Benoit, 2011). In order to ease direct comparison, we provide a table in Appendix A3 which displays standardized coefficients and interpretation for each predictor variable in model (1). As an example, for Trading volume in model (1), a 10 percent change represents a 3.181 percent change in the level of underpricing.

Model (4) and (5) have similar R^2 adjusted to model (1) and (2), while model (3) explains less of the variance in underpricing (R^2 adjusted = 0.370). The coefficients in model (3) are identical to those in models (1) and (2), albeit at lower significance levels for Coins sold ratio, Lock-up public, Lock-up private, and Pre-sale. In model (3) and (4), multiple signs differ from those in the other models, and there are fewer significant variables. Gross proceeds public and Trading volume are the only significant variables in model (4), and these two are also the only variables that are significant across all models. Whitepaper, Github, Ethereum, Polygon, and Solana are not significant in any of the models.

Table 10

OLS Regressions

	(1)	(2)	(3)	(4)	(5)
Main variables					
ICO	-0.031	-0.038	-	-	-
	(0.196)	(0.196)	-	-	-
IEO	-0.299*	-0.302*	-	-	-
	(0.157)	(0.157)	-	-	-
Predictor variables					
Gross proceeds public	0.165***	-0.165***	-0.249*	0.392**	-0.217***
	(0.040)	(0.041)	(0.129)	(0.145)	(0.042)
Age	-0.115***	-0.112***	-0.030	-0.088	-0.127***
	(0.030)	(0.030)	(0.117)	(0.127)	(0.035)
Issuer retained ratio	1.030**	1.002**	-3.193**	1.084	1.085**
	(0.473)	(0.482)	(1.365)	(1.345)	(0.537)
Fraction sold	0.103***	0.104***	0.168	-0.118	0.133***
	(0.039)	(0.039)	(0.287)	(0.099)	(0.039)
Trading volume	0.329***	0.333***	0.321***	0.236***	0.328***
	(0.018)	(0.018)	(0.072)	(0.069)	(0.019)
Coins sold ratio	0.344***	0.337***	0.939***	0.213	0.258**
	(0.074)	(0.078)	(0.192)	(0.213)	(0.111)
Market Sentiment	0.834***	0.841***	0.207	0.497	0.872***
	(0.155)	(0.152)	(0.468)	(0.729)	(0.167)
Control variables					
Offer Price	-0.108***	-0.108***	0.132*	-0.087	-0.115***
	(0.019)	(0.019)	(0.075)	(0.065)	(0.021)
Duration	-0.055	-0.059	0.415*	-0.050	-0.080
	(0.046)	(0.047)	(0.234)	(0.170)	(0.051)
Lock-up public	0.184**	0.194**	-0.005	0.616	0.173*
	(0.084)	(0.085)	(0.344)	(0.460)	(0.089)
Lock-up private	0.195**	0.205**	0.159	0.828	0.159*
	(0.078)	(0.080)	(0.420)	(0.580)	(0.086)
Pre-sale	-0.273***	-0.280***	-0.439	-0.604	-0.224**
	(0.092)	(0.094)	(0.342)	(0.524)	(0.104)
Whitepaper	-0.080	-0.083	0.331	-0.306	-0.078
	(0.072)	(0.072)	(0.338)	(0.398)	(0.082)
Github	-0.070	-0.079	-0.224	0.148	-0.088
	(0.095)	(0.096)	(0.373)	(0.412)	(0.099)
Ethereum	-	-	-0.777	-0.615	-0.040
	-	-	(0.492)	(0.385)	(0.104)
Binance	-	-	0.492*	-0.310	-0.060
	-	-	(0.255)	(0.454)	(0.096)
Polygon	-	-	-0.171	-0.798	-0.097
	-	-	(0.514)	(0.963)	(0.111)
Solana	-	-	-	-0.472	0.097
	-	-	-	(0.624)	(0.174)
Constant	-1.215**	-1.276**	1.430	-7.627***	-0.396
F-statistic	45.797***	46.275***	2.728***	4.118***	38.149***
R^2	0.502	0.504	0.584	0.712	0.523
R^2 adjusted	0.491	0.493	0.370	0.539	0.509

Note. This table shows the OLS regression results for model (1)-(5) and includes coefficients and standard errors for the respective variables, as well as the constant, *F*-statistic, R^2, R^2 adjusted, and the number of observations for the respective models. Standard errors are reported in parentheses. ***1%, **5%, and *10%, significance.

6. Discussion

In the following chapter, we establish the foundation for the conclusions of this paper. In section 6.1, we discuss the findings in relation to the literature presented throughout the paper. Section 6.2 highlights the implications of our findings and presents suggestions for further research. In section 6.3, we acknowledge and discuss the limitations of this paper.

6.1 Discussion of Findings

Our findings reveal astonishing levels of underpricing in all token offering types. This confirms the fact that IEOs and IDOs are on average underpriced, like ICOs and IPOs. The overall observed mean (median) underpricing of 1,090.5 percent (323.70 percent) is higher than in all ICO studies presented in Table 3 (section 3.5), as well as for IPOs in any year or country (Loughran et al., 2022; Loughran et al., 2022b). The only study with somewhat similar results is Adhami et al. (2018), who find a mean (median) of 919.9 percent (24.7 percent). The notable difference between our results and what is generally reported in the ICO literature can potentially be explained by a variety of factors. First, we examine IEOs and IDOs as well as ICOs, and this naturally affects the results, however, the average underpricing for ICOs separately remains higher than any previous study (10,648.24 percent). Second, our sample covers a different, and more recent, time period compared to previous studies that usually cover a period centered around the ICO boom. Third, our data collection method and primary data source differ from the conventional approach in ICO literature.

Nevertheless, the observed mean-median difference in underpricing suggests a positively skewed distribution, which is consistent with Adhami et al. (2018), as well as most studies in Table 3. This can be explained by the fact that a small number of highly successful token offerings constitutes for a large portion of the underpricing, a trend that has been noted by several scholars for the amount raised in ICOs (e.g., Momtaz, 2020; Howell et al., 2019). In our view, this highlights the uncertainty and in turn risk investors are faced with in token offerings. Investors are lured by the prospect of astronomical returns but are at the same time faced with a risk of suffering huge losses, which renders the investment decision to be a gamble based on psychological factors rather than the outcome of a rational calculus. This rationale is supported by our observed standard deviation and range in underpricing (*SD* = 282.56 percent; *min* = -94.67 percent, *max* = 37,700.00 percent).

The range and high levels of underpricing also reflect extensive information asymmetry, ulterior to the uncertainty and risk. Drawing on Rock (1986), issuers underprice their issues to compensate uninformed investors so that they will participate in the market despite the unequal allocation caused by the information asymmetry between informed and uninformed investors. An alternative explanation of the underpricing may be that issuers underprice their tokens in order to signal the project's quality in a lunatic market full of lemons (e.g., Akerlof, 1970; Welch, 1989; Allen & Faulhaber, 1989). One could also argue that the whole situation in the token offering market is simply a product of irrational exuberance, whereby the high levels of underpricing reflect an unfounded market optimism driven by investors influenced by a number of cognitive biases. Such an argument can be strengthened by the belief that cryptocurrencies have no intrinsic value, an opinion held by multiple prominent figures (e.g., Paul Krugman, Alan Greenspan, and Warren Buffet). Although from an economic and behavioral perspective, it appears rather paradoxical that we observe higher underpricing than amidst the craze in 2017. Nevertheless, with the dramatic increase in IDOs recently, we may be experiencing the beginning of a new boom in token offerings that is causing a surge in underpricing.

Regarding our purpose of examining potential differences between the token offering types, the statistical analysis rendered somewhat ambiguous results. There are, as described in section 3.3.4, distinct differences between the different token offering types in terms of their design and the characteristics of their typical projects. We argued that these differences constituted several inherent advantages for IEOs and IDOs over ICOs that would reduce the risk associated with the issuance, and in turn be reflected in the level of underpricing. Also, we argued that IDOs entail more risk than IEOs with regards to the characteristics of the projects associated with each type and their respective control mechanisms. Thus, in *Hypothesis 1*, we proposed that underpricing is higher in ICOs than in IEOs and IDOs, and in *Hypothesis 2*, we proposed that underpricing is higher in IDOs than in IEOs. Neither the t-test, nor the ANOVA revealed any significant differences in the mean underpricing between the groups. Thus, we cannot rule out the possibility that the differences are due to random chance. In regression models (1) and (2), H1 implies a positive sign for the ICO dummy, as well as a larger coefficient than for the IEO dummy (if both are positive), while H2 implies a negative sign for the IEO dummy in addition to the positive sign for the ICO dummy. The ICO dummy was not significant and displayed a negative sign in both models, while the IEO dummy was significant at the 10 percent level and displayed a negative sign. Thus, the statistical analysis failed to reject the null hypothesis in H1 using any method, while there was some support for H2 in the regression models. Since the t-tests and ANOVA show no significant differences, and that support is provided only at a 10 percent level in the regression, we regard the evidence as insufficient to reject the null hypothesis in H2. Despite the lack of significant evidence, there are some indications of a trend in the direction of our hypotheses. In addition to the IEO dummy, the group means based on the treated data follow our hypothesized relationship (see Table 11 below). One could argue that the increase in the number of IEOs, and particularly IDOs, is a sign of that the new methods are advantageous in many aspects, including risk. However, there may be other factors than underpricing that better reflect, or capture, the differences in terms of risk. Even so, it is difficult to know what factors are at play due to the newness of the field, with very limited literature on IEOs, and none on IDOs. Anson (2021) and Momtaz (2021) are the only two studies on IEOs that use a quantitative approach. Looking at the ICO literature, besides underpricing, many scholars examine ICOs in terms of successful outcomes, which also reflects risk to some extent. There are many measures of success, whereas token tradability (listing), amount raised, raised to soft cap, and ex-post performance are among the most common. Listing is guaranteed in IEOs and IDOs and as such constitutes an inherent advantage in relation to ICOs. Amount raised may be an appropriate alternative to underpricing since gross proceeds (same as amount raised) are significant in all our regression models. However, our observed mean gross proceeds are not in line with our hypotheses (ICO = $40.549 million, IEO = $11.049 million, IDO = $1.701 million), which is also consistent with Momtaz (2021) (IEOs in relation to ICOs). Anson (2021) finds that IEOs are more likely to reach their soft caps than ICOs. However, data on soft (and hard) caps are less common for IEOs and IDOs in relation to ICOs, and therefore it would be a difficult measure to use with the data sources available as of today. Ex-post performance is an interesting alternative to underpricing since the risk surrounding an issue may be better reflected over a longer horizon, rather than within just the first 24 hours. To our knowledge, Lyandres et al. (2022) are the only scholars measuring ex-post performance in terms of returns. In their study they also measure underpricing, and interestingly they find an average underpricing of 384.39 percent, while the observed average cumulative post-ICO return is -2.58 percent and -37.97 percent over 30 and 365 days, respectively. Upon hand-collecting the market data, we observed a trend similar to Lyandres et al. (2022), where high initial returns were followed by a sharp decline once the initial buzz had started to fade. Alternative explanations on why IEOs and IDOs do not exhibit significantly lower levels of underpricing compared to ICOs despite their advantages, may be related to their regulatory and legal status, which can be viewed as even more uncertain since authorities thus far have issued nearly no official statements concerning their legal status.

Aside from underpricing, the additional variables in the descriptive statistics and regression models also reveal interesting insights. Table 11 provides a summary of our findings from the regression models with expected signs and the corresponding ICO and IPO evidence. The average gross proceeds (public) across all token offering types ($2.321 million) is substantially lower than commonly observed in ICO literature (e.g, $15.1 million, Momtaz (2020); $15.8 million, Howell et al. (2020); $11.5 million, Benedetti and Kostovetsky (2020)). Although looking at the ICOs in our sample, the average gross proceeds ($11.049 million) is more similar to previous studies covering the boom years. While the median gross proceeds across the token offering types are in line with Table 2 in section 3.3.4, the mean values are not. This is likely due to a few IDOs raising exceptionally high amounts, including BitDAO that raised the highest amount in all of our sample ($379.261 million). IDOs have an average age nearly half that of ICOs and IEOs, which, along with the median gross proceeds, suggests that IDOs are characterized by smaller, less-known projects that are likely attracted by the low transaction costs. IEOs have by far the highest average trading volume, nearly three times higher than ICOs, and ten times higher than IDOs, presumably due the guaranteed launch at a centralized exchange, which accounts for the majority of the trading volume in the crypto currency market (Matovskyy, 2019). In our view, this finding points to a major advantage for IEOs, wherein access to these levels of liquidity may justify their high cost. Interestingly, we find that most IDOs are based on Binance Smart Chain rather than Ethereum, which contrasts sharply with ICOs in our sample, and the findings in ICO literature that consistently find that a majority are based on Ethereum (e.g., 67 percent, Momtaz (2020); 74 percent, Howell et al. (2020); 88 percent, Amsden & Schweizer (2018)). This may be a consequence of the gas fees (transaction costs depended on the Ethereum token price and network traffic) in the Ethereum network that have risen substantially over the last few years to the point where a single transaction can cost over $50.[56] Compared to other blockchains, Binance Smart Chain has much lower transaction fees (and faster transactions), hence it is arguably better suited for smaller projects (IDOs) in which individual investors likely invest a smaller amount of money.

[56] See for example https://www.statista.com/statistics/1221821/gas-price-ethereum/

We find significant support for many of the control variables across the regression models, although model (1) exhibits the most significant control variables. In comparison to ICO literature, the R^2 of our regression models are high (e.g., 6.79 percent, Momtaz (2020); 17 percent, Lee et al. (2019); 33 percent, Felix & von Eije). Looking at the R^2 adjusted, model (3) (ICOs) has the lowest value, whereas model (4) and (5) (IEOs and IDOs) have the highest, which suggest that our control variables better explain underpricing in IEOs and IDOs than in ICOs. In our primary model (1), all control variables from IPO literature are significant and exhibit signs consistent with our expectations, except for fraction sold, which displays signs opposite to our expectations. This suggests that traditional explanations of IPO underpricing also extend to token offerings. Regarding Whitepaper and Github where we had no prespecified assumptions on the signs, we observe negative signs in all models except (3), which is not in line with the arguments of Adhami et al. (2018), Blaseg (2018), and Fisch (2018) that these actions represent a signal of quality, it seems that it rather reduces the information asymmetry as we suggested in section 3.6.1. The signs for several control variables in model (3) are the opposite to model (4) and (5), indicating a difference in the underlying explanations of underpricing for the different token offering types. Trading volume has the greatest impact on underpricing and is significant across all models. Drawing on Rock (1986) and Miller & Reilly (1987), this suggests that there is substantial uncertainty among investors about the after-market equilibrium token prices, which is understandable given the difficulty of valuing tokens (Zetzsche et al., 2018). Market sentiment is the second most influential variable and is significant in all models except (3) and (4). This is consistent with ICO underpricing studies (e.g., Felix & von Eije, 2019; Momtaz, 2020; Drobetz et al., 2019), as well as Benedetti & Kostovetsky (2020), which find that ICO activity is strongly driven by Bitcoin and Ethereum prices.

The fact that we observe no security tokens in the sample may be explained by the fact that these tokens are traded on exchanges that facilitate trading for security tokens exclusively and are, therefore, not included in the exchanges CryptoRank aggregates data from. This further strengthens our argument that STOs, or security tokens, are inherently different from ICOs and should not be considered a successor or direct alternative to ICOs.

Table 11

Summary of Findings for the Predictor Variables

Variable	IPO paper	Sign	ICO paper	Sign	Exp. sign	(1)	(2)	(3)	(4)	(5)
Gross proceeds	Habib & Ljungqvist, 2001 Beatty & Ritter, 1986	(-)	Lyandres at al., 2022 Felix & von Eije, 2019	(-)	(-)	(-)***	(-)***	(-)*	(+)**	(-)***
Age	Habib & Ljungqvist, 2001 Loughran & Ritter, 2004	(-)	Chanson et al., 2018 Benedetti & Kostovetsky 2021	(-)	(-)	(-)***	(-)***	(-)	(-)	(-)***
Issuer retained ratio	Welch, 1992 Grinblatt & Wang 1989	(+)	Felix & von Eije, 2019	(+)	(+)	(+)**	(+)	(-)**	(+)	(+)
Fraction sold			Lyandres et al., 2022	(-)	(-)	(+)***	(+)***	(+)	(-)	(+)***
Lock-up public	Mohan & Chen, 2001 Ibbotson & Ritter, 1995	(+)	Bourveau et al., 2018	(-)	(+)	(+)**	(+)**	(-)	(+)	(+)*
Lock-up Private					(+)	(+)**	(+)**	(+)	(+)	(+)*
Trading volume	Rock,1986 Miller & Reilly,1987 Falconieri et al., 2009	(+)	Felix & von Eije, 2019 Howell et al., 2020	(+)	(+)	(+)***	(+)***	(+)***	(+)***	(+)***
Coins sold ratio	Chowdhry & Sherman, 1996	(+)	Felix & von Eije, 2019 Chanson et al., 2018	(+)	(+)	(+)***	(+)***	(+)***	(+)**	(+)**
Market sentiment	Loughran and Ritter, 2002 Ljungqvist and Wilhelm, 2003 Ljungqvist et al., 2006	(+)	Felix & von Eije, 2019 Momtaz, 2020 Drobetz et al., 2019	(+)	(+)	(+)***	(+)***	(+)	(+)	(+)***
Offer price	Fernando et al., 2004 Sandu & Guhathakurta, 2020	(-)	Benedetti & Kostovetsky, 2021	(-)	(-)	(-)***	(-)***	(+)*	(-)	(-)**
Pre-sale			Momtaz, 2020 Felix & von Eije, 2019	(-)	(-)	(-)***	(-)***	(-)	(-)	(-)**
Duration	Mollick, 2014 Lukkarinen, 2020	(-)	Fisch, 2018; Momtaz, 2020	(-)	(-)	(-)	(-)	(+)*	(-)	(-)
Whitepaper			Adhami et al., 2018 Blaseg, 2018 Fisch, 2018	(+)	(+)	(-)	(-)	(+)	(-)	(-)
Github			Adhami et al., 2018 Blaseg, 2018 Fisch, 2018	(+)	(+)	(-)	(-)	(+)	(-)	(-)
Ethereum			Fisch, 2018 Momtaz, 2020	(+)	(+)			(-)	(-)	(-)
Binance				(-/+)	(-/+)			(+)*	(-)	(-)
Solana				(-/+)	(-/+)			(-)	(-)	(-)

Note. This tables shows a comparison between coefficients for the predictor variables in all five regression models and the respective IPO and ICO paper used to set the expected signs. was based. The +/- indicates whether the coefficient is positive. ***1%, **5%, and *10%, significance.

6.2 Implications and Further Research Suggestions

As one of the first studies to examine IEOs, and the first to include IDOs at all, we bridge the gap between ICO literature and what is going on in the crypto market today. Since IDOs account for over 85 percent of market activity, it is of particular importance to further explore how this new fundraising method differs from ICOs, and IEOs, and what its implications are for token offering market, issuers, and investors. We bring updated evidence on ICO underpricing and valuable insights on the characteristics of the different token offering types, as well as evidence for IPO underpricing theories from a new field. In the ICO literature, there are both empirical and theoretical subjects that can be extended to IEOs and IDOs, whereas this study can serve as a basis for such an expansion. In our view, it would be particularly interesting to explore ex-post performance on a longer horizon, similar to that of Lyandres et al. (2022), but for the different token offering types to investigate whether this better reflects their risk differences. Given the rapidly changing nature of the crypto market, there is also a need to clarify the current legal and regulatory situation of ICOs, and how IEOs and IDOs are related or differ in this regard.

6.3 Limitations

Limitations will inevitably arise early on in a new field of research. Research on cryptocurrencies has parallels with traditional finance as many theories can be applied analogously, but it is also a unique market in many ways. In finance, a new field may be covered by the same well-regarded databases and have a solid theoretical basis that developed on the same underlying market conditions. Data inconsistency remains the biggest limitation to this paper, which has been discussed throughout the paper. We have relied on hand collecting data and were required to complement it using several sources. Such manual collection is prone to human error and data inconsistency which may have impeded the reliability of our results. This may be an explanation for the large discrepancies between the findings of the studies presented in Table 3, even though they cover similar time periods. Similarly, as discussed in section 3.6.2, the data inconsistency, or lack of availability, forced us to exclude multiple predictor variables that we intended to include in the analysis. Moreover, we had to rely on multiple sources of non-academic standards due to the absence of studies on IEOs and IDOs, and we noticed several discrepancies between them. We also identified several inaccuracies in the ICO literature that contrasted with more technical publications, where some concepts were simplified to such an extent that they were false, or scholars simply provided inaccurate information. We initially relied almost exclusively on ICO literature for this paper, but we eventually realized this had led us to misunderstand several important aspects. Thus, we had to revise the research question and rework multiple sections, and instead look beyond academic literature on ICOs to find more accurate information in several instances. In terms of sample sizes, a more even distribution across the different token offering types would be preferable, however, this is a result of the time period we chose in order to examine the different types as they coexisted.

The validity of our results can also be questioned since there may be other factors than underpricing that better reflect risk as discussed above. Nevertheless, we assert that our method of hand collecting data from CryptoRank allowed us to more accurately capture the true level of underpricing in comparison to the standard practice of using market data from CoinMarketCap via API. Comparing different methods of data collection and sources in future studies would be a valuable contribution to the field. These limitations highlight the disadvantages of the decentralized and unregulated nature of the crypto market. A decision by regulators to extend the scope of financial law to include token offerings, or to introduce formal requirements for the information disclosed in whitepapers, would facilitate research and reduce the extent of scams and asymmetric information, but would at the same time undermine the fundamental idea of cryptocurrencies.

7. Conclusion

In this study, we explored the evolution of the ICO market and the recent development towards the rise of IEOs, and particularly IDOs. ICOs, or token offerings in general, have gained increasing attention in recent years from scholars, investors, media, regulators, and entrepreneurs due to their astronomical returns and because they can theoretically replace all other financing methods by mimicking their distinct characteristics by using smart contracts at nearly zero transaction cost. This paper provided a comprehensive review of ICO literature and a comparison of token offering types, both qualitatively, and quantitatively. In our view, the success of IEOs and IDOs can be attributed to the fact that, by reintroducing an intermediary, most of the inherent problems of ICOs that facilitate scams and misconduct are addressed, and to some extent resolved. Thus, we proposed that IEOs and IDOs are associated with less risk than ICOs, and drawing on IPO theories, that this should be reflected in the level of underpricing, whereas our two hypotheses together implied an order of ICO>IDO>IEO.

After examining 749 token offerings conducted between July 2019 and December 2021, our statistical analysis revealed an average level of underpricing of 1,090.5 percent, although without significant differences between the token offering types at the 5 percent level or below. [57] Thus, we regarded the evidence insufficient to reject the null hypothesis in both hypotheses. However, the mean underpricing across the groups and the IEO dummy in model (1) and (2), gave an indication of a trend in line with our hypotheses.[58] The fact remains that IEOs and IDOs are still associated with substantial information asymmetry and risk; however, we interpret this trend to be an indication that IDOs and IEOs have taken a step in reducing the risks associated with ICOs, and that IEOs are the least risky alternative given its more rigid due diligence. Another possibility is that there are in fact significant differences in risk between the token offering types, just that they are reflected in other factors than underpricing. Moreover, we cannot exclude that the data inconsistency, which was the biggest limitation of the study, affected the results. Despite the notion that IDOs, and perhaps IEOs as well, may be the successors to ICOs, one could argue that each type serves a different purpose in the token offering market, where they are better suited to certain projects, purposes, or funding stages by virtue of their individual characteristics and advantages.

[57] 745 observations were used in the t-tests, ANOVA, and regression analysis.
[58] The trend was observed in the means of the treated data, see Appendix A1.

Despite their increase in popularity, there is little research on IEOs, and none so far on IDOs. This paper adds to the nascent literature by providing empirical insights on todays' token offering market and the characteristics of the token offering types, as well as evidence for IPO theories from a new field. In light of the fact that we are the first study to examine IDOs, and one of the first few to look at IEOs, there are a plethora of potential research questions for scholars to explore. To further examine the differences between token offering types, there are several models for ICO success that can be employed, whereas we suggest examining ex-post performance on a longer time horizon to determine whether it better reflects risk. We hope that this paper can help point scholars in the right direction and serve as a basis for future studies that can further bridge the gap between the ICO literature and the new token offering methods. Moreover, our findings can assist issuers in making the right design choices and finding the best timing to leave less money on the table. Investors can also benefit from the knowledge generated in this paper; when market sentiment is positive and trading volume is expected to be high, investors are likely to achieve high returns.

Today, the blockchain and cryptocurrency landscape is a myriad of technologies, applications, and networks with a vast range of capabilities, whereas token offerings represent a dynamic method for entrepreneurs to finance their ventures. Even though many firms operate within the crypto space, the technology spur innovation and enables new businesses within industries from healthcare, to supply chain, to FinTech and beyond. What lies ahead is still unknown, but the crypto revolution is here to stay. However, this paper also highlights the volatile and uncertain downside of the crypto market wherein issuers must underprice their issues to compensate investors for the high degree of asymmetric information and uncertainty. In our view, the observed extreme levels of underpricing cannot be seen as a market anomaly, but rather a recurring phenomenon in an imperfect market.

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9. Appendices

Appendix A1

A1 – Descriptive statistics on Treated Data

Variable	# Obs.	Mean	Median	Minimum	Maximum	SD
Panel A: All token offerings						
Underpricing	745	1.44	-2.93	5.75	1.34	1.46
CCI30 return on issue dates	745	0.02	-0.43	1.03	0.27	0.07
Market adjusted underpricing	745	1.45	-3.58	5.75	1.35	1.46
Gross proceeds public	745	12.61	9.16	19.75	1.38	12.86
Age	745	-0.93	-5.90	2.54	0.50	-0.86
Issuer retained ratio	745	0.13	0.00	0.75	0.07	0.13
Fraction sold	745	-3.84	-8.52	0.00	1.20	-3.74
Trading volume	745	14.62	4.73	21.56	2.48	14.33
Coins sold ratio	745	0.00	-5.33	2.30	0.38	-0.02
Market Sentiment	745	0.02	-0.43	1.03	0.27	0.07
Offer Price	745	-2.53	-15.90	3.91	2.13	-2.70
Duration	745	0.69	0.00	3.66	0.82	0.70
Lock-up public	745	1	0	1	0.50	0.54
Lock-up private	745	1	0	1	0.50	0.54
Pre-sale	745	1	0	1	0.48	0.63
Whitepaper	745	1	0	1	0.49	0.60
Github	745	0	0	1	0.44	0.27
Ethereum	745	0	0	1	0.50	0.50
Binance	745	1	0	1	0.50	0.54
Polygon	745	0	0	1	0.30	0.10
Solana	745	0	0	1	0.22	0.05
Panel B: Initial Coin Offerings (ICOs)						
Underpricing	51	1.56	1.29	-0.67	4.67	1.28
CCI30 return on issue dates	51	0.13	0.09	-0.43	0.72	0.29
Market adjusted underpricing	51	1.55	1.28	-0.62	4.67	1.28
Gross proceeds public	51	14.88	15.52	10.82	17.99	2.11
Age	51	-0.35	-0.21	-3.13	2.52	1.38
Issuer retained ratio	51	0.13	0.15	0.00	0.30	0.08
Fraction sold	51	-3.11	-3.00	-5.36	-1.10	0.87
Trading volume	51	15.83	15.89	9.62	20.34	2.15
Coins sold ratio	51	-0.02	0.00	-1.84	1.90	0.57
Market Sentiment	51	0.13	0.09	-0.43	0.72	0.29
Offer Price	51	-1.81	-1.51	-5.46	0.69	1.54
Duration	51	0.94	0.69	0	3.50	0.93
Lock-up public	51	0.51	1	0	1	0.51
Lock-up private	51	0.47	0	0	1	0.50
Pre-sale	51	0.47	0.50	0	1	0.50
Whitepaper	51	0.69	1	0	1	0.47
Github	51	0.53	1	0	1	0.50
Ethereum	51	0.75	1	0	1	0.44
Binance	51	0.26	0	0	1	0.44
Polygon	51	0.04	0	0	1	0.20
Solana	51	0	0	0	0	0

Variable	# Obs.	Mean	Median	Minimum	Maximum	SD
Panel C: Initial Exchange Offerings (IEOs)						
Underpricing	49	1.31	1.24	-2.35	4.63	1.46
CCI30 return on issue dates	49	0.12	0.10	-0.31	0.80	0.26
Market adjusted underpricing	49	1.31	1.25	-2.35	4.63	1.47
Gross proceeds public	49	13.17	13.28	10.31	16.15	1.60
Age	49	-0.08	0.15	-4.29	2.30	1.38
Issuer retained ratio	49	0.16	0.15	0.00	0.75	0.12
Fraction sold	49	-3.81	-3.22	-8.52	0.00	1.94
Trading volume	49	15.47	15.84	9.83	21.30	3.06
Coins sold ratio	49	-0.17	0.00	-5.33	1.42	0.91
Market Sentiment	49	0.12	0.10	-0.31	0.80	0.26
Offer Price	49	-2.45	-2.30	-15.90	2.68	2.95
Duration	49	1.09	0.69	0.00	3.64	1.14
Lock-up public	49	0.16	0	0	1	0.37
Lock-up private	49	0.25	0	0	1	0.43
Pre-sale	49	0.41	0	0	1	0.50
Whitepaper	49	0.67	1	0	1	0.47
Github	49	0.29	0	0	1	0.46
Ethereum	49	0.67	1	0	1	0.47
Binance	49	0.27	0	0	1	0.45
Polygon	49	0.04	0	0	1	0.20
Solana	49	0.10	0	0	1	0.31
Panel D: Initial DEX Offerings (IDOs)						
Underpricing	645	1.47	1.48	-2.93	5.75	1.33
CCI30 return on issue dates	645	0.06	0.01	-0.43	1.03	0.26
Market adjusted underpricing	645	1.46	1.48	-3.58	5.75	1.35
Gross proceeds public	645	12.67	12.56	9.16	19.75	1.14
Age	645	-0.96	-1.00	-5.90	2.54	1.26
Issuer retained ratio	645	0.13	0.13	0.00	0.45	0.07
Fraction sold	645	-3.79	-3.91	-7.38	-0.31	1.14
Trading volume	645	14.12	14.45	4.73	21.56	2.39
Coins sold ratio	645	-0.01	0.00	-4.19	2.30	0.28
Market Sentiment	645	0.06	0.01	-0.43	1.03	0.26
Offer Price	645	-2.80	-2.66	-13.23	3.91	2.09
Duration	645	0.65	0.69	0.00	3.66	0.77
Lock-up public	645	0.57	1	0	1	0.50
Lock-up private	645	0.57	1	0	1	0.50
Pre-sale	645	0.66	1	0	1	0.48
Whitepaper	645	0.58	1	0	1	0.49
Github	645	0.25	0	0	1	0.43
Ethereum	645	0.47	0	0	1	0.50
Binance	645	0.59	1	0	1	0.49
Polygon	645	0.11	0	0	1	0.31
Solana	645	0.05	0	0	1	0.22

Note. This table shows descriptive statistics on the log transformed data and without the four outliers by token offering type, and includes the number of observations, mean, median, minimum, maximum, and standard deviation values.

Appendix A2

A2 – Frequency and Percentage Distribution of Categories.

	ICO	IEO	IDO	Total
Observations	51	50	648	749
	0.068	0.067	0.865	1
Inactive	1	1	14	16
	1.96%	2.00%	2.16%	2.14%
		Panel A: Cryptocurrency type		
Security token	0	0	0	0
	0%	0%	0%	0%
Utility token	43	46	646	735
	84.31%	92.00%	99.69%	98.13%
Coin	8	4	2	14
	15.69%	8.00%	0.31%	1.87%
		Panel B: Blockchain		
Binance	13	14	381	408
	25.49%	28.00%	58.80%	54.47%
Ethereum	38	34	304	376
	74.51%	68.00%	46.91%	50.20%
Polygon	2	2	71	75
	3.92%	4.00%	10.96%	10.01%
Solana	0	5	33	38
	0.00%	10.00%	5.09%	5.07%
Own	8	4	2	14
	15.69%	8.00%	0.31%	1.87%
Other	2	12	51	65
	3.92%	24.00%	7.87%	8.68%
		Plan C: Category		
DeFI	18	18	193	229
	35.29%	36.00%	29.78%	30.57%
Gaming	5	7	208	220
	9.80%	14.00%	32.10%	29.37%
Blockchain	16	7	71	94
	31.37%	14.00%	10.96%	12.55%
NFT	1	4	53	58
	1.96%	8.00%	8.18%	7.74%
Financial	3	1	31	35
	5.88%	2.00%	4.78%	4.67%
Exchange	3	5	26	34
	5.88%	10.00%	4.01%	4.54%
Entertainment	0	3	28	31
	0%	6.00%	4.32%	4.14%
Business	2	1	4	7
	3.92%	2.00%	0.62%	0.93%
Other	3	4	34	41
	5.88%	8.00%	5.25%	5.47%

Note. A token can be based on multiple blockchains; therefore, the respective cumulative percentage distribution can equal over 100 percent.

Appendix A3

A2 – Standardized Coefficients and Interpretation of Predictor Variables

Variable	Standardized Coefficient	Standard Error	t	*p*	Lower	Upper
Intercept	-1.215	0.573	-2.119	0.034	-2.341	-0.090
ICO	-0.031	0.196	-0.157	0.875	-0.415	0.354
IEO	-0.299	0.157	-1.910	0.057	-0.607	0.008
Offer Price	-0.108	0.019	-5.598	<0,0001	-0.145	-0.070
Trading volume	0.329	0.018	18.143	<0,0001	0.293	0.364
Market Sentiment	0.834	0.155	5.380	<0,0001	0.530	1.139
Gross proceeds public	-0.165	0.040	-4.089	<0,0001	-0.245	-0.086
Fraction sold	0.103	0.039	2.652	0.008	0.027	0.180
Coins sold ratio	0.344	0.074	4.647	<0,0001	0.199	0.490
Issuer retained ratio	1.030	0.473	2.178	0.030	0.101	1.958
Age	-0.115	0.030	-3.768	0.000	-0.175	-0.055
Duration	-0.055	0.046	-1.182	0.238	-0.145	0.036
Lock-up public	0.184	0.084	2.182	0.029	0.018	0.349
Lock-up private	0.195	0.078	2.505	0.012	0.042	0.348
Pre-sale	-0.273	0.092	-2.956	0.003	-0.454	-0.092
Whitepaper	-0.080	0.072	-1.124	0.262	-0.221	0.060
Github	-0.070	0.095	-0.737	0.461	-0.256	0.116

Panel A: Dummy Variables - Change in Y due to Switch from 0 to 1

Change in X	1
ICO	*-3.034%*
IEO	*-25.868%*
Lock-up public	*20.195%*
Lock-up private	*21.561%*
Pre-sale	*-23.874%*
Whitepaper	*-7.728%*
Github	*-6.740%*

Panel B: Log Transformed Variables - Percentage Change in Y due to Percentage Change in X

Change in X	1%	5%	10%	25%	50%
Offer Price	*-0.11%*	*-0.52%*	*-1.02%*	*-2.37%*	*-4.27%*
Trading volume	*0.33%*	*1.62%*	*3.18%*	*7.61%*	*14.25%*
Gross proceeds public	*-0.164%*	*-0.803%*	*-1.562%*	*-3.620%*	*-6.480%*
Fraction sold	*0.103%*	*0.505%*	*0.989%*	*2.330%*	*4.274%*
Coins sold ratio	*0.343%*	*1.695%*	*3.337%*	*7.989%*	*14.989%*
Age	*-0.114%*	*-0.559%*	*-1.089%*	*-2.531%*	*-4.551%*
Duration	*-0.054%*	*-0.266%*	*-0.519%*	*-1.210%*	*-2.188%*

Panel C: Variables in Normal Form - Percentage Change in Y due to a Change in Percentage Units in X

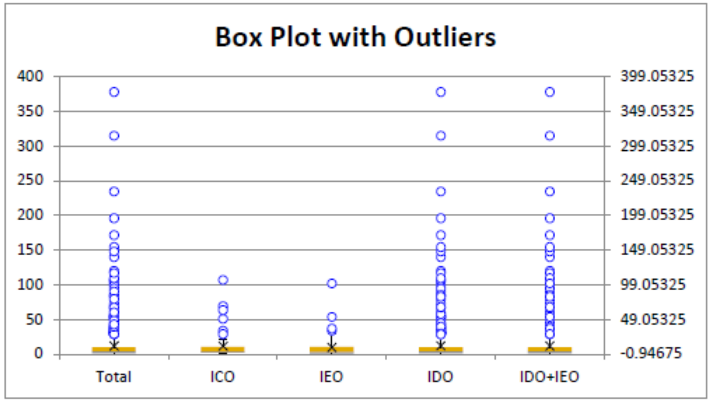
Change in X	1	5	10	25	50
Market Sentiment	*0.838%*	*4.260%*	*8.701%*	*23.192%*	*51.762%*
Issuer retained ratio	*1.035%*	*5.282%*	*10.844%*	*29.354%*	*67.325%*

Note. This table shows the standardized coefficients to ease interpretation and comparison between predictor variables. The three panels display the impact on Y (Underpricing) due to a change in X (Predictor variable).

Appendix B1

B1 – Normality tests on raw data for t-tests and ANOVA

Group	Observations	Minimum	Maximum	Mean	Std. deviation	Kurtosis	Skewness
Total	749	-0.947	377.000	10.905	28.256	66.083	6.967
ICO	51	-0.490	106.000	10.648	20.239	10.790	3.142
IEO	50	-0.905	101.000	8.672	17.153	17.495	3.800
IDO	648	-0.947	377.000	11.098	29.473	64.010	6.957
IDO+IEO	698	-0.947	377.000	10.924	28.765	65.831	7.012

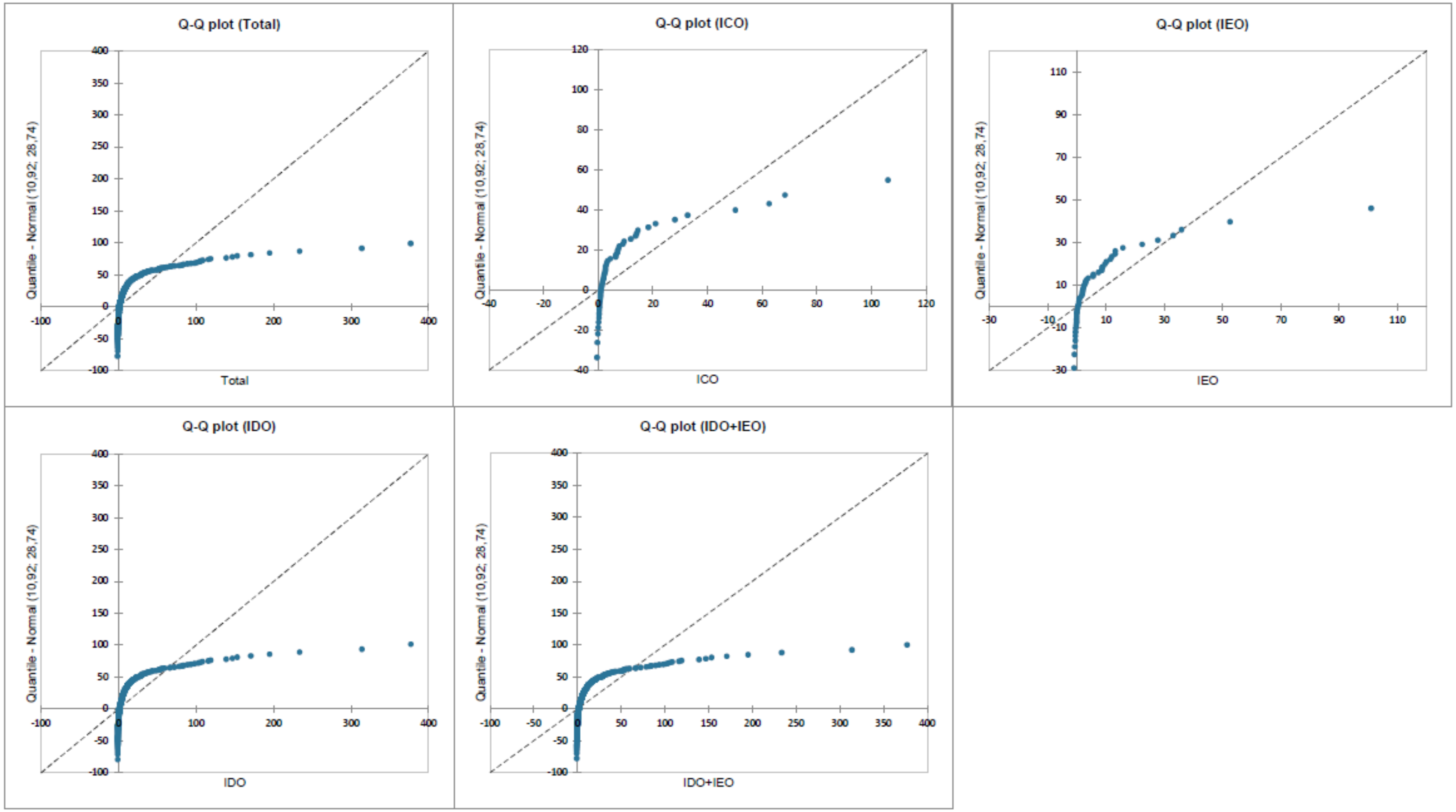


Test	Total	ICO	IEO	IDO	IDO+IEO
Shapiro-Wilk					
W	0.373	0.560	0.548	0.362	0.365
p	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*
Jarque-Bera					
JB (Observed value)	140478.068	276.683	625.109	114102.371	129904.798
JB (Critical value)	5.991	5.991	5.991	5.991	5.991
p	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*	*<0.0001*

Test interpretation:

H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.

As the computed p-value is lower than the significance level alpha=0,05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.



Appendix B2

B2 - Normality tests on treated data for t-tests and ANOVA

Group	Observations	Minimum	Maximum	Mean	Std. deviation	Kurtosis	Skewness
Total	745	-2.933	5.753	1.462	1.337	0.121	0.173
ICO	51	-0.673	4.673	1.558	1.277	-0.267	0.594
IEO	49	-2.351	4.625	1.312	1.462	-0.133	-0.031
IDO	645	-2.933	5.753	1.466	1.333	0.165	0.173
IDO+IEO	694	-2.933	5.753	1.455	1.342	0.140	0.150

Test	Total	ICO	IEO	IDO	IDO+IEO
Shapiro-Wilk					
W	0.996	0.962	0.993	0.996	0.997
p	*0.060*	*0.097*	*0.989*	*0.111*	*0.140*
Jarque-Bera					
JB (Observed value)	4.113	3.094	0.124	3.829	3.096
JB (Critical value)	5.991	5.991	5.991	5.991	5.991
p	*0.128*	*0.213*	*0.940*	*0.147*	*0.213*

Test interpretation:

H0: The variable from which the sample was extracted follows a Normal distribution.

Ha: The variable from which the sample was extracted does not follow a Normal distribution.

As the computed p-value is greater than the significance level alpha=0,05, one cannot reject the null hypothesis H0.

Student's t-test

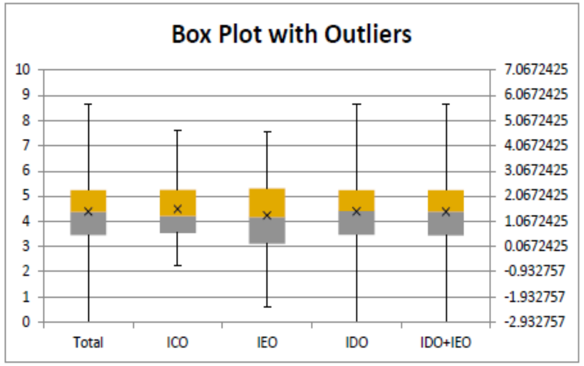
Test on the normality of residuals

Shapiro-Wilk	ICO comp. IEO+IDO	IEO comp. IDO
W	0.962	0.993
p	*0.097*	*0.989*

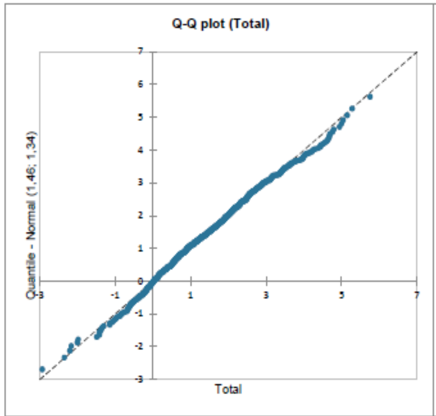
ANOVA

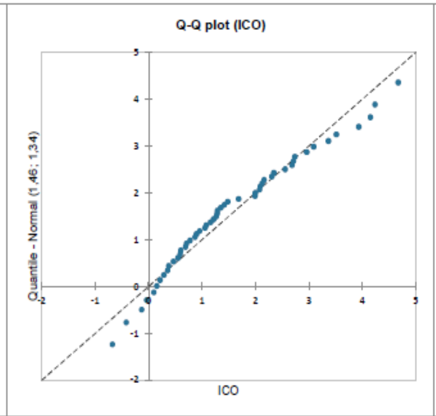
Test on the normality of residuals

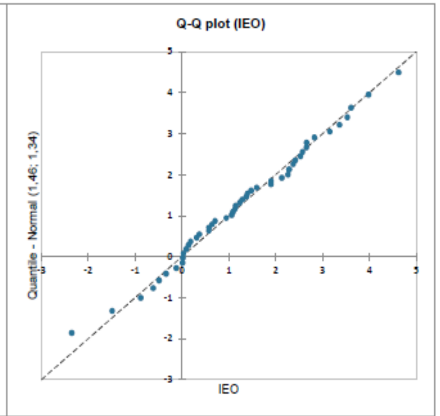
Shapiro-Wilk	
W	0.995999
p	0.053810

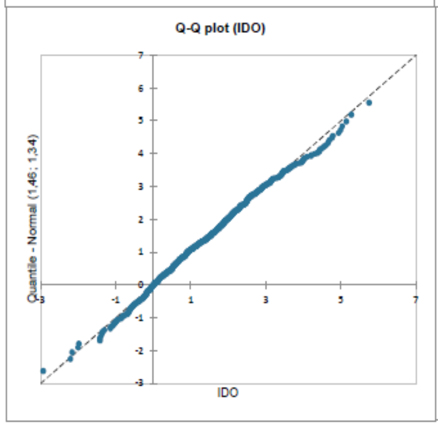


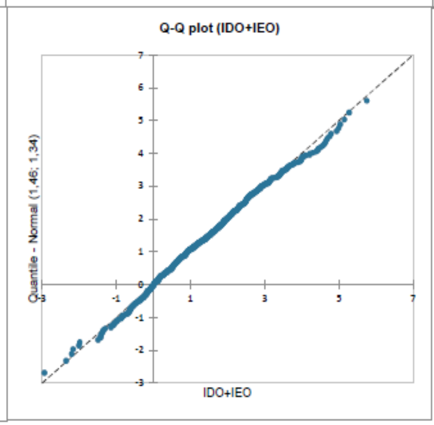
Box plot with outliers after log transformation and outliers removed





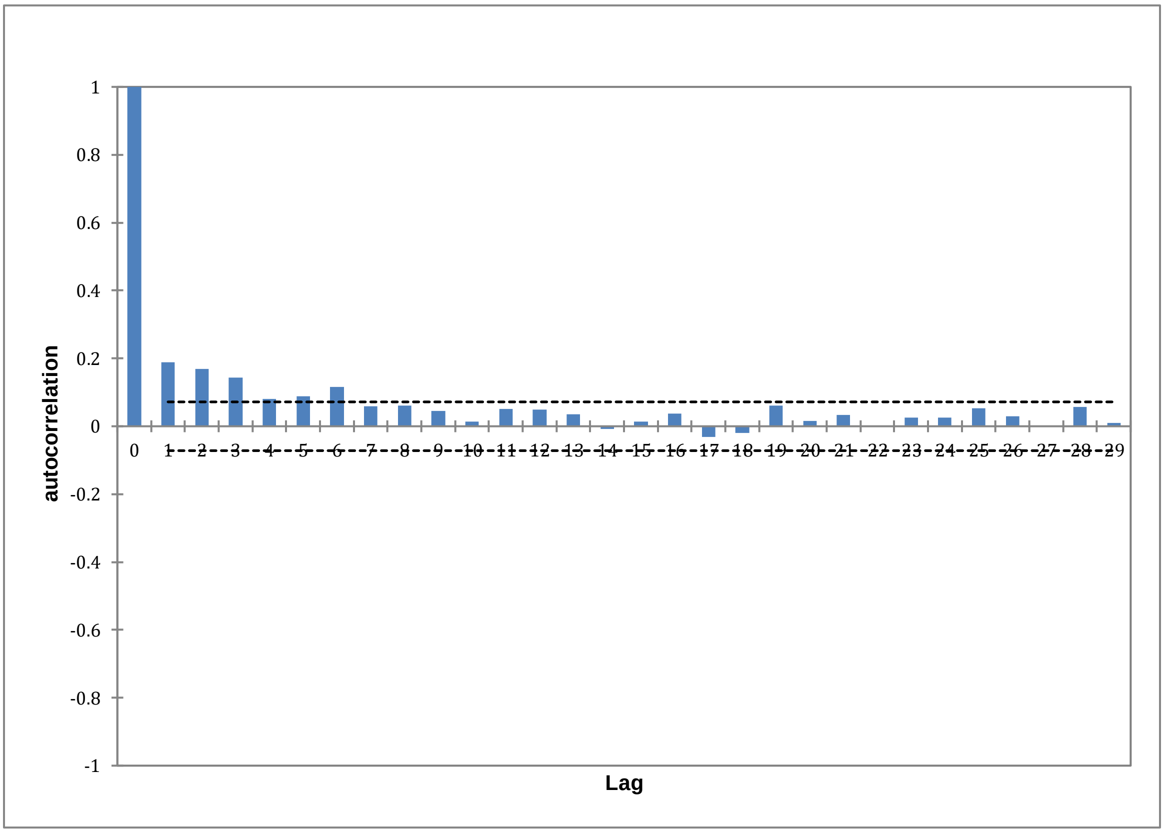






Appendix B3

B3 – Correlogram for Underpricing



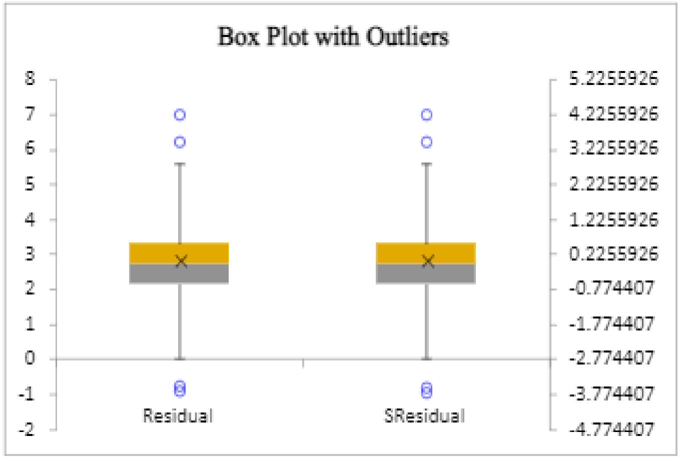
Note. This figure shows the autocorrelation between the residuals for the ANOVA test using unadjusted underpricing.

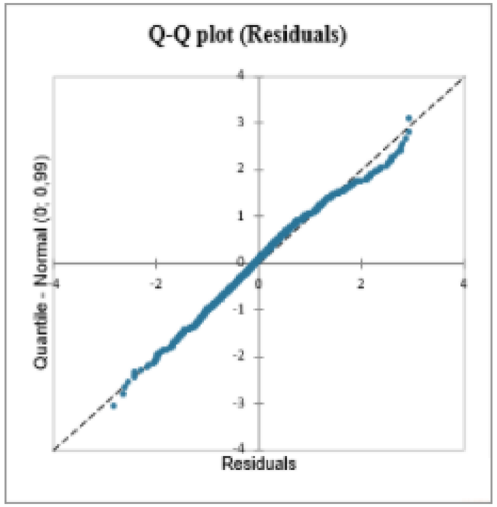
Appendix C1

C1 – Normality Tests on both Raw and Treated Data for Regression Model (1)

Raw data

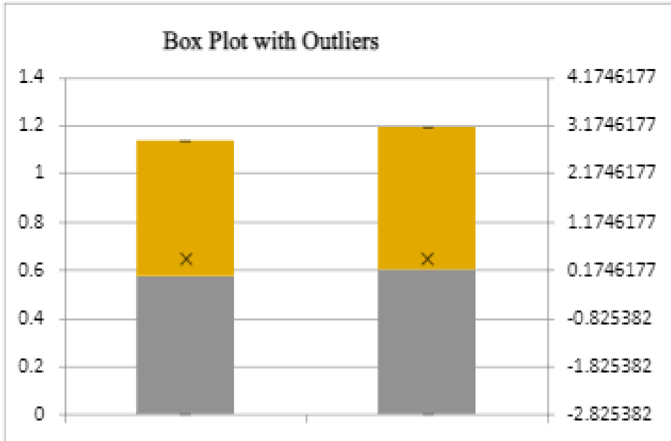
Variables	Kurtosis	Skewness
Underpricing	66.083	6.967
Underpricing_ma	66.114	6.969
Offer Price	193.194	12.458
Trading volume	130.883	10.782
Market Sentiment	-0.564	0.436
Fraction sold	33.345	4.876
Gross proceeds public	475.458	20.137
Coins sold ratio	190.227	12.811
Age	18.400	3.951
Issuer retained ratio	8.140	0.906
Duration	21.845	4.157

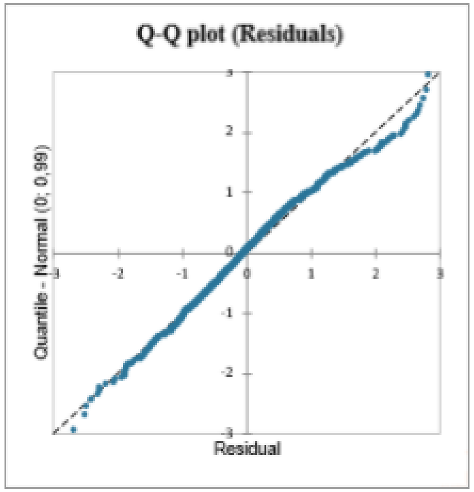




Treated data

Variables	Kurtosis	Skewness
Underpricing	0.121	0.173
Underpricing_ma	0.293	0.109
Offer Price	3.840	-0.889
Trading volume	0.833	-0.484
Market Sentiment	-0.555	0.436
Fraction sold	0.882	-0.049
Gross proceeds public	2.955	1.432
Coins sold ratio	86.710	-6.468
Age	0.472	0.096
Issuer retained ratio	8.211	0.915
Duration	0.755	1.145





Shapiro-wilk	1	2	3	4	5
W	0.990	0.990	0.982	0.947	0.989
p-value (Two-tailed)	**<0,0001**	**<0,0001**	0.637	**0.029**	**0.000**
alpha	0.050	0.050	0.050	0.050	0.050

Residuals

Shapiro-wilk	1	2	3	4	5
W	0.990	0.990	0.982	0.947	0.989
p-value (Two-tailed)	**<0,0001**	**<0,0001**	0.637	**0.029**	**0.000**
alpha	0.050	0.050	0.050	0.050	0.050

Appendix C2

C2 – Autocorrelation Test for all Regression Models

Measure	(1)	(2)	(3)	(4)	(5)
DW	1.810	1.827	1.446	2.037	1.775
rho	0.094	0.086	0.262	-0.022	0.112
p-value (one-tailed)	0.008	0.015	0.022	0.926	0.003
alpha	0.050	0.050	0.050	0.050	0.050

Note. This table shows one-tailed Durbin-Watson test for autocorrelation on all regression models

Appendix C3

C3 – Multicollinearity Test for All Regression models

Variables	(1)	(2)	(3)	(4)	(5)
ICO	1.255	1.255	-	-	-
IEO	1.163	1.163	-	-	-
Offer Price	1.166	1.166	1.419	1.814	1.198
Trading volume	1.163	1.163	1.938	2.200	1.148
Market Sentiment	1.158	1.158	1.449	1.717	1.210
Gross proceeds public	1.683	1.683	3.981	2.631	1.436
Fraction sold	1.296	1.296	2.439	1.796	1.310
Coins sold ratio	1.09	1.09	1.370	1.834	1.072
Issuer retained ratio	1.089	1.089	1.457	1.363	1.116
Age	1.117	1.117	1.908	1.500	1.100
Duration	1.158	1.158	1.489	1.813	1.141
Lock-up public	1.219	1.219	2.089	1.436	1.290
Lock-up private	1.794	1.794	2.738	3.091	1.755
Pre-sale	1.740	1.740	2.176	3.303	1.718
Whitepaper	1.042	1.042	1.447	1.734	1.062
Github	1.087	1.087	1.613	1.727	1.071
Ethereum	-	-	1.942	1.619	1.677
Binance	-	-	1.641	1.999	1.568
Polygon	-	-	1.358	1.806	1.054
Solana	-	-	-	1.774	1.231

Note. This table shows variance in factor (VIF) values for all predictors variables used in the respective regression models (after removal of multiple variables).

Appendix C4

C4 - Heteroscedasticity Tests for all Regression Models

Measure	(1)	(2)	(3)	(4)	(5)
			Breusch-Pagan test		
LM (Observed value)	30.310	30.281	18.374	13.851	30.849
LM (Critical value)	26.296	26.296	27.587	28.869	28.869
DF	16	16	17	18	18
p-value (Two-tailed)	0.016	0.017	0.366	0.739	0.030
alpha	0.05	0.05	0.05	0.05	0.05
			White test		
LM (Observed value)	162.019	163.900	51.000	49.000	190.928
LM (Critical value)	181.770	181.770	201.423	222.076	222.076
DF	152	152	170	189	189
p-value (Two-tailed)	0.274	0.241	1.000	1.000	0.447
alpha	0.05	0.05	0.05	0.05	0.05

Note. This table shows Breusch-Pagan and White test for heteroscedasticity.

Appendix D

D1 – Regression Models

Regression model (1)

$$UP = \alpha + \beta_1 \times ICO_{dummy} + \beta_2 \times IEO_{dummy} + \beta_3 \times ln\ Gross\ proceeds\ public_i + \beta_4 \times ln\ age + \beta_5 \times Issuer\ retained\ ratio_i + \beta_6 \times ln\ Fraction\ sold_i + \beta_7 \times ln\ trading\ volume_i + \beta_8 \times ln\ Coin\ sold\ ratio_i + \beta_9 \times market\ sentiment_i + \beta_{10} \times ln\ Offer\ price_i + \beta_{11} \times ln\ Duration_i + \beta_{12} \times Lockup\ public_{dummy} + \beta_{13} \times Lockup\ private_{dummy} + \beta_{14} \times Presale_{dummy} + \beta_{15} \times Whitepaper_{dummy} + \beta_{16} \times Github_{dummy} + \varepsilon_i.$$

Regression model (2)

$$UP\_m = \alpha + \beta_1 \times ICO_{dummy} + \beta_2 \times IEO_{dummy} + \beta_3 \times ln\ Gross\ proceeds\ public_i + \beta_4 \times ln\ age + \beta_5 \times Issuer\ retained\ ratio_i + \beta_6 \times ln\ Fraction\ sold_i + \beta_7 \times ln\ trading\ volume_i + \beta_8 \times ln\ Coin\ sold\ ratio_i + \beta_9 \times market\ sentiment_i + \beta_{10} \times ln\ Offer\ price_i + \beta_{11} \times ln\ Duration_i + \beta_{12} \times Lockup\ public_{dummy} + \beta_{13} \times Lockup\ private_{dummy} + \beta_{14} \times Presale_{dummy} + \beta_{15} \times Whitepaper_{dummy} + \beta_{16} \times Github_{dummy} + \varepsilon_i.$$

Regression model (3)

$$UP = \alpha + \beta_1 \times ln\ Gross\ proceeds\ public_i + \beta_2 \times ln\ age + \beta_3 \times Issuer\ retained\ ratio_i + \beta_4 \times ln\ Fraction\ sold_i + \beta_5 \times ln\ trading\ volume_i + \beta_6 \times ln\ Coin\ sold\ ratio_i + \beta_7 \times market\ sentiment_i + \beta_8 \times ln\ Offer\ price_i + \beta_9 \times ln\ Duration_i + \beta_{10} \times Lockup\ public_{dummy} + \beta_{11} \times Lockup\ private_{dummy} + \beta_{11} \times Presale_{dummy} + \beta_{12} \times Whitepaper_{dummy} + \beta_{13} \times Github_{dummy} + \beta_{14} \times Ethereum_{dummy} + \beta_{15} \times Binance_{dummy} + \beta_{16} \times Polygon_{dummy} + \varepsilon_i.$$

Regression model (4)

$$UP = \alpha + \beta_1 \times ln\ Gross\ proceeds\ public_i + \beta_2 \times ln\ age + \beta_3 \times Issuer\ retained\ ratio_i + \beta_4 \times ln\ Fraction\ sold_i + \beta_5 \times ln\ trading\ volume_i + \beta_6 \times ln\ Coin\ sold\ ratio_i + \beta_7 \times market\ sentiment_i + \beta_8 \times ln\ Offer\ price_i + \beta_9 \times ln\ Duration_i + \beta_{10} \times Lockup\ public_{dummy} + \beta_{11} \times Lockup\ private_{dummy} + \beta_{11} \times Presale_{dummy} + \beta_{12} \times Whitepaper_{dummy} + \beta_{13} \times Github_{dummy} + \beta_{14} \times Ethereum_{dummy} + \beta_{15} \times Binance_{dummy} + \beta_{16} \times Polygon_{dummy} + \beta_{17} \times Solana_{dummy} + \varepsilon_i.$$

Regression model (5)

$$UP = \alpha + \beta_1 \times ln\ Gross\ proceeds\ public_i + \beta_2 \times ln\ age + \beta_3 \times Issuer\ retained\ ratio_i + \beta_4 \times ln\ Fraction\ sold_i + \beta_5 \times ln\ trading\ volume_i + \beta_6 \times ln\ Coin\ sold\ ratio_i + \beta_7 \times market\ sentiment_i + \beta_8 \times ln\ Offer\ price_i + \beta_9 \times ln\ Duration_i + \beta_{10} \times Lockup\ public_{dummy} + \beta_{11} \times Lockup\ private_{dummy} + \beta_{11} \times Presale_{dummy}. + \beta_{12} \times$$

$Whitepaper_{dummy} + \beta_{13} \times Github_{dummy} + \beta_{14} \times Ethereum_{dummy} + \beta_{15} \times Binance_{dummy} + \beta_{16} \times Polygon_{dummy} + \beta_{17} \times Solana_{dummy} + \varepsilon_i.$