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VALUING UNCONVENTIONAL STARTUP FUNDING MECHANISMS: CROWDFUNDING AND INITIAL COIN OFFERINGS

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Nas últimas décadas, a Internet e outros novos desenvolvimentos tecnológicos, tais como os avanços na criptografia, permitiram que as empresas se lançassem em novas formas criativas de procurar financiamento. Uma grande variedade de artigos na literatura económica têm sido escritos sobre crowdfunding e Initial Coin Offerings (ICO), embora poucos deles façam uma comparação direta entre estes mecanismos de financiamento. Este projeto de trabalho tenta preencher essa lacuna através da análise das relações entre oferta pública inicial (IPO), ICOs e projetos de crowdfunding que tiveram uma data final entre Abril de 2017 e Setembro de 2019. A principal área de foco deste trabalho foi a teoria da sinalização e o grau de subpreço / subcotação de preços (underpricing) das IPO e das ICO. Para analisar as hipóteses, utilizei um conjunto de dados transversais, que foram recolhidos de fontes secundárias como o NASDAQ.com, Kickstarter.com e Icobench.com, para produzir uma regressão linear OLS. Fiz uma regressão de múltiplos possíveis sinais em relação ao capital angariado por qualquer um dos mecanismos de financiamento anteriormente mencionados. Em primeiro lugar, testei o efeito da percentagem de retenção das ICO e das IPO. Em segundo lugar, testei o efeito do objetivo de financiamento das ICO e do crowdfunding. Por último, testei o efeito do tempo de financiamento das ICOs e do financiamento por crowdfunding. Além disso, foram discutidas três hipóteses relativas aos fatores determinantes dos subpreços nas ICO e nas IPO. Testei se o montante médio de subcotação de preços, o número de emissões anteriores e o montante do capital mobilizado poderiam explicar nível de subpreço verificado. Por último, testei se o tempo decorrido até à cotação estava positivamente relacionado com o montante da subcotação de preços nas ICO. Os resultados sugerem que o ICO e os projetos de financiamento em regime de crowdfunding com um tempo de financiamento mais longo são menos financiados. Além disso, encontrei uma relação positiva entre o objetivo de financiamento e o montante do capital angariado nas ICO e no Crowdfunding.

JEL tags: G11 E22 M13 O16 G39

Palavras-chave: IPO, ICO, Crowdfunding, Mecanismos de financiamento, *Tokens* digitais

Abstract

In the last few decades, the internet and other new technology developments, such as advancements in cryptography have allowed ventures new creative ways to seek funding. In the economic literature, there is a large variety of papers that have been written on crowdfunding and Initial Coin Offerings (ICO). Though few of them do a direct comparison between these funding mechanisms. This work project tries to fill that gap by analyzing relationships between Initial public offerings (IPOs), ICOs, and reward-based crowdfunding projects that had an ending date between April 2017 and September 2019. The main area of focus of this paper was signaling theory and the degree of underpricing of IPOs and ICOs. For analyzing the hypotheses, I have utilized a cross-sectional dataset, that was gathered from secondary sources such as NASDAQ.com, Kickstarter.com, and Icobench.com to conduct an OLS linear regression. I have regressed multiple possible signals on the capital raised by any of the previously mentioned funding mechanisms. Firstly, I tested the effect of the retention percentage of ICOs and IPOs. Secondly, I have tested the effect of the funding goal of ICOs and crowdfunding. Finally, I have tested the effect of the funding time of ICOs and crowdfunding. Furthermore, three hypotheses regarding the determinants of underpricing in ICOs and IPOs were discussed. I have tested if the average amount of underpricing, the number of previous issues, and the amount of capital raised could explain the amount of underpricing. Finally, I tested if the time to listing was positively related to the amount of underpricing in ICOs. The results suggest that ICO and crowdfunding projects with a longer funding time are less funded. Furthermore, I've found a positive relationship between the funding goal and the amount of capital raised in ICOs and Crowdfunding.

JEL tags: G11 E22 M13 O16 G39

Keywords: IPO, ICO, Crowdfunding, Funding mechanisms, Digital tokens

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1. Introduction

Initial Public Offerings (IPOs) have been an important way of funding companies for centuries. In the last decade, other pathways opened for start-ups seeking funding. With the advent of the Internet, crowdfunding grew into a viable alternative to traditional funding mechanisms. In recent years Initial Coin Offerings (ICOs) were popularized as being a viable path to funding as well. The estimated world market for crowdfunding was almost 11 billion dollars in 2018 (QYResearch, 2019). Similarly, in 2019 about 11 billion dollars has been raised by ICOs (Icobench, 2019).

The upside of these new ways of funding is that companies can attract money without having to give equity in. They lower the costs of capital raising and (at least for now) bypass most regulations (Clayton, 2017). However, these options pose a new question: How does a start-up know which funding mechanism has the highest chance of success? While there is research done on how crowdfunding and ICOs compare to IPOs, there are far as we know there are no papers that compare all three funding mechanisms.

Another attribute of these new funding mechanisms is that there is no central authority where researchers can get reliable information. Due to this spread of information, the datasets research teams use differ wildly (especially those used in ICO research). Therefore, retesting some results from earlier studies with a new dataset might uncover interesting results.

The objective of this study is to create a comparative analysis of IPOs, crowdfunding, and ICOs. Secondly, with this study, I try to reproduce some of the results other studies have found when comparing crowdfunding and ICOs with IPOs.

The starting point of this research was the creation of a database containing time series data on IPOs, crowdfunding, and ICOs. The database contains data on funding projects with an end date between April 2017 and September 2019, as ICOs were not quite common before 2017.

The main concepts related to crowdfunding and Initial Coin Offerings are described more in-depth in chapter 2. In the same chapter, the main topics of the work are linked together. While in chapter 3 testable statements are synthesized within those topics. The statements are then operationalized in chapter 4. In chapter 5 the dataset used to test the hypotheses is described. The results of the research can be found in chapter 6. Finally, in chapter 7 I discuss the results, limitations, and possibilities for future research.

2. Related research

The first part of this chapter consists of a small introduction to the selected funding mechanisms. The second part contains a summary of areas where comparable research has been done on these mechanisms.

2.1. Initial Public Offerings (IPOs)

As legislation between countries varies considerably, I will focus on the IPOs of companies incorporated in the United States unless stated otherwise. The IPO process is often similar to the following (Corporate finance institute, 2020): Firstly an underwriter to guide the IPO process is picked. Thereafter the firm can choose to do a best-effort order, where the underwriter only sells the security or a firm commitment order, where an underwriter guarantees the sale of securities. A roadshow is held to market the shares to investors and a prospectus with company information is provided. Finally, the share price is determined, and the stock is listed on an exchange.

2.2 Reward-based crowdfunding

Crowdfunding is usually defined as raising small amounts of money from a large group of people (the crowd). There are multiple types of crowdfunding, i.e. reward-based, equity-based, debt-based, and donation-based crowdfunding (Bird & Meyskens, 2015). As the names suggest, these types of crowdfunding differ primarily in the way investors are compensated. Due to data being more readily available, this paper will focus primarily on reward-based crowdfunding.

The majority of reward-based crowdfunding is done for small projects amounting up to 10.000 USD (Kickstarter, 2019), but a large part of crowdfunding is being done to seed entrepreneurial capital (Schwienbacher & Larralde, 2010). When utilizing crowdfunding, start-ups often use intermediate companies (e.g. Kickstarter or Indiegogo) to help with the process. These intermediaries usually offer an escrow service and a place to advertise the project. The benefits of crowdfunding extend beyond obtaining a loan. Companies use crowdfunding as a marketing opportunity, for attracting venture capital (Dingman, 2018) or to learn more about the preferences of future customers (Tinn & Chemla, 2019). Research suggests that investors assess companies that acquire funding through venture capital and crowdfunding in a similar way (Mollick, 2013). This indicates that previous research with a focus on venture capital investors might apply to investors who fund companies through crowdfunding.

2.3 Initial Coin Offerings (ICOs)

ICOs are another funding mechanism that makes use of the crowd. In contrast to reward-based crowdfunding, ICOs sell tokens to the crowd. Fish (2019) argues that due to ICOs using a similar process as crowdfunding many similarities can be found between them.

The tokens sold in the ICO can be roughly categorized into cryptocurrency, utility- and/or security tokens (Oliveira, Zavolokina, Bauer, & Schwabe, 2018). Utility tokens make up the vast majority of the tokens sold and provide some way of accessing services and products. An example of a utility token would be a token that can be traded for storage space. When a token gives right to contribute to a company's capital and share's in its profits or if the proceeds of a token are the sole result of individuals other than the issuer, then the token is regarded as a security and must comply with the same SEC regulations as other securities (Sameeh, 2018).

A whitepaper describing the capabilities of the token and the funding process is often made available for potential investors. According to Howell et al. (2019), ICOs have a higher success rate when they disclose information in a whitepaper and when the whitepaper specifies the use of the proceeds of the ICO.

Companies might take away some doubts of investors by communicating their intentions. However, it is often unclear if investors have any possibility of legal recourse when these intentions fail to materialize. Zetzsche et al. (2019) found that only 33% of ICO's had any information about which laws were applicable to them. Furthermore, they found that, in 40% of the researched cases, the whitepaper writer differed from the ICO issuer/initiator. This uncertainty about the legal responsibility of ICOs might invite some entities to take advantage of this situation. And in fact, over 80 percent of ICOs in 2017 were allegedly scams (Satis Group, 2018). However, the impact of scam-ICOs looks slightly less bad when the researches adjusted for volume. They then identified that over 70 percent of ICO volume as high-quality.

A recent development in the issuing process of ICOs is the Initial Exchange Offering (IEO). Where ICO s are usually managed completely by the issuing company themselves, the IEO has a cryptocurrency exchange to act as an intermediary between issuer and investor (Binance, 2019). Investors buy the tokens from the exchange and can trade it immediately after the IEO period. For brevity's sake, this paper will refer to both as ICOs.

There is one extra hurdle compared to IPOs and crowdfunding, which is that investors usually (EY Research, 2018) need some form of cryptocurrency to be able to invest in ICOs. On the other side of this issue is the issuer, who will typically receive the funding in cryptocurrency as well and thus is exposed to an exchange rate risk. This hurdle might be smaller in the future, with many new cryptocurrencies being tied to fiat money (Bezverhi, 2019).

2.4 Costs

There are many papers written on the successes of IPOs, ICOs, and crowdfunding. However, there is not a lot of in-depth data to go on which accurately describes the costs of ICOs and crowdfunding. As to somewhat estimate the costs displayed in Table 1,2 and 3 I had to rely on news and blog posts.

Table 1: IPO costs in Millions of USD for an IPO raising between 25 to 100 million USD

Accounting	0,8
Legal	1,4
Printing	0,3
Other	0,5
Underwriting	4,3
Total	7,3

Source: PwC 2017, Insight into the costs of going public and being public, PwC Deals, viewed 01-12-2019, https://www.pwc.com/us/en/deals/publications/assets/cost-of-an-ipo.pdf

Table 2: Low and high estimate of ICO costs in USD

	Low estimate	*High estimate*
Concept development	$ 15 000	$ 75 000
Tech development	$ 25 000	$ 50 000
Legal	$ 100 000	$ 200 000
Platform	$ 65 000	$ 100 000
Cybersecurity	$ 40 000	$ 40 000
Marketing	$ 40 000	$ 400 000
ICO development	$ 55 000	$ 100 000
Total	$ 340 000	$ 965 000

Source: Grace Zhai 2018, *ICO Budgets: How much does it really cost to do an Initial Coin Offering?,* Medium.com, 07-12-2019, https://medium.com/blockchain-review/ico-budgets-how-much-does-it-really-cost-to-do-an-initial-coin-offering-eb1031e8d893

Table 3: Cost estimate of reward-based crowdfunding campaign raising 54 000 USD

Platform fees (~5%)	$ 2 700
Payment fees (~5%)	$ 2 700
Marketing, video production, photography, etc.	$ 25 000
Total	$ 30 400

Source: Enventys Partners 2019, *How Much Does It Cost to Run Crowdfunding Campaigns?,* enventyspartners.com, https://enventyspartners.com/blog/how-much-does-it-cost-to-run-a-crowdfunding-campaign/

One look at the tables gives away the vast size differences between the funding mechanisms. These differences are hardly surprising, as Belleflamme et al. (2014) estimate the median amount an entrepreneur is looking to raise is 150 000 EUR, while the median crowdfunding campaign raises only 6 500. One of the reasons why crowdfunding is not attractive for big companies could be the 10% fee that has to be paid when using a crowdfunding platform. As we can see in the tables, 10% is already not far off from what a small IPO needs to pay in total costs. In fact, the same EY report estimates that the costs of an IPO that raises between 500 million and 1 billion USD to be less than 8,5% of the proceeds.

The costs between IPOs and ICOs look more comparable, with the caveat that the estimations for an ICO might be the most variable of them all. Adding to that, there are some extra costs that are not compulsory, but common and substantial enough to mention. For instance, listing on a popular crypto exchange is prohibitively expensive, with prices ranging between 1 to 3 million dollars (Autonomous.com, 2018), compared to an IPO listing fee of about 125-300K USD (Euronext, 2019). Additionally, as most ICOs are funded with cryptocurrency, a conversion fee (2-4%) (OECD, 2019) must be paid when costs are made in fiat.

2.5 Signaling

When there is a high degree of information asymmetry between two parties, one side may look for signals that tell them something about the true quality of the object that the other party is offering. For signaling to be possible, the cost of a signal needs to be lower for high-quality firms (Connelly, Certo, Ireland, & Reutzel, 2011) otherwise low-quality firms would simply imitate the signal to achieve more funding.

ICOs (Ofir & Sadeh, 2019) and crowdfunding (Belleflamme, Lambert, & Schwienbacher, 2014) are both characterized as having high degrees of information asymmetry. This is due to the absence of reporting requirements, probably even more so than the traditional IPOs. According to Ofir and Sadeh (2019), the main drivers of information asymmetry in ICOs is threefold. Firstly, there are no standard disclosure requirements or any other kind of standard. Secondly, the companies usually don´t have much of a track record during the offering. Thirdly, the investors lack enough fundamental technical knowledge to determine ICO quality.

Belleflame et al. (2014) looked specifically at information asymmetry coming from the start-up knowing the product better than the investors. The result of their research was that higher levels of when information asymmetry about the product increases startups are more likely to get their funding through equity crowdfunding instead of reward-based crowdfunding, as people who buy equity are more concerned with profitability than product quality.

As for IPOs, underpricing has long been seen as a signal for quality. Arthurs et al. (2009) found some results that the lock-up period might be a signal for quality. A longer lock-up period would signal to the investors that management is in no hurry to sell the stock on the market, thus making the stock more attractive as a long-term investment.

2.6 Underpricing

"Underpricing is estimated as the percentage difference between the price at which the IPO shares were sold to investors (the offer price) and the price at which the shares subsequently trade in the market" (Lljungqvist, 2007, p. 381). It has long been a topic of interest for researchers, as at first glance the act of selling equity too cheap doesn't make much sense intuitively. This paper uses the terms underpricing, excess returns, and first-day returns interchangeably.

The first research on underpricing has been done by Ritter (1987), who found that on average IPOs were priced about 21% higher at the end of the first day of trading compared to the offering price. The amount of underpricing varies over time. For instance, the proceeds-weighed first-day average-return was about 18,4% in 2018 (Ritter, Initial Public Offerings: Underpricing, 2018). Recent studies have also found underpricing to be common in ICOs as well (Lyandres, Palazzo, & Rabetti, 2019).

Like ICOs and IPOs, pre-sale crowdfunding is often paired with offering things at a discount. According to Tinn and Chemla (2019), companies will give a discount at the pre-selling stage as the uncertainty about the ability to deliver is higher when the assumption is made that consumers are rational.

All funding mechanisms have some rationale for underpricing to be present. Firstly, companies seeking crowdfunding through Kickstarter need to raise a self-determined goal within 60 days. If the amount is not raised within the time allotted, then the company receives none of the pledged funding. Secondly, one of the main determinants of the value of a token is the network size (Momtaz, 2018), which in turn is affected by the number of persons buying into an ICO. Lastly, IPO underpricing has a multitude of reasons, some researchers attribute it to information asymmetry between the investors and the issuer or between the issuer and the underwriter (Rock, 1986). Others argue that IPO underpricing is intentional (Baron, 1982), with managers underpricing stock to raise the price at lock up-expiration (Rajesh, Aggarwala, Krigman, & Womack, 2002) or firms underpricing the stock to obtain a higher price at a seasoned offering (Welch, 1989).

3. Problem description and List of Hypothesis

In the previous chapter, I've described some similarities in research done on IPOs, ICOs, and crowdfunding. In this chapter, I formulate hypotheses related to signaling theory and underpricing. All relationships hypothesized have been confirmed to exist at least once in one of the funding mechanisms by previous research.

3.1 Signaling theory

I pose that there are some similarities between how receivers rate signalers. I try to capture these similarities trough comparing signals that have been tested at least in one of the funding mechanisms in previous research.

Only part of the equity(tokens) is sold in an IPO(ICO). The rest is kept by the signalers to keep the benefits and/or to be sold at a later moment. From a receiver's perspective, a higher retention percentage of equity(tokens) by the venture might signal for quality. For example, the signalers assure investors that they sell to fund the venture rather than selling stock to cash out. Or conversely, a low retention rate might signal for low quality. Similar findings have been reported in the past for IPOs (Sindelar, Ritter, & Roger, 1994) and ICOs (Lyandres, Palazzo, & Rabetti, 2019). To test these relationships, I pose the following hypothesis:

H1A. A higher retention percentage will be beneficial for the amount raised of ICOs and IPOs.

The goal in crowdfunding might be seen as a proxy for the amount of effort a company will put in the funding process. In crowdfunding, the company is highly penalized for not reaching the funding goal (no funding received, but there are costs). Thus, a higher goal implies the amount of trust a company has in its project. In ICOs we can see a similar relationship between the amount of funding and the hard cap. Some ICOs pledge to give back their funding to their investors when they don't reach a certain funding goal (soft cap) Furthermore Fish (2019) found that a higher funding goal was associated with a higher amount raised. In concurrence with Fish, Lyandres et al. (2019) found that a higher funding goal was correlated with a higher absolute and relative amount raised. Seeing as there are similar forces on both mechanisms, I propose the following hypothesis:

H1B. A higher funding goal will be positively correlated with returns in crowdfunding and ICOs

Most ICOs and crowdfunding projects have a period in which they offer their product. A longer funding period allows for higher funding as it runs longer (Fisch, 2019) Thus, a shorter funding period might indicate that a venture has faith in its product. Furthermore, a shorter funding period has been found to signal for success in crowdfunding (Mollick, 2013) and in ICOs (Fisch, 2019).

H1C. A longer funding period will have a negative effect on the amount raised through ICO and crowdfunding.

3.2 Underpricing

In the literature review, we have seen that underpricing has historically been observed in ICOs and IPOs and that there was significant oversubscription on crowdfunding.

A study by Kadlec & Edelen (2005) found a significant positive relationship between the average return of IPOs completed 30 days earlier and the excess return of an IPO. Ibbotson et al. (1994) found that hot markets might be explained by traders following a momentum strategy, as monthly average returns and the monthly number of issues are correlated. If such a strategy exists in ICOs and IPOs, then we might see some of the underpricing being positively correlated with underpricing in the previous months

H2A. Excess returns and the number of listings are cyclical in both ICOs and IPOs.

Chowdry and Sherman (1995) found a link between the amount of underpricing and the time between the pricing date and the first day of trading in IPOs. The authors reasoned that this was due to a higher chance of information leakage if this time period was longer. In addition, they assumed that, on average, underpricing would already be present as uninformed investors have to be compensated (Rock, 1986). With this in mind, it is not a stretch to assume that uninformed investors in ICOs need some degree of underpricing as well to make investing attractive. Furthermore, I assume that the degree of underpricing is modulated by the amount of time between the end of the ICO and the listing on an exchange as seen in IPOs as well. This statement can be further formalized as:

H2B. The amount of underpricing in ICOs is positively correlated with the number of days between the ICO and listing time.

Lastly, Ibbotson et al. (1994) found that smaller issues are commonly underpriced more than larger issues. The rationale behind smaller issues being underpriced more is that smaller firms are often younger than older firms and as a result, there is more uncertainty. This relationship has been found previously in ICO research as well (von Eije & Heine, 2019). Thus, I pose my final hypothesis:

H2C. Smaller issues should see higher excess returns than larger IPO and ICO issues.

4. Methodology and Data collection

Like the previous part of the work, the part of the chapter where the methodology is discussed is divided into the respective areas of research. The rationale for the chosen dependent and independent variables can be found in this chapter. A description of the control variables is available in the appendix (Table 12 & Table 13) In the second part of the chapter I describe the data gathering process more in detail.

4.1 Signaling

Signaling theory has been applied in the past to funding mechanisms. For a signal to be viable over a longer period of time it needs to have some cost and shouldn't be easy to fake. I chose signals that were used in previous studies done on IPO, ICO, and crowdfunding.

There are two prominent ways to test for the effect of signals on the success in crowdfunding/ICO literature. The first way is to regress the signals on the success rate (Kunz, Bretschneider, Erler, & Leimeister, 2017). The second method is to regress the signals on the amount raised (Fisch, 2019). Data on the success rate of IPOs is particularly hard to come by. Thus, I've chosen to go for the latter as this method makes it viable to include IPO data into the models.

In the previous chapter I've stated that investors are looking for signals of quality. In this part, I will elaborate on the signals I've used for the model. In line with previous research in finance and ICOs (Fisch, 2019), the natural logarithm of the gross amount raised in US dollars is used as the dependent variable for all three funding methods. Furthermore, I will estimate the coefficients by doing an ordinary linear squares regression.

To test the hypotheses, I've added the following independent variables to the model:

Percentage offered: Calculated by dividing the shares offered by the shares outstanding for the IPO. Percentage offered in ICO is given on index sites.

Goal: The hard cap values were denominated in fiat, cryptocurrency, and native tokens. All amounts were converter to USD by taking the median exchange rate found for the duration of the ICO.

Funding time: Crowdfunding the difference between the deadline and the launch date

Control variables: A list of the control variables can be found in the appendix (Table 12). The control variables are variables that might affect the dependent variable and don't necessarily represent a signal.

The estimation of the statistical effect of the independent variables on the amount raised can be expressed as follows:

$$\begin{aligned} &log(amount\ raised\ by\ IPO_i) \\ &\qquad = \alpha + \beta_1 * \%\ offered + \beta_2 * log(employees) + \beta_3 * log(total\ assets) + \beta_4 \\ &\qquad * Shareholder\ shares\ sold + \beta_5 * China\ \beta_6 * log\ (total\ offering\ expenses) + \varepsilon_i \end{aligned}$$

$$\begin{aligned} &log(amount\ raised\ by\ crowdfunding_i) \\ &\qquad = \alpha + \beta_1 * log(goal) + \beta_2 * duration + \beta_3 * average\ amount\ pledged\ per\ backer \\ &\qquad + \beta_4 * staff\ pick + \beta_5 * United\ States + \varepsilon_i \end{aligned}$$

$$\begin{aligned} &log(amount\ raised\ by\ ICO_i) \\ &\qquad = \alpha + \beta_1 * duration + \beta_2 * log(hard\ cap) + \beta_3 \\ &\qquad * log(Number\ of\ currencies\ accepted) + \beta_4 * \%offered + \beta_5 * PreICO * + \beta_6 \\ &\qquad * United\ States + \beta_7 * Europe + \beta_8 * Whitelist|KYC + \beta_9 * MVP|Prototype + \beta_{10} \\ &\qquad * Bounty + \beta_{11} * Bonus + \beta_{12} * Ethererum + \beta_{13} * Fiat\ accepted + \varepsilon_i \end{aligned}$$

4.2 Underpricing

In many studies (Ritter, 1987; Ibbotson, 1975) the amount of underpricing is measured as the difference between the offer price and the closing price of the first day of trading. Studies that were done on ICO overpricing commonly (Lyandres, Palazzo, & Rabetti, 2019)) measure the amount of underpricing by calculating the difference between the price offered in the ICO and the closing price at the first day of listing. In addition, some studies (Momtaz, 2018) measure underpricing as the difference between the open and closing price. ICOs are traded continuously and as a result, the closing date is the same as the end of the day.

To test the hypotheses, I have added the following independent variables to the model:

Number of IPOs (ICOs) in the preceding 30 days: Sum of IPOs (ICOs) that were listed in the 30 days preceding the listing of the individual IPO(ICO).

30-day average excess return of preceding IPOs (ICOs): Average excess return of IPOs (ICOs) that were listed in the preceding 30 days.

Days between the ICO and listing time: Time in days between the end of the ICO and the first day an ICO is listed on an exchange.

Amount raised (log): This is the same variable used as a dependent variable in the signaling model.

Control variables: A list of the control variables can be found in the appendix (Table 13). The control variables are variables that might affect the dependent variable and don't necessarily represent a signal.

The estimation of the statistical effect of the independent variables on the excess return can be expressed as follows:

$$\begin{aligned} &Excess\ return\ of\ IPO_i \\ &\quad = \alpha + \beta_1 * Number\ of\ IPOs\ preceding\ 30\ days + \beta_2 \\ &\quad * Underpricing\ of\ preceding\ IPOs\ (30\ days) + \beta_3 * \log(amount\ raised) + \beta_4 \\ &\quad * \log(employees) + \beta_5 * \%\ \text{offered} + \beta_6 * \log(volume) + \beta_7 * China + \beta_8 \\ &\quad * shareholder\ shares\ offered + \varepsilon_i \end{aligned}$$

$$\begin{aligned} &Excess\ return\ of\ ICO_i \\ &\quad = \alpha + \beta_1 * \text{ICOs preceding 30 days} + \beta_2 * \text{Underpricing of preceding ICOs (30 day)} \\ &\quad + \beta_3 * \text{Days between ICO} - \text{Notation} + \beta_4 * \text{log (Amount raised)} + \beta_5 \\ &\quad * \text{log (BTC price at listing)} + \beta_6 * \text{Ethereum} + \beta_7 * \text{US} + \beta_8 * \text{Europe} + \beta_9 \\ &\quad * \text{Whitelist/KYC} + \beta_{10} * \text{Fiat accepted} + \varepsilon_i \end{aligned}$$

4.3 Data Collection

To be able to compare the funding mechanisms somewhat, the full dataset had to have the same starting- and endpoint for all funding mechanisms researched. The starting point of April 2017 was easy to determine, as ICOs were quite rare before 2017. There was no up-to-date database available and thus the data was collected manually. No data on funding projects ending after September 2019 was collected. The data was gathered from September 2019 until January 2020.

4.3.1 IPO Dataset

Data on 640 IPOs was gathered from the NASDAQ IPO calendar. The sample consists of best effort and firm commitment offers. The data was scraped by indexing the IPO calendar and subsequently query the NASDAQ API. Thereafter, I have pulled pricing data using the symbol and date of pricing obtained in the previous step. As not every IPO had data on every variable the dataset had to be shrunk to 575 observations for the signaling model. I was able to match 493 IPOs with pricing data for the underpricing model.

4.3.2 Crowdfunding dataset

The website webrobots.io serves scrapes from the Kickstarter and Indiegogo websites. It took some trial and error to parse the data correctly as the data strings were longer than the maximum string size of an excel cell. During this process, it came to light that the data from Indiegogo wasn`t usable due to the success identifier missing. The full process is described more detailed in appendix III. The full dataset contained 88586 crowdfunding projects. I had 16499 observations left after removing duplicates, ongoing projects, old projects, projects denominated in other currencies, and projects that had a goal under 5.000 USD.

4.3.3 ICO dataset

The data has been collected from *icobench.com* as it is considered one of the leading sources for ICO information (Lyandres, Palazzo, & Rabetti, 2019). At first, a list of 5595 ICOs was created by scraping the names and links to individual pages of ICOs with a google chrome extension (Webrobots.io, 2019). The data collection process from *icobench.com* is described more in detail in appendix (III). Missing ICO dates, token price and the number of offered tokens were supplanted with data from *Trackico.com*

Pricing data on 4044 crypto tokens was obtained via the *Coinpaprika API* and thereafter imported into excel with the *power query* add-in. Due to a limited number of matches, I have pulled data on the closing price from *coingecko.com* as well. The ICOs were matched by using their website as an identifier. Firstly, I stripped the addresses gathered from ICObench down to their name + domain name and subsequently searched the websites in the other datasets with wildcards for the start and end of the string. About 75 percent of the pricing data is from *Coinpaprika*, and 25 percent originates from *Coingecko*.

4.2.3 Data Quality

The data from crowdfunding and IPOs is only from companies that have chosen to use an intermediary. The use of a dataset consisting of only using ICOs that made use of an intermediary (IEO) was considered, but IEOs only started to become popular since early 2019 (MPCX Platform, 2019) and thus would have shrunk the dataset considerably

5. Descriptive statistics

This chapter contains a description of the dependent, independent, and control variables used in the regression analysis. The signaling datasets have 575, 16499, and 1216 observations for IPOs, crowdfunding, and ICOs, respectively. The total amount raised is about 154 billion USD through IPOs, 350 million through crowdfunding, and 12 billion through ICOs. The biggest outlier for the amount raised is the EOS ICO that raised 4.1 billion dollars compared to an average amount raised of 2,9 million USD.

Table 4: Descriptive statistics of the signaling dataset

IPO signaling	Mean	Median	Minimum	Maximum	Std. dev	C.V.	Skewness	Ex. Kurtosis	0.05	0.95	IQ-range
Amount raised (log)	18.61	18.64	14.69	22.95	12.15	0.07	-0.23	0.91	16.14	20.48	13.34
% offered	0.30	0.24	0.03	1.00	0.17	0.57	11.42	24.62	0.10	0.50	0.28
Total offering expenses (log)	14.64	14.91	10.63	18.29	0.94	0.06	-0.35	0.28	13.12	15.90	14.93
Employees (log)	47.04	47.71	0.00	10.78	26.01	0.55	-0.03	-10.12	0.69	87.84	40.74
Total assets (log)	17.50	18.15	69.08	26.19	33.60	0.19	-0.61	-0.43	11.39	21.91	38.95
Dummy variables											
China	0.20	0	0	1	0.40	20.32	15.37	0.36	0	1	0
Shareholder shares offered	0.13	0	0	1	0.34	25.37	21.40	25.81	0	1	0
q201702	0.11	0	0	1	0.31	28.80	25.30	44.02	0	1	0
q201703	0.07	0	0	1	0.26	36.28	33.50	92.19	0	1	0
q201704	0.11	0	0	1	0.31	28.31	24.75	41.25	0	1	0
q201801	0.10	0	0	1	0.30	29.86	26.48	50.12	0	1	0
q201802	0.13	0	0	1	0.33	26.33	22.50	30.65	0	1	0
q201803	0.11	0	0	1	0.32	28.07	24.48	39.93	0	1	0
q201804	0.09	0	0	1	0.29	31.98	28.82	63.06	0	1	0
q201901	0.06	0	0	1	0.24	38.83	36.22	11.12	0	1	0
q201902	0.13	0	0	1	0.34	25.93	22.05	28.63	0	1	0
q201903	0.09	0	0	1	0.29	31.98	28.82	63.06	0	1	0

Crowdfunding signaling	Mean	Median	Minimum	Maximum	Std. dev	C.V.	Skewness	Ex. Kurtosis	0.05	0.95	IQ-range
Goal (log)	9.50	9.21	8.52	15.52	0.82	0.09	0.95	1.04	8.52	11.00	1.15
Pledged (log)	8.83	9.18	3.22	16.31	2.00	0.23	-0.49	0.26	4.88	11.75	2.25
Duration (days)	33.63	30.00	1.00	97.78	10.44	0.31	1.13	1.55	20.00	60.00	5.00
Pledged/backer	122.57	82.00	1.00	10000	172.19	1.40	16.46	711.14	25.00	336.31	86.02
Dummy variables											
Staff pick	0.20	0.00	0.00	1.00	0.40	2.02	1.52	0.32	0.00	1.00	0.00
United States	0.74	1.00	0.00	1.00	0.44	0.59	-1.09	-0.80	0.00	1.00	1.00
q201702	0.11	0.00	0.00	1.00	0.31	2.88	2.54	4.43	0.00	1.00	0.00
q201703	0.10	0.00	0.00	1.00	0.30	2.97	2.63	4.94	0.00	1.00	0.00
q201704	0.11	0.00	0.00	1.00	0.31	2.88	2.54	4.43	0.00	1.00	0.00
q201801	0.07	0.00	0.00	1.00	0.26	3.54	3.26	8.60	0.00	1.00	0.00
q201802	0.09	0.00	0.00	1.00	0.29	3.13	2.81	5.89	0.00	1.00	0.00
q201803	0.09	0.00	0.00	1.00	0.29	3.17	2.85	6.15	0.00	1.00	0.00
q201804	0.11	0.00	0.00	1.00	0.32	2.80	2.45	3.98	0.00	1.00	0.00
q201901	0.08	0.00	0.00	1.00	0.28	3.33	3.03	7.17	0.00	1.00	0.00
q201902	0.12	0.00	0.00	1.00	0.33	2.67	2.29	3.26	0.00	1.00	0.00
q201903	0.11	0.00	0.00	1.00	0.31	2.89	2.54	4.45	0.00	1.00	0.00

ICO signaling	Mean	Median	Minimum	Maximum	Std. dev	C.V.	Skewness	Ex. Kurtosis	0.05	0.95	IQ-range
Total raised (log)	14.90	15.16	5.63	20.17	1.89	0.13	-0.90	1.49	11.49	17.43	2.46
ICO duration	59.98	41.00	2.00	428.00	55.42	0.92	2.28	7.53	5.00	169.15	51.00
Hard cap(log)(M)	16.63	16.79	1.79	22.98	1.36	0.08	-1.64	13.79	14.49	18.42	1.36
N# of currencies accepted(log)	0.60	0.69	0.00	3.40	0.65	1.08	0.63	-0.66	0.00	1.79	1.10
% Offered	0.54	0.55	0.01	1.00	0.21	0.38	-0.28	-0.32	0.15	0.85	0.30
Dummy variables											
United states	0.10	0.00	0.00	1.00	0.30	3.07	2.74	5.50	0.00	1.00	0.00
Europe	0.48	0.00	0.00	1.00	0.50	1.04	0.08	-1.99	0.00	1.00	1.00
Whitelist/KYC	0.60	1.00	0.00	1.00	0.49	0.82	-0.40	-1.84	0.00	1.00	1.00
MVP/Prototype	0.00	0.00	0.00	1.00	0.06	17.41	17.35	299.00	0.00	0.00	0.00
Bounty	0.00	0.00	0.00	1.00	0.05	20.12	20.06	400.34	0.00	0.00	0.00
Bonus	0.55	1.00	0.00	1.00	0.50	0.90	-0.21	-1.96	0.00	1.00	1.00
Ethereum	0.89	1.00	0.00	1.00	0.31	0.35	-2.52	4.33	0.00	1.00	0.00
Fiat accepted	0.19	0.00	0.00	1.00	0.39	2.05	1.57	0.46	0.00	1.00	0.00
q201702	0.00	0.00	0.00	1.00	0.03	34.87	34.83	1211.00	0.00	0.00	0.00
q201703	0.03	0.00	0.00	1.00	0.16	6.09	5.92	33.03	0.00	0.00	0.00
q201704	0.09	0.00	0.00	1.00	0.28	3.22	2.91	6.46	0.00	1.00	0.00
q201801	0.15	0.00	0.00	1.00	0.35	2.42	2.00	2.00	0.00	1.00	0.00
q201802	0.23	0.00	0.00	1.00	0.42	1.83	1.28	-0.36	0.00	1.00	0.00
q201803	0.15	0.00	0.00	1.00	0.35	2.42	2.01	2.04	0.00	1.00	0.00
q201804	0.16	0.00	0.00	1.00	0.36	2.32	1.89	1.59	0.00	1.00	0.00
q201901	0.08	0.00	0.00	1.00	0.28	3.32	3.02	7.13	0.00	1.00	0.00
q201902	0.07	0.00	0.00	1.00	0.26	3.60	3.32	9.05	0.00	1.00	0.00
q201903	0.05	0.00	0.00	1.00	0.22	4.28	4.04	14.36	0.00	1.00	0.00

All off the variables used for the regression are summarized in Table 4.

Interestingly, the average running period of an ICO is almost twice as long as the funding period of a crowdfunding project. Suggesting that the duration effect is stronger in crowdfunding projects than in ICOs.

A high percentage of ICOs is Ethereum based. This is in line with my expectations, as its arguably the easiest platform to launch a token on.

On average ICOs issued 54% of their tokens, while IPOs only sold 30% of their shares on average. Furthermore, we can see that the amount of observations is fairly stable in IPOs and Crowdfunding when compared with ICOs that almost have a quarter of observations in the second quarter of 2018.

The dataset for crowdfunding has a higher success rate on average than the all-time average. This is probably due to the method of data collecting. The crawler used to collect the data would only register active and successfully completed projects as failed projects don't show up in Kickstarter search results. The average funding time of 32 days is expected as a funding time of around 30 days is recommended by the crowdfunding platform used (Kickstarter, 2011).

Table 5:Descriptive statistics of the underpricing dataset

IPO underpricing	Mean	Median	Minimum	Maximum	Std. dev	C.V.	Skewness	Ex. Kurtosis	0.05	0.95	IQ range
Excess returns	0.25	0.04	-0.58	20.20	1.34	5.29	11.55	143.87	-0.18	0.71	0.27
IPOs preceding 30 days	20.29	20	3.00	39.00	8.03	0.40	0.09	-0.78	7.00	33.00	13.00
Underpricing of preceding IPOs(30 days)	0.27	0.18	-0.07	2.39	0.36	1.33	3.28	11.47	-0.01	1.19	0.14
Amount raised(log)	14.78	14.98	12.42	18.29	0.88	0.06	-0.29	-0.03	13.22	15.98	1.30
Employees(log)	5.06	5.09	0	10.78	2.43	0.48	-0.12	-0.77	0.69	8.93	3.47
% Offered	-1.11	-1.29	-3.43	0	0.80	0.72	-0.02	-1.01	-2.31	0	1.47
Volume(log)	14.87	14.96	7.13	19.04	1.57	0.11	-0.76	1.89	12.05	17.30	1.77
Dummy variables											
China	0.21	0	0	1	0.41	1.92	1.40	-0.04	0	1	0

ICO underpricing	Mean	Median	Minimum	Maximum	Std. dev	C.V.	Skewness	Ex. Kurtosis	0.05	0.95	IQ
Excess returns	0.63	-0.58	-1.00	143.01	64.45	10.18	15.77	319.07	-0.99	45.30	11.40
Underpricing of preceding IPOs(30 days)	19.24	0.23	-0.84	34.76	61.29	31.85	38.96	14.29	-0.73	20.84	11.78
ICOs preceding(30 days)	45.20	44.00	30	89.00	18.34	0.41	-0.02	-0.36	11	75.00	24.00
Days between notation and listing	94.39	56.50	0	751	107.96	11.44	20.11	47.91	20	325.00	110
Raised(log)	15.58	15.86	71.32	20.72	16.85	0.11	-10.47	25.20	12.45	17.73	20.19
Bitcoin(price @ listing(log)	88.01	88.50	70.85	98.60	0.45	0.05	-0.60	10.62	79.90	95.44	0.44
Dummy variables											
Ethereum	0.89	1	0	1	0.31	0.34	-25.69	45.99	0	1	0
United states	0.11	0	0	1	0.32	28.00	24.40	39.55	0	1	0
Europe	0.42	0	0	1	0.49	11.75	0.32	-18.96	0	1	1
Whitelist/KYC	0.46	0	0	1	0.50	10.94	0.18	-19.68	0	1	1
Fiat accepted	0.14	0	0	1	0.34	25.15	21.15	24.73	0	1	0

A summary of the variables used in the underpricing regression can be found in Table 5.

The maximum excess return of 143x looks quite steep compared to the 20x maximum return of IPOs. However, when I compare this to the data gathered by other ICO studies(e.g. (Lyandres, Palazzo, & Rabetti, 2019)), this amount of overpricing is quite common to see in ICOs.

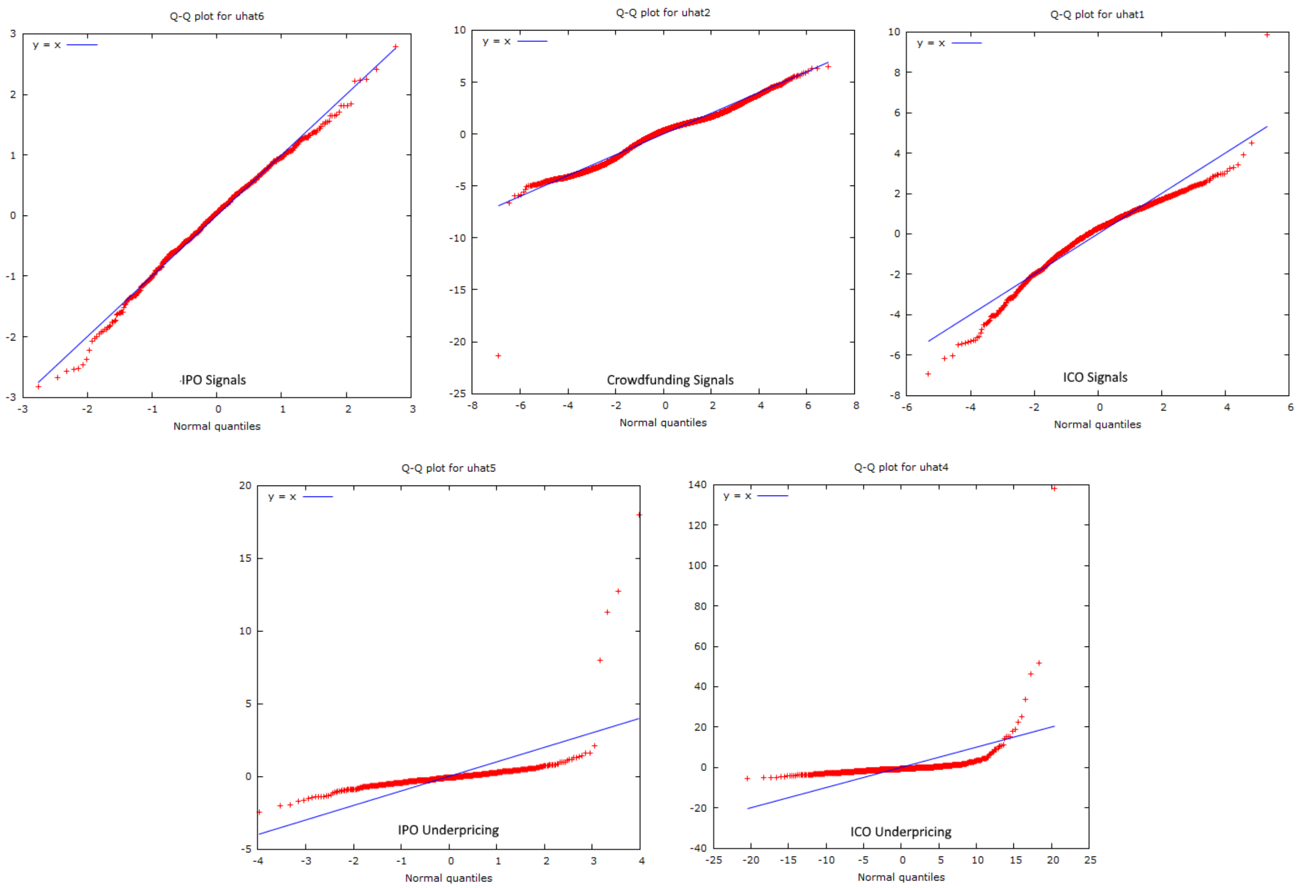
The mean amount of overpricing (25%) is quite similar to the mean amount of underpricing found (21.22%) in other IPO research. (Ibbotson, 1975). This might indicate that past results are reproducible.

6. Results

At the start of this part, I display the results of some tests for heteroskedasticity. Thereafter the results of the main regression are discussed. Finally, I test for collinearity between the variables and display some further tests.

Because the natural log of the dependent variable has been taken, the results of the independent variables on the dependent variable approximate a percentage change in the dependent variable. Inspecting the models with a Q-Q plot (Figure 1) indicated that the residuals might have a heteroskedastic distribution. In addition, a Breusch-Pagan test could not confirm homoscedasticity for any of the models (Table 14). As a result, I've opted to do an OLS estimation with robust standard errors.

Figure 1: Q-Q plots of regressions



6.1 Results from the signaling models

The results below are referring to the values found in Table 6. The models have an adjusted R2 of 0.432, 0.257, and 0.273 for IPO, crowdfunding, and ICO respectively.

In both the IPO and ICO a higher offering percentage is significantly($P<0.01$) related to the amount raised. Curiously, I find a negative relation between the percentage offered and the amount raised for ICOs, while I find the inverse relation for IPOs. Therefore, there doesn't seem to be much proof of hypothesis H1A.

A higher hard cap was significantly ($P<0.01$) correlated with a higher funding amount. In concurrence with that result, a bigger goal has a positive ($P<0.01$) effect on the amount raised through crowdfunding. Thus, both results are in line with hypothesis H1B

A longer funding period was significantly ($P<0.01$) negatively correlated with the amount raised in both crowdfunding and ICOs. These results are in line with my expectations stated in hypothesis H1C.

6.1.2 Control variables of the signaling models.

The following results pertain to the control variables found in the signaling model(Table 6). All results below are significant to the 5% level unless stated otherwise.

The offering expense of IPOs is highly positively correlated with the amount raised, which is slightly surprising when considering the expected variability when expressed as a percentage of offering size. In addition, the total asset size is slightly negatively correlated with the amount raised.

Projects that raised money through crowdfunding raised a higher amount when they were highlighted. The amount pledged per backer had the same effect, albeit much weaker.

The amount raised by ICOs was negatively correlated with the Europe location dummy, but positively correlated with the Whitelist/KYC dummy. In addition, ICOs with a bonus scheme performed worse than ICOs without ($P<0.10$). Finally, the median bitcoin price does have a strong correlation with the amount raised in ICOs as expected.

The last time dummy variable has been dropped due to collinearity. Thus, the coefficients of the time dummies can be interpreted as relative to the dropped time dummy. Interestingly the highest amount of observed ICOs in a quarter(Q201802) succeeded the quarter where the time dummy of ICOs had the highest value(Q201801).

Table 6: Regression results of signals on the amount raised

Initial Public Offering				Crowdfunding				Initial Coin Offering			
Dep. Var: Amount raised(log)	**Coeff.**	**SE**		**Dep. Var: Amount raised(log)**	**Coeff.**	**SE**		**Dep. Var: Amount raised(log)**	**Coeff.**	**SE**	
% Offered	2.312	0.255	***	Goal(log)	0.609	0.027	***	ICO duration(days)	-0.002	0.001	**
Total offering expenses (log)	0.958	0.074	***	Duration(days)	-0.025	0.002	***	Number of currencies accepted(log)	0.193	0.087	**
Employees(log)	0.039	0.033		Pledged/backer	0.002	0.000	***	Hard cap(M)(Log)	0.585	0.084	***
Total assets(log)	-0.126	0.028	***	United States	0.037	0.030		% Offered	-0.996	0.246	***
China(dummy)	-0.655	0.100	***	Staff pick	1.413	0.026	***	Median BTC price(log)	0.463	0.241	*
Shareholder shares sold(dummy)	0.462	0.119	***	Constant	3.712	0.219	***	US(dummy)	-0.041	0.168	
Constant	6.219	0.905	***					Europe(dummy)	-0.350	0.104	***
								Whitelist(dummy)	0.260	0.115	**
								MVP/Prototype(dummy)	-1.214	0.596	**
								Bounty(dummy)	-4.385	1.675	***
								Bonus(dummy)	-0.276	0.095	***
								Ethereum(dummy)	-0.027	0.152	
								Fiat accepted(dummy)	-0.135	0.143	
								Constant	1.365	2.519	
q201702	-0.404	0.167	**	q201702	-0.693	0.059	***	q201702	-1.680	0.755	**
q201703	-0.389	0.187	**	q201703	-0.746	0.060	***	q201703	0.982	0.486	**
q201704	-0.247	0.163		q201704	-0.751	0.059	***	q201704	0.693	0.279	**
q201801	-0.157	0.168		q201801	-0.817	0.067	***	q201801	1.179	0.232	***
q201802	-0.318	0.159	**	q201802	-0.528	0.060	***	q201802	0.373	0.206	*
q201803	-0.351	0.163	**	q201803	-0.535	0.060	***	q201803	0.430	0.224	*
q201804	-0.282	0.172		q201804	-0.189	0.057	***	q201804	0.203	0.244	
q201901	-0.202	0.190		q201901	-0.005	0.063		q201901	0.506	0.314	
q201902	-0.214	0.158		q201902	0.064	0.056		q201902	0.101	0.302	
N	575				16499				1216		
R^2 (Adjusted)	0.432				0.257				0.273		

*Notes: * P < 0.10, ** P < 0.05, *** P < 0.01, All models have robust standard errors*

6.2 Results from the models regarding underpricing

The adjusted R^2 of the models is 0.101 and 0.013 for the IPO and ICO models respectively. In this paragraph, I describe the results found in Table 8.

The number of ICOs in the preceding months is negatively correlated (P<0,05) with the excess return, though I don't find any other significant results regarding the other variables relevant to hypothesis H2A. As such, there seems to be not much proof for hypothesis H2A. I've calculated the Pearson correlation to see there is any persistence in underpricing in the sample at all(Table 6, Table 7). In the IPO sample, there seems to be no relationship between the variables and the lagged variables. Conversely, the aggregate ICO listing time is positively and significantly(P<0.10) correlated with the 1-month lag.

Table 7: Pearson correlation coefficients of the lagged aggregate variables.

	Number of monthly offerings	Amount of overpricing
Correlation with previous month (IPO)	0.287 *(N=623)*	0.047 *(N= 591)*
Correlation with previous month (ICO)	0.364* (*N=1282)*	*-0.054 (N=1282)*

*Notes: Significance (p) for Two-Tailed Test. * P < 0.10, ** P < 0.05, *** P < 0.01. Correlations calculated between 30 months.*

There seems to be no relation between the time to listing and the amount of ICO underpricing. Therefore, I can't confirm hypothesis H2B.

There seems to be a relation between the size of the offering and excess returns in both funding mechanisms. I find a negative (P<0.10) relation between offering size and excess return in IPOs and a positive (P<0.10) relation in ICOs. These findings are contrary to the expectation in hypothesis H3C

6.2.2 Control variables

IPO volume is negatively related to excess returns and ICOs that have gone through the whitelist/KYC process are significantly (P<0.05) less underpriced than their non-approved counterparts. The number of employees is positively related to the amount of underpricing. Surprisingly, I find no correlation between the fact that a token is built on Ethereum.

Table 8: Regression results of underpricing

Initial Public offering				Initial Coin Offering			
Dep, Var: Excess returns(percent)	**Coeff.**	**SE**		**Dep, Var: Excess returns(percent)**	**Coeff.**	**SE**	
IPOs preceding 30 days	0.006	0.009		ICOs preceding 30 days	-0.018	0.009	**
Underpricing of preceding IPOs (30 day)	-0.014	0.092		Underpricing of preceding ICOs (30 day)	0.044	0.032	
Amount raised (log)	0.252	0.157		Days between ICO-Listing	0.007	0.008	
Employees (log)	0.158	0.070	**	Amount raised (log)	-0.147	0.086	*
% Offered	0.511	0.305	*	BTC price at listing (log)	0.411	0.706	
China (dummy)	-0.370	0.239		Ethereum (dummy)	-0.205	0.826	
Volume (log)	-0.494	0.273	*	US (dummy)	0.224	0.378	
Constant	1.879	1.176		Europe (dummy)	0.117	0.432	
				Whitelist/KYC (dummy)	-0.933	0.471	**
				Fiat accepted (dummy)	0.319	0.539	
				Constant	-0.097	5.445	
N	493				768		
R^2(Adjusted)	0.101				0.013		

*Notes: * P < 0.10, ** P < 0.05, *** P < 0.01, All models have robust standard errors*

6.3 Collinearity

When doing a multivariate regression, the OLS estimator assumes that the independent variables don't have a high degree of collinearity. If this assumption proves to be false, then the estimation of the coefficients becomes less precise and the P-value tends to be unreliable. The amount of collinearity was tested by computing the variance inflation factors(Table 15 and Table 16) All variables were tested to have a variance inflation factor smaller than 10.

6.4 Further tests

I've used the hard cap in the ICO model to assess the funding goal of the ICO. However, a case could be made for testing the funding goal with the hard cap. The soft cap might act more alike the funding goal in Crowdfunding, as failure to reach the funding goal should, in theory, prevent the company doing the ICO from collecting the proceeds. The regression with the soft cap added instead of the hard cap (Table 9) shows that the effects of the soft and hard cap are quite similar in effect size and significance ($P<0.01$). In this model the bounty dummy and bitcoin price during funding lose significance. Though this might be due to the smaller sample size (N=768) compared to the full model (N=1216).

When calculating the bitcoin price and the ICO hard cap the median price has been used to transform the values in USD. I assumed that the median would be a better number to represent the value of bitcoin during the funding period as the median is less dependent on extreme values. However, I would be cutting out information if investors react stronger to these extreme values. Therefore, I've estimated the ICO signaling model again (Table 7), with this time the conversions to USD dollar done by taking the average value at the time of funding.

Table 9: Extra robustness test pertaining the ICO signaling model

ICO model with Soft cap				*ICO model with averages*			
Dep. Var.: Amount raised	**Coeff.**	**SE**		**Dep. Var.: Amount raised**	**Coeff.**	**SE**	
Soft cap (M) (Log)	0.349	0.060	***	Average BTC price(log)	0.531	0.247	**
Median BTC price (Log)	0.114	0.309		Hard cap(log)	0.585	0.084	***
ICO duration	-0.001	0.001		ICO duration	-0.002	0.001	**
Number of currencies (log)	0.153	0.103		Number of currencies(log)	0.525	0.190	***
Hard cap(log)(M)	0.426	0.068	***	Distributed in ICO	-1.001	0.245	***
Distributed in ICO	-0.620	0.289	**	US (dummy)	-0.038	0.167	
US (dummy)	-0.267	0.234		Europe(dummy)	-0.343	0.104	***
Europe dummy	-0.385	0.114	***	Whitelist/KYC (dummy)	0.264	0.115	**
Whitelist/KYC (dummy)	0.249	0.130	*	MVP/Prototype (dummy)	-1.263	0.598	**
MVP/Prototype (dummy)	-0.885	0.658		Bounty (dummy)	-4.444	1.680	***
Bounty (dummy)	-8.281	0.145	***	Bonus (dummy)	-0.276	0.095	***
Bonus (dummy)	-0.163	0.112		Ethereum (dummy)	-0.016	0.152	
Ethereum (dummy)	0.004	0.172		Number of currencies (log)	-0.122	0.064	*
Fiat accepted (dummy)	-0.191	0.153		Fiat accepted (dummy)	-0.154	0.144	
Constant	1.920	2.751		Constant	0.806	2.579	
				q201702	-1.529	0.759	**
q201703	0.515	0.895		q201703	1.054	0.490	**
q201704	0.636	0.390		q201704	0.707	0.278	**
q201801	0.951	0.240	***	q201801	1.183	0.233	***
q201802	0.239	0.221		q201802	0.389	0.207	*
q201803	0.222	0.243		q201803	0.463	0.225	**
q201804	-0.006	0.271		q201804	0.249	0.249	
q201901	0.218	0.366		q201901	0.572	0.315	*
q201902	-0.281	0.374		q201902	0.165	0.300	
N	861				1216		
R2 (Adjusted)	0.347				0.273		

*Notes: * P < 0.10, ** P < 0.05, *** P < 0.01, All models have robust standard errors*

In the paper "Underpricing in the cryptocurrency world: evidence from Initial Coin Offerings" Von Eije & Heine (2019) took the natural logarithm of their excess return variable, while I used the raw percentage. Running the OLS regression again, with the same transformation as in their paper did improve the significance of the results. However, the Q-Q plot of the residuals confirmed that this transformation would not improve the model considering the current dataset.

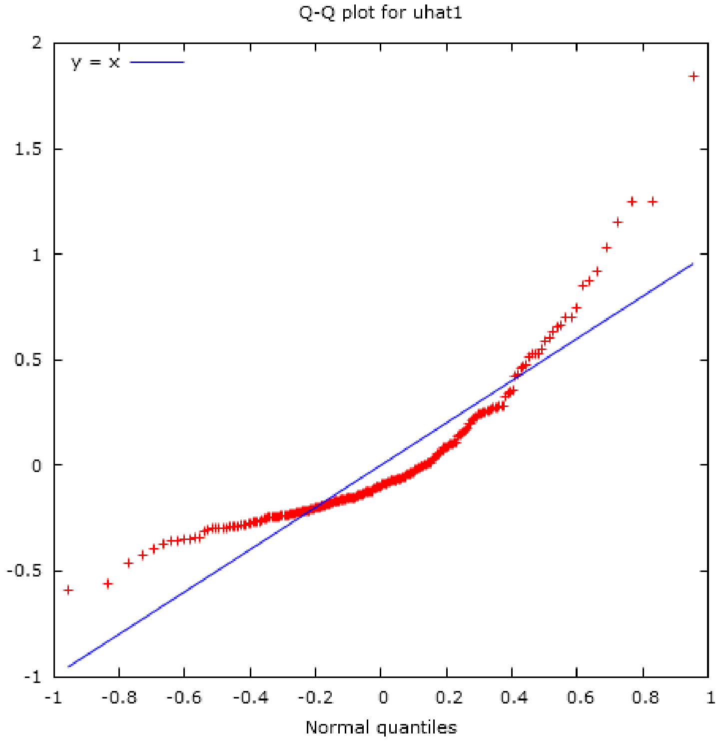


Figure 2: Q-Q plot of the residuals of the ICO-underpricing regression with a log-transformed dependent variable

7. Discussion and Conclusion

In this chapter, I will discuss the main results of the study, list the implications of the study, identify some limitations of the study, and give some advice on possible future research.

7.1 Main results

Two out of three hypotheses regarding the signaling models are supported by the results (Table 10). There was an indication that a higher funding goal has a positive impact on the amount raised in ICOs and Crowdfunding. I suspect that it is not the funding goal that has an impact on the funding amount, but that it acts as an indicator of the amount of effort a company will put into funding. Furthermore, I found that a longer funding period is negatively related to returns in ICOs and crowdfunding projects alike. This relationship was quite expected as it has been documented in multiple other studies (Momtaz, 2018; Mollick, 2013). The positive link between the percentage offered and the amount raised was the odd one out, though not completely without precedent. In 1988 researchers (Morck, Shleifer, & Vishny, 1988) found a negative relationship between firm value and the level of board ownership in the 5% to 25% range, and a positive relationship in the 0% to 5% and the 25% and up range.

Table 10: Summary of signaling results

Hypothesis	Result
H1A. A higher retention percentage will be beneficial for the amount raised of ICOs and IPOs.	Positive for ICOs, negative for IPOs
H1B. A higher funding goal will be positively correlated with returns in crowdfunding and ICOs	Positive correlation
H1C. A longer funding period will have a negative effect on the amount raised through ICO and crowdfunding.	Negative correlation

My predictions regarding underpricing were less fruitful, with none of the results supporting the hypotheses (Table 11). The finding that I didn't find a link between historical underpricing and current underpricing on the individual level was not too surprising as the effect was not seen at the aggregate level in IPOs as well. There were two notable differences between the study that found this result previously and this one (Kadlec & Edelen, 2005) that might explain the different findings. Firstly the study cited had a larger sample size (N= 4,605) than mine (N= 493 & 768). Secondly, the sample period of the study was around the internet bubble, which might have influenced the amount of underpricing.

Table 11: Summary of underpricing results

Hypothesis	Result
H2A: Excess returns and the number of listings are cyclical in both ICOs and IPOs.	Negative relation for the number of ICOs
H2B: The amount of underpricing in ICOs is positively correlated with the number of days between the ICO and listing time.	No relation
H2C Smaller issues should see higher excess returns than larger IPO and ICO issues.	Only significant for ICOs

7.2 Study implications

This study expands on the current literature by finding links between multiple funding mechanisms in a similar timeframe. Furthermore, this study might lead to more nuanced studies comparing different funding mechanisms.

7.3 Limitations:

The datasets I've collected were all pulled from aggregate websites and thus might contain some biases. This might affect the ability of the model to be generalized to the whole population. Furthermore, I've primarily focused my research on the United States. I've controlled for differences between countries in ICOs, but not in IPOs. As a result, the study might not apply to countries other than the United States.

The dataset of crowdfunding and ICOs both contain projects that were able to raise money but didn't reach the funding goal. Whereas the dataset of IPOs only contained data on successful IPOs.

Due to the estimation of multiple mechanisms, there was not enough time available to gather all control variables that were used in previous research. As a consequence, some effects found in the study might be due to other variables that were not added to the model. Many studies add some kind of control variable for 'hype' or use some way to incorporate social media data into the model (Lyandres, Palazzo, & Rabetti, 2019; Fisch, 2019).

There might be a mismatch between the listing time of an ICO noted in the source and the "true first listing". A study by EY research (2018) showed that many ICOs lose all value after some time. Thus, the average amount of underpricing might be understated if the reported listing dates are after the 'true' listing date.

7.4 Future research

Though I have tried to include as many signals as possible, there are some other promising signals that I couldn't include in the model. As an example, a more prestigious underwriter is a positive signal in IPOs (Loughran & Ritter, 2003). Due to time limitations, it wasn't possible to research the effects of platform intermediaries in crowdfunding and ICOs, but there might be some link there as well. Another example is the relationship that has been found between Spelling errors in description and the amount raised in ICOs (Fisch, 2019).

I have used the median of the bitcoin price as a control variable as the bitcoin price might affect the amount of funding an ICO would get. A better way to capture this might be some measure of the relative bitcoin price at that moment. For instance, a bitcoin price of 10.000 USD might have a different impact on investors depending on the price history.

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Annexes

I. LIST OF VARIABLES

Table 12: Control variables of the signaling models

	Control variable	*Description*
IPO	Total offering expenses(log)	"Lower quality firms have a higher underwriter spread" (Altinkilic & Hansen, 2000, p. 191)
	Employees(log)	Team size has been shown to be positively related to the amount funded
	Total assets(log)	Assets are used for firm valuation (Aggrawal, Bhagat, & Rangan, 2009). Thus, would be positively correlated with funding.
	China (dummy)	Chinese IPOs are primarily bought by insiders and thus are probably rated differently by investors (Wang & Franklin, 2019). I've added a dummy variable indicating when they have China in the description.
	Shareholder shares offered (dummy)	Dummy variable that takes the value of 1 if shareholder shares are sold during the IPO. This might have a negative effect on the valuation of IPOs
Crowdfunding	Pledged/backer	Pledged/backer Mollick (2014) found a positive relation between this and success
	United States(dummy)	A dummy variable that takes the value of 1 when the person organizing the crowdfunding project is located within the United States and 0 when located outside of the US. An international project might be seen as riskier, as there are more costs involved. For crowdfunding due to its online context. Some studies control for locational effects (Aggrawal, Bhagat, & Rangan, 2009).
	Staff pick (dummy)	Kunz et al (2017) found a positive effect of staff pick on the success rate

ICO	N# of currencies accepted(log)	The number of currencies that are accepted in the ICO. Might affect funding positively trough lower costs for investors.
	United States (dummy)	Takes a value of 1 when originating from the respective region. Originating from Europe was found to affect funding negatively (Fisch, 2019).
	Europe (dummy)	
	Whitelist/KYC (dummy)	Takes a value of 1 when investors must comply with KYC or a whitelist. Was found to positively correlate with funding (Lyandres, Palazzo, & Rabetti, 2019)
	MVP/Prototype (dummy)	Dummy variable takes 1 if the ICO has a minimum viable product or a prototype.
	Bounty (dummy)	Takes a value of one when the ICO awards a bounty for tasks.
	Bonus (dummy)	Takes a value of 1 when the ICO has some kind of bonus scheme. Was found to have a positive relation with funding (Lyandres, Palazzo, & Rabetti, 2019)
	Ethereum (dummy)	Takes a value of 1 if the ICO is based on the Ethereum platform. Was found to have a positive relation with funding (Fisch, 2019)
	Fiat accepted (dummy)	Dummy variable that takes 1 if any kind of fiat currency is accepted in the ICO. Stable coins are not regarded as fiat. (Momtaz, 2018)

Notes: Time dummies have been added to all regressions in addition to the control variables above to control for changes in effects over time (Fisch, 2019).

Table 13: Control variables of the underpricing models

	Control variable	Description
IPO	Employees(log)	Control for target size (employees) like Ragozzino R (2011), as it is believed that larger firms have less information asymmetry
	% Offered	Fractional ownership has been shown to affect firm value (How & Low, 1993)
	Volume(log)	Adapted from von Eije & Heine (2019)
	China (Dummy)	Dummy takes a value of one when China is in the description
ICO	Bitcoin price @ listing(log)	Bitcoin is one of the most common payment methods that ICOs accept in exchange for their tokens. Due to the high variability of the price, I've chosen to take the median bitcoin price of the funding time for each ICO. When the bitcoin price is high, Due to the high variability of the price I've opted for the median bitcoin price of the funding period. Fish, for instance, controls for the bitcoin price only at the start of the ICO, which is strange considering the high variability of the bitcoin price during an ICO.
	Ethereum (Dummy)	ERC20 tokens can be traded over the counter and on several decentralized exchanges. This might lower the amount of underpricing.
	United States (Dummy) Europe (Dummy)	Eije & Heine (2019) found a positive (but not significant) relation between underpricing and region.
	Whitelist/KYC (Dummy)	Investors might perceive an ICO without KYC/Whitelisting as riskier.
	Fiat accepted (Dummy)	Investors might perceive an ICO that accepted fiat as more reliable.

II. Gathering the crowdfunding data

At first, I pulled the datasets from

https://webrobots.io/kickstarter-datasets/ for Kickstarter

https://webrobots.io/indiegogo-dataset/ for Indiegogo

The data in these files was cut off in irregular intervals and continued the next few lines. This was solved by using a formula to identify the start of the breaks and locating how many lines down the rest of the data was located. Then another formula was used to concatenate the strings. After concatenating the strings, the data was split to columns and it became possible to remove duplicates. The data still looked quite messy, with over a few 1000 error values, so I went back to the drawing board and tried importing the JSON files and the CSV files with the excel query wizard. Importing the CSV all at once proved to be the most fruitful method. The Kickstarter data proved usable, but the IndieGoGo data didn't have an identifier to tell if the project was still ongoing.

The data was in JSON streaming format, which means that instead of the file being a valid JSON file, every line in the file is a valid JSON object, which excel can't read. Changing the file type to .TXT and then importing it with the query editor in excel proved to be the solution

III. Gathering the ICO data

The Xpath of data tables was then copied to a googles sheet and the data of each individual ICO was imported using the IMPORTXML function. This avenue worked but populating the sheets this way would have taken weeks. Then I've tried to upload the data into excel with the help of an extension[1] and the following formula:

=XPathOnUrl(URL;Xpath;"";HttpSettings(;;;"500|1000|Host");"text")

Retrieving data from the following Xpaths: //*[@id="financial"]/div/div[2] | //*[@id="financial"]/div/div[1] | /*[@id="profile_header"]/div/div[2]/div[3]

The data came out in one string, for each of the retrieved tables, so some manipulation was needed to extract the needed information. One formula was used for getting the rightmost data from the string =RIGHT(Cell with string; LEN(Cell with string)-FIND(Category name; Cell with string)-LEN(Category name)), and this formula was used to cut the retrieved information out of the string =LEFT(Cell with string; LEN(Cell with string)-LEN(Category name)-LEN(Cell with category info))

11 ICOs out of 5596 in total in the master list were not found on ICObench

Information about: start/end date(duration), Emission amount, soft cap, hard cap, Platform, Type, bounty program, Origin country, Restricted country, Whitepaper/yes/no

The profile information needed 4-5 different Xpaths to retrieve the information

The amount raised in multiple cryptocurrencies was in one string as well. Sadly, there was no separator between the amount in cryptocurrencies and the guestimate of ICObench. Thus,

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[1] https://seotoolsforexcel.com/

I had to retrieve every cryptocurrency amount separately, sort them correctly and cut the original string by the length of the separately obtained info.

IV. Results of the Breusch-Pagan test

Table 14: Results of the Breusch pagan test.

	LM	p-value
IPO	32.263	0.005928
Crowdfunding	2589.01	0
ICO	173.158	1.85E-25
IPO underpricing	3213.95	0
ICO underpricing	3945.98	0

Note: P<0,05 implies heteroskedasticity

V. Variance inflation factors

Table 15: Variance inflation factors of the signaling models

IPO		Crowdfunding		ICO	
% Offered	1.299	Goal(log)	1.113	ICO duration	1.282
Offering expenses(log)	3.305	Duration(days)	1.023	# currencies accepted(log)	1.496
Employees(log)	5.396	Staff pick	1.036	Hard cap(M)(USD)	1.110
Total Assets(log)	6.332	Pledged /backer	1.077	United States dummy	1.169
China dummy	1.209	United States dummy	1.008	Europe dummy	1.199
Shareholder shares offered dummy	1.247			Whitelist/KYC dummy	1.476
				MVP/Prototype dummy	1.018
				Bounty dummy	1.014
				Bonus dummy	1.080
				Ethereum dummy	1.060
				Fiat accepted dummy	1.426
				Median BTC price(log)	2.963
				% Distributed	1.127
q201702	1.92	q201702	1.788	q201702	1.105
q201703	1.617	q201703	1.752	q201703	2.158
q201704	2.004	q201704	1.790	q201704	2.962
q201801	1.89	q201801	1.566	q201801	3.642
q201802	2.085	q201802	1.693	q201802	4.469
q201803	1.986	q201803	1.678	q201803	3.586
q201804	1.82	q201804	1.823	q201804	4.078
q201901	1.628	q201901	1.628	q201901	3.631
q201902	2.113	q201902	1.886	q201902	2.649

Table 16: Variance inflation factors of the underpricing models

IPO		ICO	
IPOinpreceding30days	1.011	PricechangeICOfirstdayclos	1.026
AVGofIPOsinpreceding30day	1.017	AVGexcessreturn30daysprior	1.174
Offering size (USD)	3.919	ICOspreceding30days	1.222
Employees(log)	1.699	Timebetweennotationicoend	1.094
% offered	1.299	Raised(log)(USD)	1.051
SSO dummy	1.181	Bitcoin price @ listing(log)	1.092
China dummy	1.332	Ethereum dummy	1.027
Volume(log)	4.099	United States dummy	1.157
		Europe dummy	1.126
		Whitelist/KYC dummy	1.148
		Fiat accepted dummy	1.027