Cryptos Left on the Table?

Underpricing in Initial Exchange Offerings

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Bachelor Thesis

Stockholm School of Economics

2021

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Abstract:

This study empirically examines underpricing in the newest phenomenon of cryptocurrency fundraising: initial exchange offerings (IEO). Drawing from the well-supplied initial public offering (IPO) literature, we study the existence and level of underpricing in IEOs and whether theories on asymmetric information and behavior can help explain it. In a dataset of 186 manually collected IEOs conducted between January 2019 and April 2021, we find an average underpricing of 412.02 percent and a median of 90.49 percent. Regression results show that some attempts at mitigating information asymmetry might decrease underpricing, such as having a pre-sale prior to the IEO, having a longer whitepaper, and a larger issue size. Conversely, conducting an IEO on a trusted and reputable cryptocurrency exchange and during high cryptocurrency market sentiment is positively correlated with underpricing. We suggest that IEOs are subject to severe underpricing and that theories from IPO literature can provide explanations to help understand underpricing in an IEO context.

Keywords:

Initial exchange offering, Underpricing, Cryptocurrency, Tokens, Initial coin offering

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Bachelor Thesis
Bachelor Program in Business and Economics
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1. Introduction

New ventures often need external financing to further develop and launch their business ideas. For start-up companies operating on *blockchain technology*, recent advances give companies new opportunities to raise capital in suggestively convenient and cheap ways. In what is known as an *initial coin offering* (ICO), companies raise capital by creating and issuing *coins* or *tokens* to investors in what is similar to a type of crowdfunding (Catalini & Gans, 2019). Most of the ventures conducting ICOs have the goal of launching online platforms on which the tokens can be used in a variety of ways, i.e. purchasing services or products, or receiving specific benefits. ICOs have several advantages over traditional financing methods, such as initial public offering (IPO), venture capital, angel investment or debt instruments, in that ICOs have close-to-zero transaction costs. In addition, ICOs are highly unregulated and documentation requirements are kept at a minimum (Momtaz, 2020).

Despite its advantages, the ICO market has been criticized for the presence of scams and frauds, due to lack of regulation and absence of functioning institutions. In fact, there has been a sharp decline in the number of ICOs in recent years (Haffke & Fromberger, 2020). The fall of ICOs has been countered with the rise of a new form of cryptocurrency crowdfunding during 2019: *initial exchange offering* (IEO). An IEO is similar to an ICO, with the distinguishing difference that the fundraising is administered by a cryptocurrency exchange instead of by the fundraisers themselves.

This paper aims at exploring the existence and possible explanations of *underpricing* in IEOs. The phenomenon of "underpricing" refers to when new shares issued through an initial public offering (IPO) experience a price jump on the first day of trading. This ultimately leaves issuers with less capital than if shares would not have been underpriced, or as commonly said, "leaves money on the table". IPO underpricing is a well-documented phenomenon in research. Recent studies have also shown the existence of severe underpricing in ICOs (Felix & von Eije, 2019; Benedetti & Kostovetsky, 2018; Momtaz 2020). However, there is yet no published research regarding the existence or level of underpricing in IEOs. This gives this study scientific value as it will be first to examine this relationship. Therefore, this study has two main purposes. First, to explore if and to what extent underpricing exists in IEOs. Second, seek to provide a set of possible explanations to underpricing using theories from IPO literature, which would constitute a basis from which future research can benefit from.

The results show that underpricing does exist in IEO at a 0.01 percent significance level. In a sample of 186 IEOs, the average level of underpricing is 412.02 percent, and the median is 90.49 percent, suggesting that the level of underpricing in IEOs is significantly higher than in IPOs, and within the range of ICO underpricing levels. Moreover, the regression results show that there is significant correlation between IEO underpricing and the following proxies drawn from the IPO underpricing theories: issue size, whitepaper pages, market sentiment, crowdedness, exchange trustfulness, and pre-sale. This indicates that IPO underpricing theories are in fact relevant in an IEO context.

The paper proceeds as follows: Section 2 reviews the related literature; section 3 presents the hypotheses; section 4 describes the research design; section 5 describes the data; section 6 presents the empirical results; section 7 discusses the results, and section 8 concludes.

2. Literature Review

2.1. Cryptocurrency as a way of financing

2.1.1. Blockchain, Bitcoin and Altcoins

As of April 30, 2021, the global market cap of cryptocurrencies amounts to 2.1 trillion USD, with almost 50 percent being made up by *Bitcoin.* On the same day five years prior, cryptocurrency had a market cap of 8.4 billion USD, representing an approximate of 25 thousand percent increase in only five years (CoinMarketCap, 2021). Nevertheless, Bitcoin has been characterized as a speculative bubble by eight winners of the Nobel Memorial Prize in Economic Sciences[1] (Krugman, 2018; Shiller, 2014; Costelloe, 2017; ECO News, 2018; Wolff-Mann, 2018).

Cryptocurrency is a subset of the class of digital currency with the distinctive characteristic of being built on *blockchain technology*. Iansiti and Lakhani (2017) define a blockchain as "an open, distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way". They suggest that if adopted effectively, blockchain may cause transaction intermediaries to no longer be necessary, and could allow for the "free interaction between individuals, organizations, machines, and algorithms".

Bitcoin tries at implementing this technology. Introduced in 2008 by Satoshi Nakamoto, Bitcoin aimed at providing an answer to the lack of confidence in the financial system after the global financial crisis. By using blockchain as the public ledger, Bitcoin transactions are operated by a decentralized authority, are flexible, transparent, fast, and promise low transaction fees (Chuen, 2018).

Because Bitcoin is not perfect, the invention of new coins is constantly incentivized to address specific issues and explore new purposes. Examples could be the invention of new coins to further lower costs, increase speed, and alter transparency on the Bitcoin blockchain. Recent years have also seen the creation of more sophisticated blockchains, which enable a wide range of applications, such as insurance contracts, voting schemes, and contingent investment products. *Ethereum* is an example of such a blockchain. This has spurred the invention of new coins to explore completely new purposes, for example to be used on a specific platform such as a phone application or provide other unique features. These additional cryptocurrencies are referred to as *alternative cryptocurrencies* or *altcoins* (Chuen, 2018).

2.1.2. Token Sales and the ICO

The creation and emission of altcoins is known as *token sales* or *initial coin offerings* (ICO). Tokens and coins are as concepts often used interchangeably. By selling tokens, new and early-stage blockchain ventures can raise capital from external sources to fund further development and launch expenses. Conceptually, tokens represent "entries" or transactions on a blockchain. The owner of

[1] Namely Paul Krugman, Robert J. Shiller, Joseph Stiglitz, Richard Thaler, James Heckman, Thomas Sargent, Angus Deaton, and Oliver Hart.

the token has a *key* that lets him create new entries on the blockchain on which the token functions on and can thus reassign the token ownership to someone else and conduct a transaction.

Tokens can be divided into three different types: *security tokens*, *utility tokens* and *cryptocurrency tokens*. Security tokens represent security against an underlying asset exchanged on a blockchain. This to reduce transaction costs and create a record of ownership. Security tokens are comparable to equity shares. The second type, utility tokens, equip the owner with rights to consume utility from the issuer's products or service. Utility tokens may be comparable to vouchers. The last type, known as cryptocurrency tokens, are general purpose medium of exchange and store-of-value tokens. Bitcoin is an example of such a token. Most tokens are issued and designed as utility tokens. Until the end of 2019, over 5,600 ICOs had collectively raised more than 27 billion USD (Momtaz, 2020).

There are certain advantages to ICOs in comparison to more traditional financing methods such as an initial public offering (IPO), venture capital, angel investment or debt instruments. In terms of deal characteristics, a major reason for the high popularity of ICOs is close-to-zero transaction costs. ICOs are highly unregulated and documentation needs are kept at a minimum. This way, start-ups can raise large external funding without the need of costly and highly regulated venture capital transactions or IPOs. In addition, post-deal characteristics offer major incentives for investors to invest in ICOs. Within three months after the token sale ends, many tokens get the opportunity of being listed on a 24/7 online trading token exchange platform. This aspect provides investors with added value in the form of substantial market liquidity.

Despite these advantages, investing in cryptocurrency projects brings certain risks and challenges. Firstly, the ICO market has been criticized for the existence of scams and frauds. Due to its unregulated nature and absence of functioning institutions, asymmetric information is a major challenge (Momtaz, 2020). Howell, Niessner, and Yermack (2020) provide a thorough mapping of which issuer and ICO characteristics predict successful real outcomes. They conclude that variables that predict future ICO operational success are largely related to mitigating information asymmetry, such as certification, voluntary disclosure, bonding, social media presence and displaying code development publicly on platforms such as GitHub.

2.2. IPO vs ICO vs IEO

As we attempt at bridging the gap between well supplied initial public offering (IPO) literature, and mechanisms in the initial coin offering (ICO) and initial exchange offering (IEO), we provide a distinction on the differences between the three. The main differences are summarized in *Table I*.

2.2.1. Initial Public Offering (IPO) vs. Initial Coin Offering (ICO)

There are significant differences between an initial public offering (IPO) and an initial coin offering (ICO). In an initial public offering, shares are issued which represent a fraction of a real business with ownership, cash flows, valuable assets and voting rights. In an ICO, the business issuing the tokens may not even yet exist. An IPO often represents

an exit strategy for the original shareholders of a more mature company, whereas an ICO is a mean of raising capital to further launch a business. The rights granted to token holders in an ICO may differ, but typically represent access and right-of-use to a digital product or service. Furthermore, IPOs require significant preparations in terms of legal backing, reporting, book building and other requirements. ICOs however, require considerably less preparations. In addition, in an IPO, the underwriter handles the administers the share issuance, whereas in an ICO the token sale is completely handled by the fundraising company (Sánchez, 2017).

Lack of regulation and lower participation of reputable external parties might result in ICO investors to become victims of fraudulent behavior. Many token issuers do not provide core information related to initiators and backers, applicable law, segregation or pooling of client funds, or the existence of an external auditor (Zetzsche et al., 2017). This causes large information asymmetry between investors and the issuing company, making ICOs substantially riskier than IPOs.

2.2.2. Initial Coin Offering (ICO) vs. Initial Exchange Offering (IEO)

Recent years have seen a decline in the amount of ICOs. According to Haffke & Fromberger's ICO Market Report 2018/2019, more than $14 billion was collected via ICO in 2018. However, according to the same report 2019/2020, this number shrunk to $3 billion in 2019. Haffke & Fromberger state that it is likely that the number of ICOs will continue to decrease in the future, and that 2018 was a record year in terms of ICO activity and the market has now become more mature (Haffke & Fromberger, 2020).

The downturn of the ICO market has been countered with the rise of a new form of cryptocurrency crowdfunding during 2019: initial exchange offering (IEO). An IEO is similar to an ICO, with the distinguishing difference that the fundraising is administered by a *cryptocurrency exchange* instead of by the fundraisers themselves. Through an exchange's fundraising platform, commonly referred to as a *launchpad*, users who are registered on the exchange can purchase issued tokens and thus participate in the token sale. The exchange also handles aspects such as KYC checks on buyers, listing, reporting and other related functions.

The distinct difference between IEOs and ICOs gives issuers several benefits to conduct an IEO. Firstly, for a project looking to raise funds, an IEO offers exposure to an immediate userbase. The venture could therefore reduce their marketing costs. Secondly, since users participate completely through the exchange's fundraising interface, they do not need to manage different wallets on different blockchains. This significantly simplifies the user experience of participating in the token issuance. Lastly, the exchange is staking its reputation behind the projects it lists on its platform, offering a higher degree of trust to investors by assessing the quality of the project. This increased level of due diligence also increases token fundraising success (Binance Academy, 2021).

Table I

IPO vs ICO vs IEO

	IPO	**ICO**	**IEO**
What is issued?	Shares	Tokens	Tokens
Company development stage	Mature	Start-up	Start-up
Utility from participation	Rights such as dividends and voting rights	Usually provides access to services or products	Usually provides access to services or products
Legal backing and regulation	High	Low/none	Low/none
Amount of preparations	High	Low	Low
Issuance handled by	Underwriter	The fundraisers themselves	Crypto exchange
Assessment of issuer	Done by underwriters, auditors etc.	None	Done by Exchange
Risk	Lower	Higher	Lower than ICOs

Table I outlines an overview of the fundamental differences between an initial public offering (IPO), an initial coin offering (ICO), and an initial exchange offering (IEO). An IPO is significantly different from both an ICO and an IEO on most aspects. The most fundamental difference between an ICO and an IEO is then that the issuance of tokens is handled by a cryptocurrency exchange, as opposed to the fundraisers themselves.

2.3. Initial Exchange Offering (IEO)

There is currently little to no published research on IEOs. Anson (2021) presents the only currently published paper focusing on IEOs "Initial Exchange Offering: The Next Evolution in Cryptocurrencies". He demonstrates how the increased due diligence in an IEO increases token fundraising success. His empirical results show that firms are more successful in raising money through an IEO than in an ICO due to the less risky nature and advantages of the tokens being sold on an exchange (Anson, 2021).

Examples of successful IEOs are BitTorrent, which raised more than 7.2 million USD in just 18 minutes, and Fetch.ai, which raised 6 million USD in 22 seconds. The more well-known and reliable exchanges and launchpads are for example *Binance*, *Huobi*, *OKEx*, *Bittrex,* and *Kucoin*. In 2019, IEOs are most popular by number of projects in Singapore, South Korea, Estonia, USA, and Hong Kong (Myalo, 2019).

2.4. Theories of Underpricing

When firms decide to go public, issued shares tend to experience a price jump on the first day of trading, indicating that the shares are "underpriced". Ritter (2020) shows that IPOs experience a mean underpricing of 18.4 percent. This causes firm to essentially "leave money on the table" since they sell shares at a seemingly lower price than the true value. Ljungqvist (2007) groups theories of causes of IPO underpricing under four broad headings: *asymmetric information*, *institutional*, *control* and *behavioral*. Since this study aims to relate these theories to underpricing in IEOs, it focuses on information asymmetry models and behavioral explanations of underpricing. This is because since token offerings are still largely unregulated, institutional theories of underpricing don't apply to the same extent as in IPOs. In addition, since token holders are not granted extra control in the company as compared to shareholders, theories of underpricing related to control are also not as relevant. In contrast, due to the large information asymmetry in token offerings, these models become highly relevant in explaining potential underpricing (Momtaz, 2020). Because of largely fluctuating market sentiment and investor behavior in the cryptocurrency market (Drobetz et al. 2019), we want to also attempt at incorporating and relating theories of behavior to IEO underpricing.

2.4.1. Information Asymmetry

The most significant theories used to explain underpricing is asymmetric information models. These models assume that one or more of the key parties in an IPO transaction, the issuing firm, the underwriter, and the investors, have more information about the transaction than the other parties. When the buyers have less information about the product than the sellers, IPOs become subject to the "lemon problem". This problem, as described by Akerlof (1970), causes buyer's average willingness-to-pay to decrease when they cannot distinguish been goods of high and low value. Sellers of high-quality goods will eventually leave the market when they do not receive the correct price, leaving behind only a market of low-quality goods, or "lemons". IPOs are subject to this problem in the sense that when buyers struggle to recognize true firm value, they require shares to be underpriced.

An application of the lemon problem is Rock's (1986) *winner's curse,* which follows information asymmetry between informed and uninformed investors. Uninformed investors may be reluctant to participate in an IPO since their demand might partly be crowded out by more informed investors. Since an underwriter wants to avoid the failure of an IPO, he would lower the price to attract not only informed but also uninformed investors. The firm seeking to go public therefore also benefit from underpricing even though money is left on the table.

To mitigate this information asymmetry, evidence suggests that firms can hire reputable underwriters. When prestigious intermediaries "confirm" the quality of the issuance, the information asymmetry between informed and uninformed investors is relaxed and underpricing reduced. Underwriters which value their reputation will be reluctant to underwrite low-quality firms (Booth & Smith, 1986; Carter & Manaster, 1990; Michaely & Shaw, 1994). However, the empirical evidence on this point is mixed. Betty and Welch (1996) use data from the early 1990s, and instead suggest that more

prestigious underwriters are correlated with *higher* underpricing. Loughra and Ritter (2004) hypothesize that this is because underwriters strategically underprice IPOs to increase their own or their client's wealth. Megginson and Weiss (1991) also show that the certification of IPOs by venture capitalists results in less initial return and gross spreads. This is consistent with the certification hypothesis, in that information asymmetry between inside and outside investors may be mitigated when third party specialists "certify" the value of securities issued by relatively unknown firms.

Furthermore, other models assuming information asymmetry are *signaling theories*. These theories once again assume firms have more information about the present value or risk of future cash flows than do investors. To signal their true value, firms of high quality can benefit by underpricing in its IPO and then recouping these costs later through a seasoned issue. A low-quality firm would be reluctant to underprice due to the risk of being detected and thus not being able to recoup the cost of underpricing at a later date (Allen & Faulhaber, 1989). If shares are then sold sequentially, investors can also learn by the decision of early investors and the information asymmetry may be mitigated by the next share issuance (Welch, 1992).

2.4.2. Behavioral Explanations

Besides information asymmetry, evidence suggests behavioral theories also explain underpricing. These suggests that "irrational" investors bid up market prices beyond their true value when market sentiment is high. Excessive optimism of companies' earnings potential results in higher-than-average IPO underpricing (Ritter, 1991; Derrien, 2005; Ibbotson et al. 1994). According to Ibbotsson et a. (1994) "hot" markets and excessive optimism can cause a high concentration of sentiment investors who follow a certain positive feedback or "trend" chasing strategy. If recent issues have risen in price, sentiment investors are willing to bid up the price of new issues as well, causing positive autocorrelation of initial returns. For example, during the "dot-com bubble", U.S. issuers left an aggregate of $62 billion on the table, and IPO underpricing was measured to an average of 71 percent in 1999 (Ljungqvist, 2007). Additionally, these periods of high initial returns in IPOs, known as "hot issue" markets, have been documented to be correlated with higher IPO volume. Firms find "windows of opportunities" to go public when investor sentiment is high even though they underperform in the long run (Ritter, 1991; Ibbotson et al. 1994).

Additionally, Ljungqvist, Nanda and Singh (2004) model an IPO company's optimal response to the presence of "irrational" or "sentiment" investors. They show that from the point of the issuer, the optimal share selling strategy usually involves *staggered sales*. Such sales can be implemented by allocating the IPO to cooperative, "regular" institutional investors for subsequent resale to overoptimistic sentiment investors. Since this overoptimism or hot market can end abruptly and prematurely, carrying IPO stock in inventory is risky. To break even, regular investors require the IPO to be underpriced. The issuer would benefit from this mechanism since the offer price of the IPO still exceeds fundamental value, as it includes the regulars' expected gain from trading with sentiment investors. This would help explain why underpricing is high in the presence of overly optimistic sentiment investors such as in the dot-com bubble.

2.4.3. *Strategic Explanations*

There are research suggesting that firms underprice to generate information momentum in terms of research coverage, which leads to increased demand for the stock. Aqqarwal, Krigman and Womack (2002) show that if managers underprice, they can generate attraction from investors due to information momentum, and thus increase demand. Therefore, they can sell their shares at a higher price than they otherwise could, and thus recoup the losses caused by strategically offering shares at a price below their true value. In a test on a sample of IPOs in the 1990s, they find positive correlation between underpricing and research coverage as well as positive correlation between research coverage and stock returns. In addition, in the theoretical model of Grinblatt and Hwang (1989), IPO issuers can attract more investors to their share issuance by underpricing it below its true value and thus eventually reaching a higher market price than without initial underpricing.

2.5. Underpricing in ICOs

There are previous papers published which have studied underpricing in ICOs. Adhami et al (2018) find that success of ICOs is more probable when investors can access the source code and when issuers conduct a pre-ICO (issuing a limited number of tokens to a restricted group of investors before the actual ICO). They also find an average ICO underpricing of 929.9 percent and a median value of 24.7 percent in a sample of 140 ICOs.

Felix and von Eije (2019) attempt to bridge the gap between IPO underpricing literature and ICO underpricing. They find an average level of ICO underpricing of 123 percent in the US and 97 percent in other countries when studying a sample of 247 ICOs. Additionally, trading volume and good market sentiment in the ICO market cause more underpricing in ICOs. Also, they find that firms which conduct a pre-ICO and have a large issue size experience less underpricing.

Benedetti and Kostovetsky (2018) also find significant evidence of underpricing in ICOs, with average first trading day returns of 179 percent in their sample of 416 ICOs of exchange listed tokens. Furthermore, they find that underpricing is reduced when the initial offer price is higher and when there is a pre-ICO before the main offering. In the view of the authors, this is because a low ICO price attracts higher demand from investors, which results in higher performance directly after the ICO.

Momtaz (2020) finds positive first day initial returns in ICOs, however not at the same level of other findings with an average underpricing of 8.2 percent. He continues to argue that token issuers underprice strategically to attract additional market liquidity and thus signal firm growth prospects, in accordance with the model of Aqqarwal, Krigman & Womack (2002) and the signaling model of Grinblatt and Hwang (1989), as described above. In addition, Drobetz et al. (2019) conjecture that investor sentiment plays a crucial role in ICOs in that the ICO market is only affected by sentiment in the crypto-market and not by the broader capital market. They also find evidence suggesting that first-day returns are lower during periods of negative sentiment, in line with above mentioned research.

There are yet to be any published research on the underpricing of IEOs.

3. Hypothesis

3.1. Level of IEO Underpricing

There is a large body of literature supporting the existence of underpricing in IPOs, and the most significant cause of underpricing is information asymmetry between actors. Research done on ICOs provide evidence of large amounts of underpricing. Even though IEOs function to minimize risks and information asymmetry between issuers and investors, conducting an IEO is a relatively new and unregulated form of financing. Therefore, few investors are expected to know the true characteristics of the issuer. Substantial information asymmetry is thus still expected to exist. Consequently, this paper also hypothesizes that underpricing will also be present in IEOs.

$$H_1: There\ is\ underpricing\ in\ initial\ exchange\ offerings$$

3.2. Correlated Variables

Next, the theories in IPO literature related to the causes of underpricing stated in section 2.4 are translated into proxies to test if the same theories also hold for IEOs. As mentioned, some of the theories aiming at explaining underpricing are theories of information asymmetry and behavioral explanations. This paper will attempt at translating these theories into variables, which potentially increase or decrease underpricing. Additionally, we also add some variables which have been found to correlate with underpricing in the ICO literature. Each variable is presented below, along with a hypothesis of how it should correlate with the level of underpricing. The hypothesized expected correlations with underpricing are summarized in *Table II*.

3.2.1. Offer Price

Benedetti and Kostovetsky (2018) find that underpricing is reduced when the initial offer price is higher. They argue that a lower price increases demand from investors and thus increases underpricing. We hypothesize that the same theory will hold for IEOs, which leads to the following hypothesis:

$$H_2: A\ higher\ offer\ price\ is\ negatively\ correlated\ with\ the\ level\ of\ underpricing$$

3.2.2. Issue Size

Felix and von Eije (2019) find that firms which have a large issue size in terms of monetary value experience less underpricing in ICOs. It can be argued that issue size is viewed as a proxy for ex-ante uncertainty, since larger and more established companies will tend to have larger issues. More established firms, in turn, tend to have more information available about the issue than smaller firms. Less ex-ante uncertainty has been showed to decrease underpricing in the IPO literature (Ritter, 1991). Consequently, less underpricing is expected to exist in a larger token issuance. We also expect this to be true for IEOs, which leads to the following hypothesis:

$$H_3: A\ larger\ issue\ size\ is\ negatively\ correlated\ with\ the\ level\ of\ underpricing$$

3.2.3. *Whitepaper number of pages*

As mentioned, the most significant cause of underpricing is information asymmetry between actors. The whitepaper of an IEO is similar to the prospectus in an IPO. Prospectus disclosure is a widely used proxy for ex-ante uncertainty. A whitepaper often provides information about the project in general, its underlying technology, and prospects. One key difference between a prospectus and a whitepaper, however, is that whitepapers currently do not require adherence to any regulatory framework, resulting in vast differences in content and length. Thus, it is expected that longer whitepapers are correlated with less information asymmetry, resulting in the following hypothesis:

$$H_4: The\ number\ of\ pages\ in\ the\ whitepaper\ is\ negatively\ correlated\ with\ the\ level\ of\ undepricing$$

3.2.4. External Rating

Prior to an IEO, it is common for potential investors to use several third-party websites to look for external ratings of an IEO, to gauge the true value of a firm. Megginson and Weiss (1991) propose that experts can reduce information asymmetry by issuing their evaluation of an IPO. Thus, it is expected that having a rating prior to the IEO will reduce information asymmetry, resulting in the following hypothesis:

$$H_5: Having\ an\ external\ rating\ avaible\ prior\ to\ the\ IEO\ is\ negatively\ correlated\ with\ the\ level\ of\ underpricing$$

3.2.5. Market Sentiment

It has been found that IPO underpricing increases in times of "hot" markets and when investors optimism is high. In times of high market sentiment and investor demand, investors are overly optimistic about future returns and thus bid up IPO prices (Derrien, 2005; Ibbotson et al. 1994). Firms take advantage of these opportunities and increase underpricing, as suggested by Ljungqvist et al. (2004). Additionally, high sentiment in the crypto market has been shown to correlate with higher returns in ICOs (Drobetz et al., 2019; Felix & von Eije, 2019). We expect the same to hold for IEOs, which leads to the following hypothesis:

$$H_6: A\ high\ market\ sentiment\ is\ positively\ correlated\ with\ the\ level\ of\ underpricing$$

3.2.6. Crowdedness

IPO literature has thoroughly documented that "hot issue" markets are accompanied by high initial returns to investors and increased volume of IPOs (Ritter, 1991. Ibbotson et al. 1994). We thus expect underpricing to increase when IEO activity is high, which we define as the number of IEOs that have been conducted 30 days before the listing date. We call this variable "crowdedness" and hypothesize:

$$H_7: IEO\ crowdedness\ is\ positively\ correlated\ with\ the\ level\ of\ underpricing$$

3.2.7. Pre-Sale

Firms issuing tokens may conduct a pre-sale, in which they sell a limited number of tokens before the actual IEO. We assume that by having a pre-sale, firms may attract early knowledgeable investors and thus mitigate information asymmetry by signaling firm value and reduce underpricing, in line with the theory Welch (1992). In addition, previous underpricing research on ICOs have found that having a pre-sale is negatively correlated with underpricing. This leads to the following hypothesis:

$$H_8: Having\ conducted\ a\ presale\ prior\ to\ the\ IEO\ is\ negatively\ correlated\ with\ the\ level\ of\ underpricing$$

3.2.8. Trusted Exchange

In addition, previous studies in IPO literature suggest that the reputation of the underwriter correlates with the level of underpricing. Some suggest that reputable underwriters "confirm" the quality of the firm and that asymmetric information is thus relaxed, causing less underpricing (Booth & Smith, 1986; Carter & Manaster, 1990; Michaely & Shaw, 1994). However, data from the 1990s suggest the sign is flipped, that highly regarded underwriters cause increased underpricing, as underwriters strategically underprice to benefit themselves (Betty & Welch, 1996; Loughra & Ritter, 2004). We also expect that the reputation of the exchange conducting the token sale is correlated with the amount of underpricing but refrain from hypothesizing on whether the correlation is positive or negative:

$$H_9: The\ reputation\ of\ the\ exchange\ conducting\ the\ IEO\ is\ significantly\ correlated\ with\ the\ level\ of\ underpricing.$$

Table II

Hypothesis Overview

Variable	Expected Sign
Issue size	-
Whitepaper number of pages	-
External Rating	-
Crowdedness	+
Market sentiment	+
Pre-sale	-
Trusted Exchange	+/-

Table II provides an overview of the hypothesized expected sign of correlation between variables drawn from IPO and ICO literature and level of underpricing in initial exchange offerings. For a thorough overview of the definition and construction of each variable, see *Table III*.

4. Methodology and Research Design

The following section describes the three main stages of the methodology. First, we define formulas used to measure the level of underpricing. Second, we test the existence and level of underpricing. Third, we conduct a regression model and analysis to show the possible correlation between underpricing and possible correlated variables. The programming language R is used to conduct all statistical analyses.

4.1. Measuring Underpricing

4.1.1. Underpricing

The standard method in IPO literature of computing underpricing in the IPO Literature (Ljungqvist, 2007) is used to measure the first day returns in IEOs:

$$UP_i = \frac{(P_{i,1} - P_{i,0})}{P_{i,0}} \quad (Eq. 1)$$

UP_i: $Measured\ underpricing$

$P_{i,1}$: $Closing\ price\ on\ first\ day\ of\ trading$

$P_{i,0}$: $Offer\ price\ in\ IEO$

However, since cryptocurrency markets are traded continuously, no closing prices exist by definition. In order to solve this issue, the "closing price" is defined as the last price given on the listing day according to the exchange in charge of the IEO.

4.1.2. Market-Corrected Underpricing

To capture the level of underpricing that is not influenced by an overall positive market return on the listing day, the market return is subtracted from the level of underpricing. This way of correcting underpricing is commonly used in both IPO and ICO literature (Ritter, 1991; Felix & von Eije, 2019; Momtaz, 2020), resulting in the following formula:

$$MUP_i = \frac{(P_{i,1} - P_{i,0})}{P_{i,0}} - \frac{(M_{i,1} - M_{i,0})}{M_{i,0}} \quad (Eq. 2)$$

MUP_i: $Measured\ underpricing\ adjusted\ for\ market\ returns$

$P_{i,1}$: $Closing\ price\ on\ first\ day\ of\ trading$

$P_{i,0}$: $Offer\ price\ in\ IEO$

$M_{i,1}$: $Closing\ price\ of\ the\ CCi30\ index\ on\ the\ first\ day\ of\ trading$

$M_{i,0}$: $Opening\ price\ of\ the\ CCi30\ index\ on\ the\ first\ day\ of\ trading$

The CCi30 cryptocurrency index is chosen as the market portfolio, as it is the most thorough cryptocurrency index that tracks the top 30 cryptocurrencies with regards to market capitalization. Historic price data on the index is publicly available at *cci30.com*. The market-corrected version of underpricing will be used for all subsequent tests and analyses in this paper.

4.2. Testing for the Existence of Underpricing

A one-tailed t-test is performed to test for the existence of underpricing. However, since the t-test assumes data is normally distributed, the first step is to test the market-corrected level of underpricing for normal-distribution using the Jarque-Bera test and the Shapiro-Wilk test. Both tests reject the null hypothesis of a normal distribution (see *Appendix I*). For this reason, the level of underpricing is transformed using the natural logarithm to adjust for non-normality:

$$Log - adjusted\ MUP_i = \ln(MUP_i + 1.01) \quad (Eq. 3)$$

The constant 1.01 is added to the level of underpricing before the log-transformation is made, to ensure that all negative first-day returns are included in the analysis. More specifically, the lowest market-adjusted underpricing in the dataset is -100.75 percent. Thus, by adding 1.01 all data points are included in the analysis.

A one tailed t-test is then performed on the transformed level of underpricing. To add more robustness, the t-test is complemented with a non-parametric sign-test on the untransformed underpricing data.

4.3. Regression Analysis

An ordinary least squares (OLS) regression analysis is undertaken to show the possible relationship between IEO underpricing and independent variables. The following equation shows the original model of the regression:

$$\begin{aligned} MUP_i = \alpha &+ \beta_1 \times offer\ price_i + \beta_2 \times issue\ size_i + \beta_3 \times whitepaper\ size_i \\ &+ \beta_4 \times external\ rating_i + \ \beta_5 \times market\ sentiment_i \\ &+ \beta_6 \times crowdednes_i + \beta_7 \times presale_i + \beta_8 \times trusted\ exchange_i \\ &+ \epsilon_i \ (Eq. 4) \end{aligned}$$

We perform a log-transformation on the following variables: Underpricing, Offer price, Issue size and Whitepaper pages. As *Table IV* shows, these variables show high skewness, indicating a non-linear relationship between the independent and dependent variables, a log-transformation is conducted for highly skewed variables.[2] This results in the following regression model:

[2] The constant 1.01 is added to underpricing before the log-transformation (see Eq. 3), to include negative values. Since the definition of the variables offer price, issue size and whitepaper pages does not entail any negative values, no constant is added.

$$Log - adjusted\ MUP_i = \alpha + \beta_1 \times \ln(offer\ price_i) + \beta_2 \times \ln(issue\ size_i) + \beta_3 \times \ln(whitepaper\ number\ of\ pages_i) + \beta_4 \times expert\ rating_i + \beta_5 \times market\ sentiment_i + \beta_6 \times crowdedness_i + \beta_7 \times pre\ sale_i + \beta_8 \times trusted\ exchange_i + \epsilon_i \quad (Eq.5)$$

Furthermore, influential points are identified using Cooks D approach with the criteria of 4/*n*, where *n* is the sample size. As a result, 10 observations are omitted to make the regression more accurate, reducing the final dataset from 196 to 186 observations.[3] Next, we conduct a series of robustness tests. First, a White test and a Breusch–Pagan test are conducted to check for heteroskedasticity. Second, a Variance Inflation Factor (VIF) test is conducted to check for multicollinearity between independent variables. Lastly, a Ramsey RESET test is performed to see whether non-linear combinations of the fitted values help explain the response variable. The specified model passes all tests and is therefore kept (see *Appendix II)*.

[3] To be consistent, the same data of 186 observations is used throughout the paper.

5. Data

The following section describe the data collection process, descriptive statistics and construction of variables used in the study.

5.1. Data Collection

In the absence of one database containing all IEO-relevant data needed for this study, all data was manually collected from various sources. Information regarding which IEOs that had been announced within the time frame of this study was collected from *coincodex.com* and *icoholder.com*, containing large datasets of IEOs. These websites gather aggregated data on announced upcoming and ended IEOs from more than 300 cryptocurrency exchanges.

Further information regarding the specifics of each IEO, including the offer price, pre-sales, issue size, first day closing price, expert rating and number of whitelist pages was collected directly from the websites and communication channels of the issuer and exchange conducting the IEO, since these sources presumably provide the most reliable and accurate information. If information was missing on these websites, data was supplemented from the information provided on the third-party websites stated above.

Furthermore, a non-probability-based sampling approach was used. More specifically, all available data points from the selected sources have been collected. A probability-based sampling approach was also considered, as it has several advantages over a non-probability-based approach. However, due to the infancy of IEOs, entailing limited data availability, a non-probability-based sampling approach was chosen to obtain an adequate sample size.

The original data sample consisted of all announced IEOs listed on the above-mentioned websites between January 1, 2019 and April 30, 2021, which amounted to 648 announced IEOs. However, the collected sample size then amounted to a set of 196 IEOs. The main reason for omitting projects were lack of information about the first day closing price, indicating either (1) the token was never listed, or (2) the token had been delisted from the exchange. If the token was never listed, the IEO must have most likely failed to raise the required funds and can thus be regarded as incomplete. If the token had been delisted from the initial exchange of the IEO, historic trading prices were unavailable. In addition, data was not included if an issuer had already conducted prior IEOs or ICOs, or if the IEO listed on the websites were in fact pre-sales. After collecting 196 observations, an additional 10 influential data points were excluded in the analysis, as determined by Cook's D approach. The final data sample is thus comprised of 186 IEOs.

5.2. Construction of Variables

The below table presents a summary of the definitions of the independent variables.

Table III

Construction and Definition of Variables

Variable	Definition
Offer price	The price at which the token is offered during the IEO in USD.
Closing price	The closing price as defined by the given exchange of the IEO in USD.
Issue size	The number of tokens in millions offered in the IEO, multiplied with the offer price in USD.
Whitepaper number of pages	The total number of whitepaper pages available to the public before and during the IEO.
External rating	The value 1 is assigned if the IEO had received an external rating during the IEO, 0 if not.
Crowdedness	The number of IEOs that had been conducted within 30 days of the listing date.
Market sentiment	The 30-day return of the CCi30 index measured at the listing day on the exchange.
Pre-sale	The value 1 is assigned if the IEO had a pre-sale before the IEO, 0 if not.
Trusted exchange	The value 1 is assigned if the IEO was launched on a trusted exchange, 0 if not.

Table III overviews the definition of the dependent variables and how they are constructed. For exact definition on the variable Trusted Exchange, see *Appendix III*.

The definition of a trusted exchange is given by *coincodex.com.* There are several different criteria an exchange can meet in order to be regarded as a trusted exchange. This either includes membership in certain organizations, holding certain licenses, or receiving good scores in reports produced by cryptocurrency research firms. See *Appendix III* for the exact definition.

External rating refers to a rating given by certain websites that cover IEO listings. These websites are *icoholder.com*, *icodrops.com*, *icomarks.com* and *icobench.com*.

5.3. Summary Statistics

Table IV presents the summary statistics for market-corrected underpricing (without log-transformation) and the independent variables.

Table IV

Descriptive Statistics

Name	Mean	Median	Min	Max	Skew	Kurtosis	Standard dev.	N
Offer price	0.95	0.05	2.8e-5	32	5.70	36.20	3.66	186
Issue size	27.89	3.00	0.0017	1010.00	7.18	53.50	118.24	186
Whitepaper pages	32.90	28.00	6.00	146.00	1.76	5.01	32.90	131
External Rating	0.32	0.00	0.00	1.00	0.75	-1.44	0.47	186
Crowdedness	25.99	22.00	1.00	56.00	0.20	-1.37	14.73	186
Market sentiment	0.16	0.18	-0.27	0.93	0.34	-0.16	0.23	186
Pre-sale	0.27	0.00	0.00	1.00	1.03	-0.93	0.44	186
Trusted Exchange	0.52	1.00	0.00	1.00	-0.06	-2.01	0.50	186
Underpricing	4.12	0.90	-0.93	64.25	3.85	16.77	9.50	186

Table IV presents a summary of the descriptive statistics of the variables relating to the final sample of 186 initial exchange offerings (IEO) conducted between Jan 2019 and Apr 2021.

The average underpricing is 412.02 percent, meaning that the IEOs in the sample, on average, trade for 412.02 percent higher at the end of the first trading day in comparison to the offer price. As indicated by *Figure I*, most IEOs which offered substantial initial returns have been conducted during 2021. The minimum and maximum values show a wide range for several variables. The level of underpricing ranges from –92.96 percent to 6,424.88 percent. The lowest offer price was 0.0000028 USD whereas the most expensive IEO had an offer price of 32 USD. The sample also shows substantial differences in the size of IEOs with regards to issue size, with the smallest IEO issuing tokens worth 17 thousand USD and the largest issue size amounting to 1.01 billion USD. Furthermore, the underpricing median of 90.49 percent is substantially lower than its mean of 412.02 percent, indicating a high right skewness. Indeed, as *Figure II* shows, underpricing has a high right skewness. In addition, the variables offer price, issue size, and whitepaper pages have a skewness above 1. As a rule of thumb, any value above 1 or below -1 indicates high skewness. For this reason, the variables underpricing, offer price, issue size, and whitepaper pages are log-transformed in the regression analysis as described in section 4.3.

Figure I

Initial Exchange Offerings by Underpricing and Listing Date

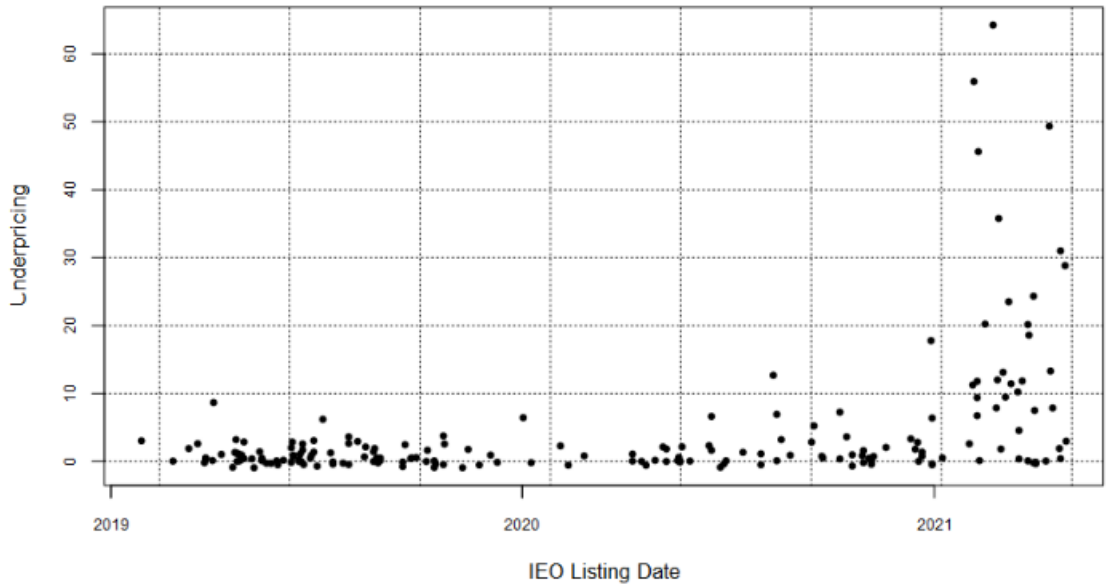

Figure I provides a plotted overview of the initial exchange offerings (not log transformed) by listing day on the x-axis and level of underpricing on the y-axis. The plotted data includes the final sample of 186 initial exchange offerings.

Figure II

Distribution of Underpricing

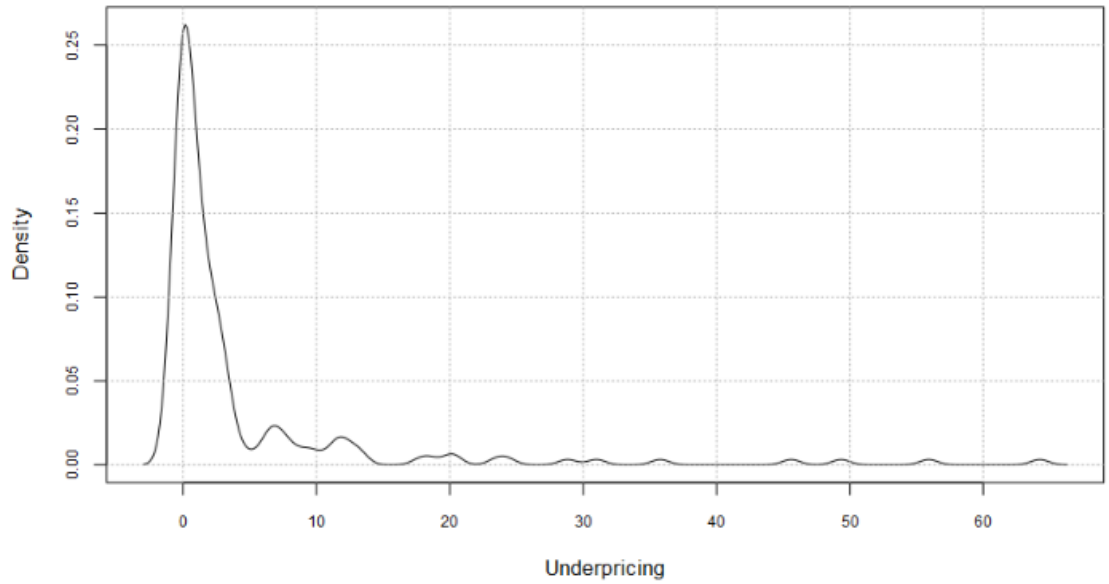

Figure II shows a distribution of the level of underpricing in the collected sample of 186 initial exchange offering (not log transformed).

6. Empirical Results

6.1. Level of Underpricing

Table V shows the results of the t-test and non-parametric sign test. We find an average of 412.02 percent and a median of 90.49 percent on the market corrected level of underpricing. The t-test results in a rejection of the null hypothesis that underpricing is equal to or less than zero at a less than 0.1 percent significance level, and this goes for the non-parametric sign test as well. This implies that there is severe and significant underpricing in IEOs, in line with hypothesis H_1.

Table V

T-test and Non-Parametric Sign Test Results

	T-test						**Non-parametric sign test**				
					95% conf. interval**					95% conf. interval	
	N	Mean*	T	p-value	Lower bound	Upper bound	N	Median	p-value	Lower bound	Upper bound
ln(MUP+1.01)	186	0.7958	8.7899	5.095e-16	0.6480	Inf					
MUP***	186	1.2063	8.7899	5.095e-16	0.9018	Inf	186	0.9049	1.404e-14	0.5003	1.3296

Table V presents the results of the t-test and non-parametric sign test. The t-test results in a rejection of the null hypothesis that the mean of the natural logarithm of underpricing adjustment for market returns plus a constant of 1.01 is equal to or less than zero. Additionally, the result of the non-parametric sign tests results in a rejection of the null hypothesis that the median of the non-log-transformed underpricing adjusted for market return is equal to or less than zero. *Mean refers to the geometric mean. **95% confidence interval around geometric mean. ***No t-test was conducted on MUP (market adjusted underpricing, not log transformed). Values stated are the inverse of the log transformed values / back transformed.

Table VI

Regression Results

Dependent variable:	$ln(MUP_i+1.01)$				
Predictive variables	Estimate	Std. Error	T value	p-value	
(Intercept)	2.9524346	0.4950472	5.9639	2.466e-08	***
ln (Offer price)	0.0042857	0.0322771	0.1328	0.8945866	
ln(Issue size)	-0.1191769	0.0398111	-2.9936	0.0033388	**
ln(Whitepaper pages)	-0.5360103	0.1158770	-4.6257	9.373e-06	***
Market sentiment	1.0502583	0.3912705	2.6842	0.0082802	**
Pre-sale	-0.3755868	0.1502237	-2.5002	0.0137402	*
External rating	0.0585216	0.1758646	0.3328	0.7398828	
Crowdedness	-0.0207514	0.0053012	-3.9145	0.0001497	***
Trusted exchange	0.3370168	0.1666089	2.0228	0.0452796	*
Significance levels	*0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*				
Multiple R^2	0.4141				
Adjusted R^2	0.3756				
F-Statistic	10.78	*p-value:* 2.187e-11			

Table VI presents estimated coefficients from regression using OLS. The dependent variable is the natural logarithm of underpricing as adjusted for market returns. For definition and construction on predictive variables, see *Table II.*

6.2. Regression Results

The regression results are presented in *Table VI*. First, we note that the pre-sale variable is negatively correlated with underpricing at a 5 percent significance level. In addition, we note that the number of pages in the white paper as released prior to the IEO has a less than 1 percent significant negative coefficient. Furthermore, our results suggest the issue size of the IEO is negatively correlated with underpricing at a 5 percent significance level. The negative correlation of these variables is thus in line with hypothesis H_3, H_4 and H_8.

Furthermore, Benedetti & Kostovetsky (2018) find that a low offer price causes increased underpricing in ICOs. However, our results do not indicate that this holds true for IEOs as the offer price is shown to have an insignificant correlation with underpricing. In addition, the external rating variable is also not as expected, with an insignificant positive correlation with underpricing. Consequently, both hypotheses H_2 and H_5 are not supported by the results.

The results also show that the market sentiment variable is positively correlated with underpricing at a 5 percent significance level. However, we cannot find any evidence that

the amount of IEOs within 30 days before the token listing has a positive correlation with underpricing. Instead, crowdedness is suggested to have negative correlation with the amount of underpricing at a significant level of 1 percent, although at a small estimate. As a consequence, we find evidence for H_6 but fail to do so for H_7.

Finally, our results suggest that IEOs which have been conducted on a reputable exchange experience are correlated with underpricing at a 5 percent significance level, in accordance with hypothesis H_9. In fact, our data suggests that if the IEO has been conducted on a trusted exchange, underpricing increases.

7. Discussion

In this section we further discuss and interpret the results of our hypothesis testing and regression model, in addition to discussing limitations and further research.

7.1. Interpretation and Analysis of Results

7.1.1. Level of Underpricing

Our results indicate that initial exchange offerings are subject to significant and large underpricing. The average underpricing of 412.02 percent is comparable to underpricing levels in ICO research, in which studies have found average levels ranging from 8.2 to 929.9 percent (Adhami et al, 2018; Felix & von Eije, 2019; Benedetti & Kostovetsky, 2018; Momtaz, 2020). The downturn of the ICO market and the increased growth of IEOs seem to have a positive effect on blockchain projects' fundraising success, as suggested by Anson (2021). However, the results from this study provide evidence that token issuers still experience large levels of underpricing.

We conjecture that the previous fraudulent behavior of ICO issuers and the extreme levels of information asymmetry (Momtaz, 2020) have caused the ICO market to become a "market for lemons" (Akerlof, 1970), causing buyers and sellers to ultimately leave the market. Consequently, the IEO market grew, promising to mitigate the information asymmetry by certifying the quality of firms and lowering risks, and buyers and sellers were thus able to participate in the market again. However, likely due to the lack of regulation and the presence of reputable actors, the market is still subject to large information asymmetry, and uninformed investors who are unable to distinct between high- and low-quality firms still require large underpricing in order to participate in the market, as suggested by Rock (1986). Also relating to this, some IEOs were announced but never listed. This might also indicate that only firms who can afford to underprice are able to successfully complete the IEO.

7.1.2. Regression Results

In the still immature market of cryptocurrency, investor sentiment and some aspects of information asymmetry mitigation seem to influence the amount of initial first day returns issuers experience. From our results, we highlight three areas of discussion.

First, positive market sentiment of the cryptocurrency market is significantly and positively correlated with IEO underpricing. As described in the IPO literature, sentiment investors are willing bid up the price of the issue if other recent issues have also risen in price, in a type of positive feedback or "trend" chasing strategy. If large enough number of investors follow this strategy, they may end up causing a positive autocorrelation of initial returns (Ibbotson el at. 1994). This could help explain the remarkable levels of underpricing in the crypto market, which becomes increasingly reasonable when considering its still young and immature nature. Aqqarwal, Krigman and Womack (2002) suggest that managers underprice to generate increased research coverage and attract more demand for the stock to then sell their shares at lock up expiration. If applied in an IEO context, token issuers could underprice to attract attention from the high

concentration of positive feedback investors, and thus bid up token prices even further. Depending on to what extent they own the token themselves, they could make a large enough return to benefit from underpricing. However, we cannot find a significant positive relationship between underpricing and the amount of IEOs conducted 30 days leading up to the listing day. The concept of more firms going public in "windows of opportunity" during hot markets, as described by Ritter (1991) and Ibbotson et al. (1994), does not seem to apply to IEOs in the same extent.

Second, the results suggest that mitigating information asymmetry to some extent may lower underpricing. More specifically, firms looking to minimize underpricing might want to conduct a pre-sale of tokens prior to the IEO. This way they can attract knowledgeable investors and decrease the level of information asymmetry at the time of the IEO, as suggested by Welch (1992). In addition, if firms release lengthy whitepapers and have large issue sizes, the ex-ante uncertainty is suggestively reduced and thus also underpricing. This is mainly in accordance with Ritter (1991). What surprised us was that having an external rating prior to the IEO does not seem to significantly influence underpricing, as suggested by the IPO literature (Megginson & Weiss, 1991). This result could have many explanations. It could suggest that investors do not look to these sources to certify the value of the firm. We also cannot verify to what extent the rating was available to investors at the time of the IEO, or who took part of the rating, which might help explain the insignificance of the variable. Nevertheless, it ultimately might suggest that not all means of reducing information asymmetry may help in reducing underpricing.

Lastly, we discuss the implication of that underpricing is seemingly increased when conducted on trusted exchanges. As mentioned, the IPO literature on this aspect is mixed. Many studies find evidence for the certification hypothesis in that reputable underwriters certify the value of the IPO and that underpricing is thus decreased (Booth & Smith, 1986; Carter & Manaster, 1990; Michaely & Shaw, 1994). On the contrary, other studies have found a negative correlation between underwriter reputation and underpricing, suggesting that underwriters underprice to increase their own or their investor's wealth (Betty & Welch, 1996; Loughra & Ritter, 2004). Our results indicate that the latter explanation is relevant in an IEO context. We conjecture that trusted exchanges can attract a larger number of potential investors and liquidity on their platform since investors look to more trusted exchanges to lower risks. Token issuers, in turn, find it preferable to sell their tokens on these platforms since they get access to more liquidity and increase probability of fundraising success. This puts the reputable exchange in a position of high negotiating power. Exchanges may be looking to underprice to generate information momentum and increase demand for the token, in line with the model of Aqqarwal, Krigman and Womack (2002). When more investors are attracted to the exchange platform, the exchange's revenues increase in terms of trading fees. The exchange is then better off than if they would have refrained from underpricing, although it is not in the interest of the issuer. This explanation becomes increasingly plausible if we consider a high concentration of sentiment investors pursuing a positive feedback strategy.

7.2. Limitations and Restrictions

7.2.1. Data Availability and Reliability

In our data collection process, we find restrictions on data availability and reliability. There are still no information requirements for issuers, and the channels through which firms communicated information about the IEO varied to a considerable extent. Therefore, there was no single and reliable database containing all IEO-relevant information. For this reason, all data had to be manually collected from various sources, including third-part websites. This caused indirect restrictions in the data collection process, as well as negative effects on data reliability.

In addition, many IEOs had missing data on closing prices on the first day of trading. These IEOs must have been either (1) unable to complete the IEO due to not raising the required funds and were thus never listed, or (2) had been delisted from the exchange they were initially listed on. It is difficult to determine which group the IEO belonged to, due to lack of information released by the firm and the exchange. Since there was no public data on historic trading prices on delisted tokens, we were unable to measure underpricing on these projects. Moreover, some data was excluded if an issuer had already conducted prior IEOs or ICOs. Consequently, the data sample initially included all announced IEOs according to the sources used in this study, but the final data sample include approximately only 30 percent of these IEOs listed on the websites.

7.2.2. Data Sampling Method

A further limitation to this paper is the data sampling method. Since the data collection was subject to limitations of data availability as described above, we choose to collect data solely based on availability instead of randomization. This was to ensure the most adequate sample size and that all data which could be included in the sample ultimately was included.

7.2.3. Survivorship Bias

The data availability issue regarding delisted tokens causes the final data set to be subject of survivorship bias, although we have tried to mitigate this bias by only including datapoints from January 1, 2019 and onwards. We recognize this as perhaps the largest limitation to this paper in the sense that the final data set to a large extent consists of tokens which have performed well on the market and have thus not been delisted. Well performing tokens might then experience increased underpricing initially due to being more positively valued by the market.

7.3. Future Research

There is still little research done on underpricing in token offerings. This study provides evidence for that IEOs experience large underpricing on average and suggests several correlating variables. However, the IEO market is still in its infancy, and there is little empirical documentation on market prices, market mechanisms, and the overall financial environment. This study is still subject to large restrictions in terms of data availability.

Replicating this study on a more comprehensive and reliable dataset is thus a suggested topic for future research.

Moreover, in this study we find a significant correlation between the underpricing and the reputation of the exchange. Another topic of interest for future research would thus be the principal-agent relationship between the firm and the exchange, in which it could be explored who ultimately is subject to the costs and benefits of underpricing. Essentially, if underpricing in IEOs is as large as suggested in this study, why are issuers not more concerned with decreasing underpricing? To what extent might cryptocurrency exchanges benefit from underpricing issued tokens? As discussed, there might be a possibility that the exchange benefits from strategic underpricing to generate large initial returns and increased information momentum. The firm issuing the tokens would rationally look to lower underpricing and sell tokens at their true value. Therefore, if the exchange benefits from underpricing, a principal-agent relationship between the exchange and the issuing firm arises. This point is of further curiosity when considering the results of this study that token offerings listed on reputable exchanges are subject to more underpricing, possibly indicating that exchanges with more negotiating power can underprice more.

8. Conclusion

This study is the first to focus on underpricing in IEOs, as previous studies on token underpricing have focused solely on ICOs. The key difference between an IEO and an ICO is the important role of the exchange conducting the token sale and listing. We study if this difference influences the existence of underpricing in IEOs and if theories from the IPO underpricing literature can help explain it.

The analysis of 186 IEOs conducted between January 2019 and April 2021 suggests that IEOs do experience severe underpricing, with a mean and median of 412.02 percent and 90.49 percent, respectively. This is in line with previous research on the underpricing levels in initial coin offerings (ICO).

We also perform a regression analysis, which shows that variables translated from IPO underpricing literature may also be relevant in an IEO context. Our data suggests that investors can earn increased initial returns if market sentiment in the cryptocurrency market is high and if token sales are conducted on a trusted exchange. In contrast, results show that firms can decrease underpricing by mitigating some aspects of asymmetric information, such as conducting a pre-sale of tokens, releasing a lengthier whitepaper, and if issue sizes are large. We hope that these results can provide a basis from which future research can benefit from.

This study is subject to large limitations in terms of data availability. General availability on firm characteristics and historic trading data is still limited in the cryptocurrency market. We find that the most important consequence of this is survivorship bias since tokens which have been delisted from exchanges lack data on trading prices. This causes well performing tokens to be overrepresented in our data and underperforming tokens to be unrecorded.

In conclusion, as token sales continue to revolutionize the way new ventures can finance continued growth, cryptos are evidently often “left on the table”. Even though due diligence is seemingly increased when token sales are conducted by an exchange, investors still require large compensation in order to participate in the crypto market.

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10. Appendix

10.1. Appendix I: Normality Tests

Table A1

Shapiro-Wilk Normality Test (Untransformed Data)

W	p-value
0.49642	< 2.2e-16

Table A1 shows Shapiro-Wilk W test on untransformed underpricing data (Market-corrected underpricing). Since the p-value for test statistic W is less than 0.05, the null hypothesis that the data is normally distributed is rejected.

Table A2

Jarque-Bera Test (Untransformed Data)

X-squared	df	p-value
2703.6	2	< 2.2e-16

Table A2 shows Jarque–Bera test whether sample data have the skewness and kurtosis matching a normal distribution. Test on untransformed underpricing data (Market-corrected underpricing). Since the p-value is less than 0.05, the null hypothesis that the data is normally distributed is rejected.

Figure A1

Normal Q-Q Plot on Untransformed Data

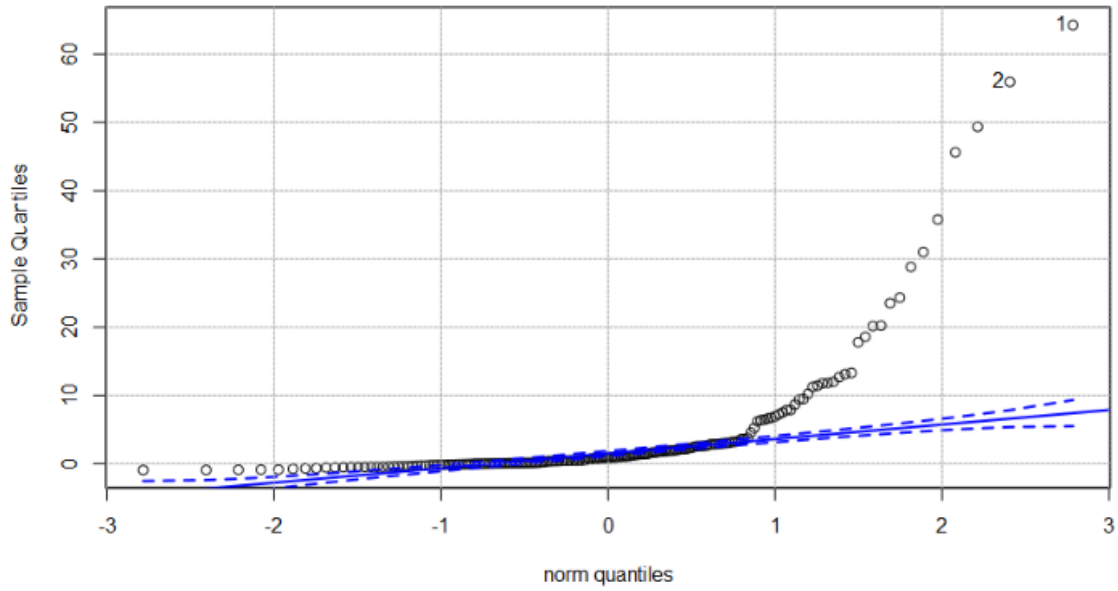

Figure A1 shows a normal quantile-quantile (Q-Q) on untransformed underpricing data (Market-corrected underpricing). Normally distributed data should lie approximately on a straight line. Since the observations fall outside of the reference lines, the untransformed data is not regarded as normally distributed.

Table A3

Shapiro-Wilk Normality Test (Transformed Data)

W	p-value
0.97189	0.0008389

Table A3 shows Shapiro-Wilk W test on transformed underpricing data (ln(Market-corrected underpricing + 1.01)). Since the p-value for test statistic W is less than 0.05, the null hypothesis that the data is normally distributed is rejected.

Table A4

Jarque-Bera Test (Transformed Data)

X-squared	df	p-value
6.1376	2	0.04648

Table A4 shows Jarque–Bera test whether sample data have the skewness and kurtosis matching a normal distribution. Test on transformed underpricing data (ln(Market-corrected underpricing + 1.01)). Since the p-value is less than 0.05, the null hypothesis that the data is normally distributed is rejected.

Figure A2

Normal Q-Q Plot on Transformed Data

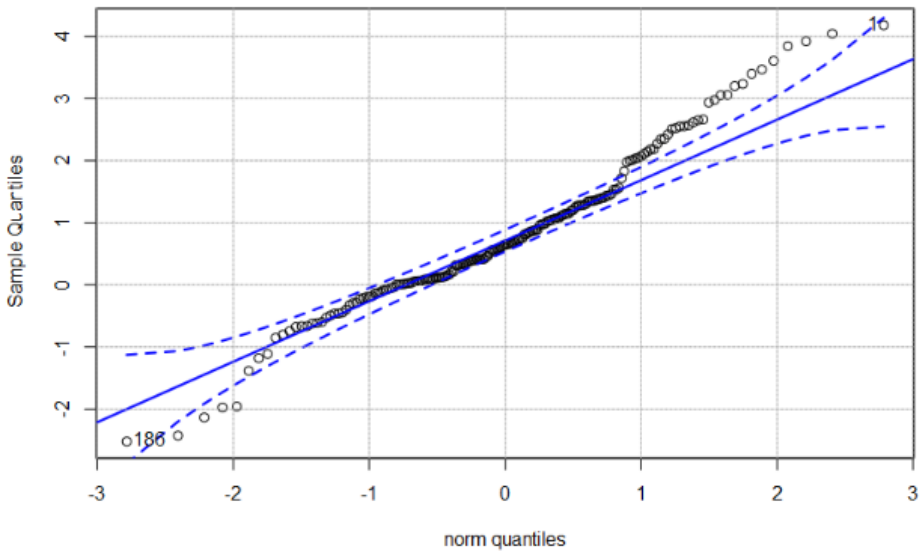

Figure A2 shows a normal quantile-quantile (Q-Q) on transformed underpricing data (ln(Market-corrected underpricing + 1.01)). Normally distributed data should lie approximately on a straight line. Since the observations fall approximately within the reference lines, the transformed data is assumed to be approximately normally distributed.

10.2. Appendix II: Regression Robustness Tests

Table A5

Studentized Breusch-Pagan Test

BP	df	p-value
14.082	8	0.07966

Table A5 shows Breusch–Pagan test for heteroskedasticity in the linear regression model. Since the p-value is above 0.05, the null hypothesis of homoskedasticity is not rejected.

Table A6

White's Test

statistic	p-value	parameter	alternative
18.5	0.295	16	greater

Table A6 shows White test for heteroskedasticity in the linear regression model. Since the p-value is above 0.05, the null hypothesis of homoskedasticity is not rejected.

Table A7

Variance Inflation Factor (VIF) Test

ln(Offer Price)	ln(Issue Size)	ln(Whitepaper Pages)	Market Sentiment
1.128468	1.132512	1.129884	1.222014
Pre-sale	**External Rating**	**Crowdedness**	**Reputable Exchange**
1.098156	1.377222	1.356518	1.103533

Table A7 shows Variance inflation factors (VIFs) to measure of the amount of multicollinearity in the linear regression model. The values for VIF indicate what percentage the variance is inflated for each coefficient. A VIF of 10 is usually regarded as a concern for multicollinearity. Since the highest value is 1.377, no signs if multicollinearity are indicated.

Table A8

Ramsey RESET Test

RESET	df1	df2	p-value
1.9852	2	120	0.1418

Table A8 shows Ramsey (RESET) test to test whether non-linear combinations of the fitted values help explain the response variable. Since the p-value is above 0.05, the null hypothesis of correct specification is not rejected. This indicates that the functional form is correct.

10.3. Appendix III: Definition of a Trusted Exchange

If a cryptocurrency exchange meets any of the following criteria, it is defined as a trusted exchange:

- The exchange holds a BitLicense with the NYDFS (New York State Department of Financial Services).
- The exchange is a member of Japan's JVCEA self-regulatory organization.
- The exchange is listed as "BTI Verified" by the Blockchain Transparency Institute (BTI).
- The exchange is one of the exchanges identified as having "real volume" by Bitwise Investments in their presentation to the Securities and Exchange Commission (SEC) from March 2019.
- The exchange was included in Group 1 AND achieved a score of 4 or higher in Alameda Research's cryptocurrency exchange volume report from July 2019.