CHEAP SIGNALING IN INITIAL COIN OFFERINGS

THE IMPACT OF CHEAP SIGNALS ON ICO FUNDING AMOUNT

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Abstract

Initial Coin Offerings (ICOs) is a fundraising model that enables blockchain startups to raise amount of capital close to IPOs at a fraction of the cost. ICOs are decentralized, with no single authority governing them. In this largely unregulated environment, investors often have to rely on unaudited information provided by ventures themselves. Some ICOs have yielded massive returns for investors, while others have failed or turned out to be fraud. This study builds on signaling theory and aims to examine signals of venture quality that entrepreneurs send to investors in ICOs. More specifically, I examine whether cheap signals have an effect on funding amount in completed ICOs. Using a global sample of 168 ICOs, I find that cheap signals of project elaboration and social media have a positive effect on funding amount. These results implicate that ICO markets might behave differently than other more mature markets and challenge the assumption that signals must be costly in order to create separating equilibrium. Since cheap signals do not require costly efforts for ventures, they could potentially be exploited by ICOs in order to influence their funding success. I argue that my findings provide insights for a regulatory debate as well as new perspectives on mechanisms underlying signaling theory, opening up for further research.

Keywords: Initial Coin Offering, Entrepreneurial Finance, Crowdfunding, Blockchain, Signaling Theory

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1. Introduction

Blockchain is an emerging technology that has generated a lot of interest in recent years. With billions of dollars already invested in cryptocurrencies and blockchain startups, more and more economists and technologists argue that the blockchain technology has the potential to reshape the whole financial system (Zhao et al., 2016; Pilkington, 2016). According to a forecast by Gartner (2018), the blockchain technology will create more than USD 176 bn worth of business value by 2025 and USD 3.1 tn by 2030.

As an increasing amount of players enter the market, new and interesting innovations are created in the blockchain ecosystem. One of them is Initial Coin Offerings (ICOs), a fundraising model that enables blockchain startups to raise amounts of capital close to IPOs at a fraction of the cost by e.g. avoiding the costs of compliance and intermediaries (Fisch, 2019). In ICOs, capital is raised by blockchain ventures issuing and selling tokens to a crowd of investors in a similar way as crowdfunding. Tokens are units of value intended to provide utility or function as securities, and often they are cryptocurrencies meant to function as a currency in the venture’s own ecosystem (Sameeh, 2018).

ICOs is a very recent phenomenon, dating only to 2013. Since the widespread adoption of the Ethereum blockchain in 2017, both the number of ICOs and the amount of capital raised have exploded, exceeding USD 11 bn in 2018 (ICObench, 2018) and attracting significant attention from ventures, investors, and policy makers (Fisch, 2019). However, because of its novelty, little is still known about the dynamics of ICOs and the decision making process of ICO investors.

The ICO market is characterized by high levels of information asymmetry. Ventures are typically in early stages with low amount of objective information and investors often have to rely on unaudited information provided by the ventures themselves. When two parties have access to different information, signaling theory is useful for describing the behavior. Generally, the sender has to choose whether and how to communicate, or signal, that information, while the receiver has to choose how to interpret the signal. It postulates that investors prefer to act on costly information since costly signals indicates higher firm quality, while cheap signals can be sent by both high- and low-quality companies (Spence 1973).

This study extends previous research on ICOs by analyzing empirically whether cheap signals have an effect on funding success in ICOs. I define funding success as the amount of funding completed ICOs succeed to collect. While there is some research on what factors that lead to funding success, there is little evidence of whether investors in the ICO context react to cheap signals or not. Cheap signals do not require costly efforts for firms and could therefore potentially be exploited by firms in order to influence their funding success. However, the unregulated environment and the lack of objective information suggests that less costly signals might be used in the ICO funding context, which could open up for a regularity discussion.

2. Theory and Hypotheses

2.1. Initial Coin Offering

In this section, the concept of Initial Coin Offerings is explained. I start by giving a brief explanation of the blockchain technology that enables this fundraising model, and thereafter provide an overview of the ICO process.

2.1.1. Background and Introduction to Blockchain Technology

Blockchain is a distributed ledger technology that forms a chain of blocks where each block includes information and data that are bundled together and verified. The technology was invented around 1991, but it was when the cryptocurrency Bitcoin was created in 2008, by one or several persons under the pseudonym Satoshi Nakamoto (Nakamoto, 2008), that the technology started to become substantial used in practice. However, it is important to emphasize that while all cryptocurrencies are blockchains, not all blockchains are cryptocurrencies. As the technology matured and a variety of blockchains bloomed, the area of application quickly broadened.

Today blockchain technology is used in a variety of areas spanning from the health care to the food industry and supply chain management, and yet the limit is not reached. Some call it the second generation of the digital revolution and claim that while the first generation of the digital revolution brought us the Internet of information, the second generation is bringing us the internet of value (Zhao et al., 2016; Pilkington, 2016, among others). All powered by blockchain technology, described as a new, distributed platform that can help us reshape the world of business and transform the old order of human affairs for the better (Zhao et al., 2016).

The technology allows digital information to be distributed, but not copied. This means that each individual piece of data can only have one owner (Nakamoto, 2008). It can be compared with the content of a book. Each line in this shared book is a “block” filled with valuable information that makes various automated processes secure. This book is not only stored in a central place that is shared by many, but it also exists an infinite number of copies stored on computers all across the world. The information in the different books can be used within various areas, one given by the following example related to cryptocurrencies.

If person A wants to send money to person B, a new line is created in the shared book/ledger that describes the details of the transaction. Since the book/ledger is shared, this line appears on all other computers as a confirmation of that the transaction has happened, simultaneously as it is verified against the book to ensure that the details in the transactions are correct. The principle is thus the same as if thousands of friends of A and B were standing around them to make sure that the transaction seemed to contain the right amount of money and recipients, and the transaction could never go through if not everyone agree.

This way of using blockchain technology is the concept behind cryptocurrencies. Thanks to this decentralized system no intermediaries such as banks are needed, and the advantages are, among other things, that transactions could be made all over the world, faster, safer and cheaper than today's money system (Nakamoto, 2008).

2.1.2. The ICO Process

ICO is a fundraising model built on blockchain technology, and is sometimes explained as a mix of an IPO and crowdfunding (Howell et al., 2018). Similar to an IPO, a company will raise money through a new issue, but instead of issuing stocks, the company will issue so called tokens. Bitcoin is one of the best-known examples of a token, but often tokens are built upon other protocols where Ethereum is the most widely used (Magas, 2018).

In short, a token is a digital asset based on blockchain technology which can be transferred between two parties without the need for a central intermediary. While Bitcoin is a coin, tokens created using the Ethereum blockchain can have a variety of attributes attached and, with “smart contracts” added, they articulate, verify and enforce agreements between parties (Magas, 2018). The difference between a coin and a token can be hard to grasp and there are no clear industry standard definition. Often, a coin refers to a standalone cryptocurrency functioning on its own blockchain platform, while a token refers to a cryptocurrency that requires the usage of a separate coin blockchain in order to operate (Howell et al., 2018). However, usually the terms are used interchangeably, and so also in this study.

The parties involved in an ICO are the issuer, the investor, and a platform comprising the network of participants who buy and hold the tokens. The ICO process is not standardized, but the main steps of tokens offerings often follow the same pattern. The procedure normally starts with the company announcing their intention to perform an ICO and informing the public about the project through a so called whitepaper, which is a non-standardized offering document that describes the offering terms and conditions of the ICO. Moreover, a paper with the more technical details of the project and a terms and conditions document may be published. The ICO can also chose to publish their source code on an online code repository, such as Github, which is a way for external industry participants to verify the code (Howell et al., 2018).

To provide updates and/or respond to potential participants of the offering, official crypto community communication channels, such as Telegram, are often used. The eventual pre announcement often starts discussions about the project on relevant platforms, which gives the issuers a possibility to estimate the demand of the tokens (Howell et al., 2018).

A minimum fundraising target floor is set, a “soft cap”, and if this floor is reached the offering can be completed. The company then creates new tokens on the blockchain, which investors thereafter receive in exchange for fiat currency or, more often, major cryptocurrencies. If the soft cap is not reached no token is issued and the money is returned to the investors (Amsden et al., 2018).

If an investor does not hold cryptocurrency but wants to participate in a token offering, the investor signs up to a digital exchange accepting fiat currency. Fiat currency is then transferred to the exchange, where it is converted to one of the major cryptocurrencies, often Bitcoin or Ether. Ether is the cryptocurrency generated by the Ethereum platform.

The investor then needs to sign up with a digital wallet provider and create an own personal private wallet, from which tokens can be bought. This crypt wallets are basically software programs that store private and public keys. A public key acts as the wallet address and can, similar to a bank account number, be known to everyone. The private key however, is a secret number that allows the investor to access and spend tokens, similar to a pin number. Together, these give complete control over the tokens and allow the investor to send and receive tokens trough blockchain transactions (Amsden et al., 2018).

To receive tokens from the offering, the investor has to send the payment from his/her own private wallet to the address of the ICO which issues the new tokens. If the ICO has been completed, the tokens will be sent to the private wallet of the investor. This newly-created tokens are most often not accepted by the exchange where fiat currency is converted to one of the major cryptocurrencies. Instead, the investor needs to use one of the other crypto exchanges that list crypto tokens. These act as secondary markets for newly-issued tokens where investors can trade them against more mainstream cryptocurrencies (OECD, 2019).

The ICO market is highly unregulated. ICOs are decentralized and most of them fall outside existing regulations. With no single authority governing them, there have been several examples of fraud and scam ICOs (Chohan, 2017). At the time of writing, almost 6 900 examples of scams have been identified in the crypto market, out of which 457 are active (Etherscamdb, 2019).

2.2. Literature and Hypotheses Development

In this section, academic research in the context of information asymmetry and signaling theory will be introduced. I thereafter build on the framework of Ante and Fiedler (2019) on cheap signals in Security Token Offerings and develop hypotheses for how cheap signals of ICOs can be related to funding success. Funding success in this context is defined as absolute funding amount a completed ICO is able to collect.

2.2.1. Information Asymmetry and Signaling Theory

Logically, an entrepreneur is assumed to have more knowledge about a venture's true value than an investor. Unlike VCs, where investors usually perform thorough due diligence, ICO investors are small investors that are less likely to have experience evaluating investment opportunities. Moreover, they need to rely mainly on the contents of the whitepaper and the terms of the ICO which are not audited by any third part. It makes it even more difficult for potential investors to define anything concrete about the value of the company. Following, information asymmetry between entrepreneurs and investors is a considerable feature of the ICO market, even more than to venture capital (VC) financing (Amsden et al., 2018).

In the context of VC investments, the problem of adverse selection is researched by, among others, Leland and Pyle (1977) who state that "where substantial information asymmetries exist and where the supply of poor projects is large relative to the supply of good projects, venture capital markets may fail to exist".

Entrepreneurs have successfully been able to raise significant funding through ICOs. Since not all ventures obtain financing, investors, to some extend seem to regard at least some of the information as attributes of venture quality or signals.

Signaling theory suggests that signals can alleviate asymmetric information (Spence 1973). There are high quality companies and there are low quality companies. The companies are aware of what category they belong to, but potential investors do not have access to sufficient information to be able to distinguish between the two types. Companies face the choice to signal or not signal their true quality to potential investors. The party who possesses the information must decide what information to communicate and how to communicate it. The other party may in turn decide on how to interpret the information (Spence 1973).

Signaling theory is commonly used to evaluate the flow of information from one party to another when the informational conditions of the parties are asymmetrical (Connelly et al., 2011). Rao, Lu and Ruekert (1999) define a signal as "an action that the seller can take to convey information credibly about unobservable product quality to the buyer”.

This is of extra relevance when the consumer cannot directly evaluate a product or service but require external information. The external information is often provided by a seller, who in theory can fake or misinform the consumer (Mavlanova et al., 2012; Wessels; 2015). For a signal to be credible, research has found that signals should be sent by trusted third parties or costly to mimic, especially of the valuation of new firms in uncertain markets (Sanders & Boivie, 2004). In more established corporate finance markets, dividends (Bhattacharya, 2979) and debt (Ross, 1973) are two signals that have been identified as relevant and costly signals of quality since companies of bad quality are not able to continually pay out interest and dividends. However, new business models combined with a lack of objective operating data result in significant information asymmetry and uncertainty, increasing the risks of both adverse selection and moral hazard.

Signals that is either costly or honest can still have an effect on the decision process of investors. If a seller lack a specific quality but realizes that the signal such a quality would bring is higher than the related costs of producing such a signal, the seller may be incentivized to falsely communicate or fake the signal. Such actions make it possible for parties to provide false signals of quality until a counterpart learns about it and not takes the signal into account in the decision process. Thus, for signals to maintain effective, the costs of signals should be structured so that dishonest signals do not pay off (Connelly et al., 2011).

Signaling theory predicts that a costly signal to capital markets will be costlier for a bad firm than a good firm, and hence a bad firm will not try to imitate such a signal. A bad firm will also avoid to imitate cheap talk since it attracts scrutiny, while a good firm can engage in cheap talk since it will not get hurt by an inspection (Bhattacharya & Dittmar, 2008). The environment can also have an impact on the effectiveness of signaling. If the signaler can easy influence the environment, there is a higher risk of faked or biased signals. An example of this is social media channels or websites, where another type of environment distortion could for example be other receivers that could impact insecure receivers and create a bandwagon effect (Sliwka, 2007).

2.2.2. What Drives the Funding Success of ICOs?

Since ICO is a new phenomenon, research analyzing the influence of ICO characteristics on the probability of success has only recently emerged. Adhami et al. (2018) look at funding success defined as ICOs that has successfully closed their offering. They consider a sample of 253 ICO campaigns and find that there is a higher probability of success when the code source is available, a presale is arranged and tokens include access to specific services or profit sharing. Fisch (2019) investigates the role of technological capability signals in ICOs in terms of the amount raised. The study builds on 423 ICOs and shows that white papers and high-quality source codes increase the amount of funding, while patents do not. Amsden & Schweizer (2018) establish token or coin tradability as the primary ICO success measure, and find that venture uncertainty is negative correlated while higher venture quality is positive correlated with ICO success. Ante et al. (2018) look at 278 ICOs and what determine funding success defined as the size of funding received, and find that ICOs exhibit similarities to classical crowdfunding and venture capital markets. Specifically, they identify similarities in determinants of funding success regarding human capital characteristics, business model quality, project elaboration, and social media activity.

However, to the best of my knowledge, no research to date has explored the correlation between cheap signals and ICO funding success. Ante & Fiedler (2019) look at this connection in terms of blockchain-based security token offerings (STOs). They investigate 151 projects and find that cheap signals of human capital and social media are used by projects and have a positive effect on funding success, while cheap signals of external network size negatively affect funding success. The aim of this study is to extend on their research. I will include all types of ICOs and a sample size of 168 projects.

In line with Ante & Fiedler (2019) I base my exploration of the causes of the ICO success on signaling theory (Spence, 1973). More in detail, I focus on specific characteristics of the ICO, distinguished by four signal categories, namely human capital, external networks, project elaboration and social media, and explore how cheap signals within this variables influence the ICO success defined as absolute funding amount a completed ICO succeeds to collect

2.2.3. Human Capital

Unger et al. (2011) claims in a meta-study that the link between human capital and venture success is one of the most robust findings in the field of entrepreneurship research. However, scholars do not agree on its magnitude and relative importance. Generally speaking, human capital is often related to education, experience, knowledge and skills with regard to various aspects of entrepreneurial success (Ahlers et al., 2015).

Hsu (2007) finds that measures of human capital are positively related to venture valuation, and argue that it is especially important in young industries as signals are more important in more uncertain situations. Ahlers, et al. (2015) look at equity crowdfunding and show that a higher number of board members are positive and statistically significant related to funding success for both higher expected number of investors, and for higher funding amount. In the context of ICOs, Ante et al. (2018) find that signals of human capital by listing team members on the project’s website have an impact on funding success.

In line with Ante & Fiedler (2019), I distinguish between team size and team quality. I measure team size by number of team members presented on a project’s website and categorize it as a cheap signal since an ICO could quite easily inflate the number. The quality of the team, e.g. level of education or previous experience, will not be in focus in this study as it is not considered a cheap signal since it involves third party endorsement and a risk of high penalty costs from false signaling (Vismara, 2018).

2.2.4. Network

A credible network can be very helpful to overcome the information asymmetries between startups and potential investors. Stuart, Hoang, and Hybels (1999) argue that third party endorsement is crucial when the startup needs legitimacy, as the endorsement of more established institutions and individuals can extend to new ventures. A company's network may also influence it performance as well as the valuation of the company by venture capital investors, the influence being more prominent the younger the firm (Zheng et al. 2010). In equity crowdfunding, studies have shown that established partnerships help to provide signals of good reputation to a project and its team (Ahlers et al., 2015, Mollick, 2014).

In the context of ICOs, Amsden & Schweizers (2018) find a positive impact of number of advisors on ICO success, while Ante & Fiedler's (2019) study STOs without finding a significant impact on funding.

In this study, communicated number of advisor serve as a proxy for network size. This is considered a cheap signal since projects can easily list all types of advisors and partnerships on relevant websites without specifying the relevance of the connections. The quality of advisors and partnerships builds on third party endorsement and requires costly efforts for ventures to signal, why it is not considered a cheap signal and is left out from this study.

2.2.5. Project Elaboration

Ahlers et al. (2015) argue that investors must assess level of uncertainty in a startup when deciding whether to invest in a startup or not and that entrepreneurs can try to reduce the level of uncertainty by publishing a business plan or other project descriptions. A startup that has not prepared such documentation signals uncertainty (Mollick, 2013; Ahlers et al., 2015). Several researchers have identified pitch quality and sound textual descriptions as a signal of quality that increases funding success in crowdfunding (Mollick, 2014; Hobbs et al., 2016; Gafni et al., 2018). Since an ICO's whitepaper is comparable to a prospectus, I operationalize this as a project elaboration signal.

Following Ante & Fiedler (2019), I separate the signal in a qualitative and a quantitative part. The quantitative signal is divided in two parts: (1) the existence of a whitepaper and (2) the number of pages and number of words of a whitepaper. While only publishing a whitepaper or influence its length is easy to do at a low cost, the quality of the whitepaper is not. Following, only the quantitative part will be considered a cheap signal and be included in this study.

ICOs can also choose to reveal their code on Github, and (3) presence on Github is also used as a project elaboration signal in this study. Several studies have found a positive effect between being presence on Github and ICO funding success (Adhami et al., 2018; Amsten and Schweizer, 2018; Jong et al. 2018). As only revealing the code does not involve a significant cost, it is considered a cheap signal.

2.2.6. Social Media

Communication through social media is one of the most popular ways for companies to interact with external stakeholders. It enables companies to communicate their identity to the crowd and offers potential investor an opportunity to understand what the company is about (Wilson et al., 2011). Yang & Berger (2017) show that a higher number of Facebook and Twitter followers usually raise startups' venture capital funding. Research on crowdfunding projects shows that being more active on social media (Nevin et al., 2017) and having a larger social media network (Kromidha & Robson, 2016) will have a positive impact on the funding of a campaign.

In the context of ICOs, investors use several information sources to assess the quality of the token sale where Telegram and Twitter is one of the most commonly used. Studies have shown that the larger Telegram groups and greater number of Twitter followers, the more successful an ICO is in terms of liquidity and trading volume (Howell et al., 2018).

In this study, social media channel size is classified as a cheap signal, as it is rather easy to manipulate the absolute size of social media networks by e.g. paying for followers.

2.2.7. Summary and Hypotheses

My general hypothesis is that investors of ICOs and traditional financial markets act on similar signals in the form of human capital, network size, project elaboration and social media characteristics. More specifically, investors should regard costly signals in their evaluation of the quality of the venture but disregard cheap signals. Following, I hypothesize that the attractiveness of a project for investors, the funding success, is not systematically related to cheap signals. Based on previous research on signals in the context of venture financing, I end up with four sub-hypotheses which are that the absolute funding amount a completed ICO succeeds to collect is:

(H1) unrelated to cheap human capital signals, which I operationalize as the communicated number of team members

(H2) unrelated to cheap network signals, which I operationalize as the communicated number of advisors

(H3) unrelated to cheap project elaboration signals, which I operationalize as (a) the availability of a whitepaper, (b) the whitepaper score, which is a measure of the number of pages and words of the whitepaper, and (c) presence on GitHub.

(H4) unrelated to cheap social media signals, which I operationalize as the number of followers on (a) Reddit, (b) Facebook, (c) Twitter and (d) Telegram.

3. Methodology

In this section, I start with describing the sample selection and data collection process. Following, all the variables are presented and explained. Subsequently, I describe the statistical methods used in this study, including the OLS regressions that the results section will build upon.

3.1. Sample Selection and Data

It has been a challenge to find data and identify a list of ICOs for the empirical analysis, since no official source exists. The number of websites that lists ICOs is numerous, and the literature on the subject is scare. In this study, I primary rely on ICObench.com, which is an ICO listing website that several studies argue provides the greatest accuracy (Amsden & Schweizer, 2018, Lee et. Al, 2018 among others). I cross-check information with other websites, including coinmarketcap.com, cointrends.top, coinschedule.com, cryptoslate.com, icodrops.com, coinmarketcap.com, tokendata.io and tokenmarket.net. I exclude ICOs listed on ICObench.com but not on any of the other websites. I obtain social media statistics from icomarks.com. I also complement information about funding amount from icomarks.com and icodata.io, as well as from the ventures whitepapers. Ether price in USD is collected from coinmarketcap.com.

Due to the limited scope of this thesis, I only examine ICOs that was finalized between 1 April 2018 and 31 March 2019. After excluding observations with missing data, I identify a final sample for my analysis that covers 168 ICOs within this period of time.

3.1.1. Description of Variables

To test the study's hypotheses of not finding a correlation between cheap signals and ICO success, a multiple regression is run. The model is based on one dependent variable along with independent and control variables. Bellow follows a description of the variables and how they are calculated. A summary is found in table 1.

3.1.1.1. Dependent Variables

In line with Ante & Fiedler (2019), Mollick (2014) and Fisch (2019), among others, my dependent variable is absolute funding amount in USD for completed ICOs. In line with prior research, I use the natural logarithm of the funding to account for the skewness of the variable (Fisch 2019, Mollick, 2014).

3.1.1.2. Independent Variables

Nr. of team members (log.) refers to all communicated members of the team. The natural logarithm of the variable is used.

Nr. of advisors (log.) signifies the natural logarithm of the communicated number of advisors.

Whitepaper (dummy) is a dummy variable that refers to whether a project whitepaper is available (1 if yes, 0 if no).

Whitepaper score is an aggregated indicator measure, provided by ICObench.com, which catches the informativeness of the whitepaper based on length and word count.

Github (dummy) is a dummy variable that indicates whether an ICO is present on Github (1) or not (0).

Reddit followers (log.), Facebook followers (log.), Twitter followers (log.) and Telegram followers (log.) indicate the number of followers on each social media platform on the ICO end date or closest available date. The natural logarithm of the variables is used since the variables are skewed. I give the variables that had zero followers the lowest number of followers found in the dataset.

3.1.1.3. Control Variables

In line with Fish (2019), I use a wide set of additional control variables to rule out confounding effects. Some of the variables are unique to the ICO context but are inspired by research on crowdfunding, which shows that several entrepreneur-determined characteristics of a campaign can influence the amount raised (e.g., Anglin et al., 2018; Mollick, 2014). For several variables, I use a natural log transformation to account for the skewness of the variable following e.g. Fish (2019) and Ante & Fiedler (2019) among others.

The variable *Soft cap (log.)* indicates the natural logarithm of the stated minimum amount of funds that the ICO need to raise before it is considered successfully completed.

Valuation approx. (log.) serves as an approximation for the implied valuation of the ICO, calculated as the amount of funds raised divided by the share of tokens for sale times total amount of tokens. The natural logarithm of the variable is used.

Duration (days) (log.) represents the natural logarithm of the total number of days the ICO lasted. Previous ICO studies have found a negative effect of duration on funding success (Fisch, 2019; Lee et al, 2018). A long duration may signal that there is a lower demand of the token, while ICOs ending within the first day often generate attention and may be perceived as more legitimate.

Pre-sale (dummy) is a dummy variable that indicates whether the ICO held a per-sale (1) or not (0). Attracting early investors can effect funding success due to e.g. word-of mouth generated by early investors and triggering imitating behavior (Fisch, 2019).

Tokens distributed (share) captures what percent of the total number of tokens the ICO offers for sale. Crowdfunding research shows that ventures which retain a higher share might indicate commitment and higher quality. However, in ICOs tokens seldom represent ownership of the venture so this might not be true in the ICO market. In line with Fisch (2019) I still include this as a control variable.

Token supply (log.) is the natural logarithm of the number of tokens a venture chooses to issue in the ICO. Ventures can freely determine the absolute number of tokens that will be issued at no extra cost. Moreover, the tokens are divisible, making it possible to by a fraction of a single token. With other words, this should not have an impact on funding success following signaling theory. However, a higher number of tokens may give the investors a feeling of lottery, which according to previous studies can affect the funding size positively (Fisch, 2019).

Ethereum based (dummy) is a dummy variable that reflects if Ethereum is the platform for the token (if yes 1, if no 0). Previous research on ICOs have found that Ethereum based tokens tend to be more successful (Amsden & Schweizer, 2018; Fish, 2018; Fenu et al. 2018).

Ether price (log.) is the natural logarithm of the price of Ether in USD at the start of the ICO using the daily opening price, collected from coinmarketcap.com. A high price may decrease ICO participation since it is more expensive to pay with Ether (Amsden & Schwezer, 2018).

KYC (dummy) is a dummy variable that equals 1 if investors are required to provide information to confirm their identity, and 0 otherwise. Research on ICOs has found contradictory results regarding the impact of KYC policies on funding success. A KYC makes the ICO process more transparent and can hence increase the credibility of the venture (Burns & Moro, 2019). However, such policies have the potential of reducing demand by investors who do not want to reveal their identity (Lee et al. 2018).

Location: US (dummy), *Location: EU (dummy)* and *Location: Singapore (dummy)* are dummy variables capturing the location of the venture. Crowdfunding research has found that a ventures location is important for attracting finance (e.g. Mollick, 2014). Fisch (2019) finds a positive effect for ICO funding for ventures located in the US, while Ante & Fiedler (2019) find similar, yet weak, results for ICOs incorporated in Singapore, explained by the country lagging behind in legal certainty.

Table 1. Description of Variables

This table illustrates the collected data points.

Variable	Description
Dependent variable	
Funds raised (log.)	Natural logarithm of funds raised in the completed ICO in USD
Independent variables	
Human Capital signals	
Number of team members (log.)	Natural logarithm of communicated number of team members
Network signals	
Number of advisors (log.)	Natural logarithm of communicated number of advisors
Project Elaboration signals	
Whitepaper (dummy)	Dummy variable that equals 1 if the ICO has published a whitepaper and 0 otherwise
Whitepaper score	Measures the length and word count on a scale from 1-5
Github (dummy)	Dummy variable that equals 1 if the ICO is represented on Github and 0 otherwise
Social Media signals	
Reddit followers (log.)	Natural logarithm of number of Reddit followers
Facebook followers (log.)	Natural logarithm of number of Facebook followers
Twitter followers (log.)	Natural logarithm of number of Twitter followers
Telegram followers (log.)	Natural logarithm of number of Telegram followers
Control variables	
Soft cap (log.)	Natural logarithm of the lowest funding amount that the ICO need to raise before it is considered successfully completed
Valuation approx. (log.)	Natural logarithm of the implied valuation of the ICO, calculated as the amount of funds raised divided by the share of tokens for sale times total amount of tokens
Duration (days) (log.)	Natural logarithm of the total number of days of the ICO campaign
Pre-sale (dummy)	Dummy variable that equals 1 if the ICO had a pre-sale and 0 otherwise
Tokens distributed in ICO (share)	Percentage of tokens distributed in the ICO
Token supply (log.)	Natural logarithm of the number of tokens offered for sale
Ethereum-based (dummy)	Dummy variable that equals 1 if the token is Ethereum-based and 0 otherwise
Ether price (log.)	Natural logarithm of the price of Ether in USD at the start of the ICO campaign
KYC (dummy)	Dummy variable that equals 1 if the ICO has a KYC process and 0 otherwise
Location: US (dummy)	Dummy variable that equals 1 if the ICO is located in US and 0 otherwise
Location: EU (dummy)	Dummy variable that equals 1 if the ICO is located in EU and 0 otherwise
Location: Singapore (dummy)	Dummy variable that equals 1 if the ICO is located in Singapore and 0 otherwise

3.2. Statistical Methods

3.2.1. Ordinary Least Square (OLS) Regression

To analyze the determinants of the amount raised in completed ICOs, several OLS regressions are performed. OLS regressions allow to test the effect of numerous independent variables on a dependent variable (Woolridge, 2003), and has been uses in many similar studies (Fish, 2019; Ante & Fiedler, 2019, among others).

In an initial model, each group of cheap signal proxies are entered stepwise together with the control variables, and finally jointly. Thereafter, a stepwise regression with backward elimination is performed to ensure that any casual relationships are not caused by overfitting the model (Wang et al., 2007), leading up to the final models which will form the basis of the discussion.

Before the regressions are run, a number of initial data analysis is performed to ensure quality in the OLS regressions.

The dataset only includes completed ICOs. With other words, it does not include ventures that failed do receive funding. Since ICO funding includes a soft cap, where fund will be returned to investors if the company do not reach its soft cap, it is possible that a company that in the data set raised zero dollars actually raised more. Following this, it is not possible to know the actually amount of these companies, and they will therefore not be included in the analysis.

3.3. Data Review

3.3.1. Assumptions for OLS Regression Analysis

To ensure statistically sound results of the OLS regression, the following four assumptions are tested.

First, it is tested whether the residuals are normally distributed. If this is not the case, some extreme values may need to be adjusted (Brooks, 2014). To test this, a normal Predicted Probability (P-P) plot is examined.

Second, the variance of the residuals has to be constant, with other words the residuals have to be homoscedastic (Brooks, 2014). The Breusch-Pagan test (1979) is a common used test for this, and it is also used in this study.

Moreover, Brooks (2014) recommend that the covariance between the residuals over time should be zero. However, since time series data is not analyzed in this study, a test for autocorrelation is not performed.

Lastly, if two or more of the independent variables are highly correlated with each other, multicollinearity exists. If so, the effects of the individual variables on the dependent variables cannot be determined, which makes it problematic to assess or explain the statistical result (Brooks, 2014). This is tested by performing a correlation test between the independent variables of the regression. If the correlation between the independent variables exceeds +/- 0.8, a correction should be made (Westerlund, 2005). To further test multicollinearity, variance inflation factor values is checked.

3.3.2. Possible Data Bias

Following, I want to highlight some of the most severe possible data bias that can be identified due to the sampling process. Since I use a number of secondary data sources and several of the ICOs did not present any data, there is a risk that ICOs are missing in the dataset that should have been included. This could cause a disparity between the actual population and the population defined in this study, a non-sampling error (Bryman & Bell, 2015). Moreover, due to the limited scope of this thesis I only study ICOs between 1st of April 2018 and the 31st of March 2019, and it is possible that this sampling frame does not represent the population in an adequate manner (Bryman & Bell, 2015). Also, due to the lack of a central database for ICOs, there is a risk for selection bias regarding which ICOs that are listed.

4. Results

The following sections starts by a descriptive analysis of the sample selection. Thereafter the assumptions for OLS regression are tested. Finally, the OLS regressions are performed in order to find the best model which will ultimately form the final regression results.

4.1. Descriptive Analysis

For a summary of the variables and descriptive statistics, see table 2.

The 168 ventures in the sample raised in total USD 1.79 bn. The mean is USD 10.63 m (mean of the logged variable is 14.68). A logarithmic transformation of the variable is performed since it is skewed – the ICO with the highest amount of funding raised USD 575 m (log 20.17) while the ICO with the lowest amount of funding raised USD 8 k (log 8.99).

The average number of team members of the ICOs is just over 8 (log 1.86), ranging from 1 to 27 (log 0.00 to 3.30), while the number of advisors is on average 10.5 (log 2.16), ranging from 1 to 43 (log 0.00 to 3.76). Almost all ICOs published a whitepaper, 98% to be exact. Revealing the source code is also common, 126 ventures had uploaded their source code to Github before their ICO. The ventures' social media presence varies considerably. While some ventures did not have any followers on Facebook at all at the time of their ICO, the most active venture had 541 k followers (log 13.20). Number of Reddit followers ranges from 0 to 32 k (log 10.38), Twitter followers 0 to 29 k (log 10.27) and Telegram followers 0 to 90 k (log 11.41).

On average, the soft cap for an ICO in this sample is USD 5.62 m (log 14.58), ranging from USD 4.4 k to USD 250 m (log 8.40 to 19.34). The valuation approximation has a mean of USD 76.79 m (log 17.28), whit a minimum of 222 k (log 12.31) and a maximum of 2 bn (log 21.42). The duration of an ICO campaign is on average 83 days (log 4.10). However, the shortest campaign only lasted in 6 days (log 1.79), while the longest lasted in 426 days (log. 6.05). Pre-sales are quite common, 118 of the ventures offered a pre-sale. While some of the ICOs distribute only 5 % of their tokens in the ICO, others distribute 100%. In average, the ICOs distribute 58% of their tokens. The number of tokens that the ventures offer in their ICO is in average 2.30 bn (log 19.26), ranging from 87 k (log 11.37) to 200 bn (log 26.21). The majority of the ICOs are Ethereum-based, 90%. The price of Ether ranges from USD 107 to USD 777 (log 4.67 to 6.66). In average, the price is USD 382 (log. 5.79). Geographically, only 5% of the ICOs are located in US, while 46 % are based in EU and 17% in Singapore.

Table 2. Summary Statistics of Data Sample

This table presents summary statistics of the data sample. All the variables used in the initial model are included, including the control variables. The sample covers 168 ICOs.

Variable	N	Min.	Max.	Mean	SD
Dependent variable					
Funds raised (log.)	168	8.99	20.17	14.68	1.74
Independent variables: cheap signals					
Human Capital signals					
Nr. of team members (log.)	168	-	3.30	1.86	0.77
Network					
Nr. of advisors (log.)	168	-	3.76	2.16	0.67
Project Elaboration					
Whitepaper (dummy)	168	-	1.00	0.98	0.15
Whitepaper score	168	1.70	4.90	3.72	0.60
GitHub (dummy)	168	-	1.00	0.74	0.44
Social Media					
Reddit followers (log.)	168	1.39	10.38	2.72	2.31
Facebook followers (log.)	168	3.14	13.20	7.26	2.62
Twitter followers (log.)	168	1.79	10.27	7.78	1.69
Telegram followers (log.)	168	1.39	11.41	7.91	2.16
Control variables					
Soft cap (log.)	168	8.40	19.34	14.58	1,35
Valuation approx. (log.)	168	12.31	21.42	17.28	1.27
Duration (days) (log.)	168	1.79	6.05	4.10	0.83
Pre-sale (dummy)	168	-	1.00	0.70	0.46
Tokens distributed in ICO (share)	168	0.05	1.00	0.58	0.17
Token supply (log.)	168	11.37	26.21	19.26	1.94
Ethereum-based (dummy)	168	-	1.00	0.90	0.29
Ether price (log.)	168	4.67	6.66	5.79	0,58
KYC (dummy)	168	-	1.00	0.80	0.40
Location: US (dummy)	168	-	1.00	0.05	0.21
Location: EU (dummy)	168	-	1.00	0.46	0.50
Location: Singapore (dummy)	168	-	1.00	0.17	0.37

4.2. Ordinary Least Square Regression Analysis

4.2.1. Assumptions for OLS Regression Analysis

Following, the results of the test described in section 3.1.1. are presented.

As seen in appendix 1, the residuals conform to the diagonal normality line indicated in the Predicted Probability plot without drastic deviations, so normality can be assumed.

The results from the Breusch-Pagan test are presented in appendix 2, which shows that the residuals are homoscedastic.

In table 3, correlations and variance inflation factors are presented. All correlations are below the critical level of +/- 0.8 (Westerlund, 2005) but some variables show significant correlations, which may partly be explained by the limited sample size. However, the variance inflation factors are far from the critical value of 8, which indicates that the results should not be affected severely by multicollinearity.

4.2.2. Initial Model

In table 4, the results of the 5 initial OLS regressions with *Funding raised (log.)* as the dependent variable are shown. Each model includes all 168 observations as well as all control variables. The cheap signals are entered stepwise in Models 1 to 4 in order to evaluate the results for the independent variables. Model 5 is chosen to test the full set of variables.

Table 3. Correlations and Variance Inflation Factors (VIFs)

This table shows the Pearson correlation coefficients for all variables. VIFs estimates are based on the initial model (without robust standard errors). N = 168 ICOs.

* $p < 0.10$
** $p < 0.05$
*** $p < 0.01$

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	VIF
	Dependent variable																						
1	Funds raised (log.)																						
	Independent variables																						
	Human Capital signals																						
2	Nr. of team members (log.)	0,18*																					1.15
	Network signals																						
3	Nr. of advisors (log.)	0.09	0.22**																				1.20
	Project Elaboration signals																						
4	Whitepaper (dummy)	-0.05	0.03	-0.03																			1.19
5	Whitepaper score	0.27**	0.18*	0.14	0.18*																		1.79
6	Github (dummy)	0.11	0.07	-0.08	0.09	0.44**																	1.41
	Social Media signals																						
7	Reddit followers (log.)	0.03	0.11	0.01	0.09	0.28**	0.13																1.23
8	Facebook followers (log.)	0.20**	0.19*	0.02	0.20**	0.41**	0.23**	0.27**															1.49
9	Twitter followers (log.)	0.13	0.12	0.05	0.27**	0.29**	0.16*	0.29**	0.24**														1.41
10	Telegram followers (log.)	0.28**	0.09	0.07	0.16*	0.33**	0.13	0.20**	0.29**	0.36**													1.35
	Control variables																						
11	Soft cap (log.)	0.49**	0.11	0.13	-0.00	0.02	-0.16*	0.04	0.01	0.02	0.07												1.96
12	Valuation approx. (log.)	0.47**	0.08	0.10	0.01	0.04	-0.06	-0.03	0.13	0.04	0.14	0.63**											2.05
13	Duration (days) (log.)	0.05	0.04	0.13	0.10	0.12	0.13	-0.01	0.13	0.03	0.05	-0.08	0.04										1.17
14	Pre-sale (dummy)	-0.05	-0.00	-0.06	-0.10	0.01	0.13	-0.04	0.10	0.02	-0.04	-0.01	0.09	0.09									1.15
15	Tokens distributed in ICO (share)	0.04	0.07	0.07	0.01	0.04	0.10	-0.02	-0.18*	-0.00	-0.06	-0.02	-0.25**	0.07	-0.01								1.33
16	Token supply (log.)	0.06	-0.04	0.05	-0.00	0.08	-0.10	0.11	0.09	0.23**	0.15*	0.20*	0.26**	-0.04	0.06	-0.23**							1.25
17	Ethereum-based (dummy)	0.06	-0.06	-0.11	-0.05	-0.05	0.09	0.04	0.03	-0.03	0.09	-0.15*	-0.04	0.15*	-0.17*	0.00	-0.02						1.22
18	Ether price (log.)	-0.06	-0.01	0.01	-.163*	-0.24**	-0.08	-0.07	-0.08	-0.18*	-0.20**	-0.07	0.07	-0.03	0.04	-0.04	0.01	0.15					1.20
19	KYC (dummy)	0.24**	0.14	0.16*	0.02	0.30**	0.05	0.16*	0.23**	0.18*	0.20**	0.07	0.08	-0.01	0.01	-0.22**	0.11	-0.11	-0.17*				1.30
20	Location: US (dummy)	0.01	0.04	0.00	0.03	0.05	0.00	0.00	0.12	0.03	0.08	-0.07	-0.06	0.11	0.08	0.10	-0.06	0.07	-0.00	0.11			1.18
21	Location: EU (dummy)	-0.14	0.07	0.06	0.07	0.04	0.03	-0.11	-0.13	-0.02	-0.03	-0.11	-0.08	-0.07	0.01	0.07	-0.11	-0.10	0.05	-0.02	-0.21**		1.44
22	Location: Singapore (dummy)	0.09	0.03	0.09	-0.03	0.07	0.01	0.12	0.12	-0.04	-0.02	0.14	0.13	-0.10	-0.09	-0.17*	0.18*	0.09	0.03	0.14	-0.10	-0.42**	1.46

Model 1 regress *Nr. of team members (log.)* as the independent variable against *Funds raised (log.)* as the dependent variable. The model is found to have an adjusted R-squared of 0.339. *Nr. of team members (log.)* shows statistical significance with a coefficient of 0.219 ($p = 0.1$). Model 2 has a comparatively low fit with an adjusted R-squared of 0.330. Moreover, the model suggests that *Nr. of advisors (log.)* do not have a significant impact on funding amount. However, in Model 3 two of the cheap signal proxies regarding project elaboration show significant results – *Whitepaper (dummy)* and *Whitepaper score* with coefficients of -0.069 ($p < 0.1$) and 0.575 ($p < 0.05$) respectively. Adjusted R-squared for the model is 0.377. In Model 4, significant results for Facebook followers (log.) and Telegram followers (log.) are identified. The variable *Facebook followers (log.)* is hardly significant positive at $p < 0.1$ (0.078) while *Telegram followers (log.)* is significant at $p < 0.05$ (0.129). R-squared is found to be 0.367.

The independent variables ending up significant in Model 5 are *Whitepaper (dummy)* ($p < 0.1$), *Whitepaper score* ($p < 0.1$), *Reddit followers (log.)* ($p < 0.1$) and *Telegram followers (log.)* ($p < 0.05$). The Model shows a considerable fit with an adjusted R-squared of 0.393.

Among the control variables, *Soft cap (log.)* is highly significant with positive coefficients across all models ($p < 0.01$). Also, the valuation approximation is highly significant ($p < 0.01$), which is not surprising since it acts as a proxy for venture size. Moreover, *Tokens distributed (share)* seems to have a slightly positive effect on funding amount in all 5 models with coefficients ranging from 0.013 ($p < 0.1$) to 0.017 ($p < 0.05$). The variable *Token supply (log.)* does only show significant results in Model 4 (-0.091; $p < 0.1$). The results from Model 1 to 4 suggest that Ethereum-based ICOs may raise a higher amount of funding than other ICOs ($p < 0.1$). However, the results are insignificant in Model 5 when all variables are included. *Ether price (log.)* does only show significant effect on funding amount in Model 4 (0.022; $p < 0.1$). The variable *KYC (dummy)* shows that a KYC process on place prior the ICO has highly significant positive effects on funding with coefficients ranging from 0.751 ($p < 0.01$) to 1.103 (p <

0.01). The only location dummy showing significant effect on funding is *Location: EU (dummy)* with negative coefficient across all 5 models at $p < 0.1$.

Table 4. OLS regression – Initial Model

This table presents an initial OLS regression analysis on the determinants of funds raised in completed ICOs (dependent variable = Funds raised (log.)).
* p < 0.10
** p < 0.05
*** p < 0.01

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	Coeff.	(SD)	Coeff.	(SD)	Coeff.	(SD)	Coeff.	(SD)	Coeff.	(SD)
Control variables										
Soft cap (log.)	0.368	(0.112)***	0.378	(0.112)***	0.410	(0.110)***	0.412	(0.110)***	0.432	(0.109)***
Valuation approx. (log.)	0.449	(0.121)***	0.458	(0.122)***	0.432	(0.118)***	0.383	(0.121)***	0.372	(0.119)***
Duration (days) (log.)	0.028	(0.138)	0.045	(0.141)	-0.002	(0.135)	0.008	(0.135)	0.011	(0.136)
Pre-sale (dummy)	-0.198	(0.248)	-0.209	(0.251)	-0.288	(0.246)	-0.219	(0.245)	-0.316	(0.246)
Tokens distributed (share)	0.015	(0.007)**	0.016	(0.007)**	0.013	(0.007)*	0.017	(0.007)**	0.014	(0.007)**
Token supply (log.)	-0.063	(0.060)	-0.068	(0.061)	-0.075	(0.059)	-0.091	(0.061)*	-0.086	(0.060)
Ethereum-based (dummy)	0.788	(0.399)*	0.749	(0.405)*	0.694	(0.390)*	0.630	(0.395)*	0.567	(0.393)
Ether price (log.)	-0.084	(0.196)	-0.075	(0.198)	0.022	(0.196)*	0.061	(0.197)	0.097	(0.197)
KYC (dummy)	1.030	(0.298)***	1.103	(0.301)***	0.826	(0.298)***	0.912	(0.298)***	0.751	(0.301)**
Location: US (dummy)	-0.278	(0.552)	-0.240	(0.556)	-0.215	(0.538)	-0.423	(0.544)	-0.349	(0.535)
Location: EU (dummy)	-0.422	(0.257)*	-0.377	(0.259)*	-0.440	(0.250)*	-0.384	(0.251)*	-0.425	(0.252)*
Location: Singapore (dummy)	-0.266	(0.346)	-0.221	(0.350)	-0.351	(0.337)	-0.174	(0.341)	-0.235	(0.340)
Independent variables: cheap signals										
Human Capital										
Nr. of team members (log.)	0.219	(0.147)*							0.152	(0.146)
Network										
Nr. of advisors (log.)			-0.040	(0.176)					-0.131	(0.173)
Project Elaboration										
Whitepaper (dummy)					-1.069	(0.724)*			-1.438	(0.747)*
Whitepaper score					0.575	(0.219)**			0.442	(0.235)*
Github (dummy)					0.289	(0.285)			0.244	(0.285)
Social Media										
Reddit followers (log.)							-0.061	(0.051)	-0.082	(0.050)*
Facebook followers (log.)							0.078	(0.047)*	0.048	(0.049)
Twitter followers (log.)							0.047	(0.073)	0.054	(0.074)
Telegram followers (log.)							0.129	(0.057)**	0.114	(0.057)**
R^2 (R^2 adjusted)	0.391	(0.339)	0.382	(0.330)	0.433	(0.377)	0.428	(0.367)	0.470	(0.393)
N	168		168		168		168		168	

4.2.3. Final Model

In line with Ante & Fiedler (2019), I develop the analysis by performing two stepwise regressions with backward elimination in order to ensure that no casual relationships in the regressions are caused by overfitting the model. In table 5, the results are shown with *Funds raised (log.)* as the dependent variable.

Two regressions are run, where both models include all the 168 observations. Model 1 is designed to evaluate the results for the independent variables and model 2 to test for additional effects of several control variables. The models are revised by removing all non-statistically significant independent variables. Following Wang et al. (2007), the backward elimination of each variable is tested using the model fit criterion $p >= 0.2$. More precisely, all variables in each model are regressed and the variable with the highest $p >= 0.2$ is deleted. Next, the model is run again and another factor is subtracted. This process is repeated until no further variables ca be deleted using the model fit criterion of $p >= 0.2$, which also represents the final models.

Model 1 is found to have an adjusted R-square of 0.124 suggesting a quite low fit.

Model 2 however shows a considerable fit with an adjusted R-square of 0.405. This may be explained by the highly significant results for the variables *Soft cap (log.)* and *Valuation (log.)*, which can act as a proxy for the size of the venture.

Nr. of team members (log.) shows statistical significance in Model 1 with a coefficient of 0.302 ($p = 0.1$). However, this variable is no longer significant when including the control variables in the analysis. *Advisors* does not end up in any final model.

Two of the project elaboration variables has statistical significance in both models – *Whitepaper (dummy)* ($p < 0.1$) and *Whitepaper score* ($p < 0.05$), where the existence of a white paper has negative coefficients while whitepaper score is found to have a positive effect on funding amount. *Github (dummy)* does not show significant results.

Telegram followers (log.) is the only social capital signal ending up in a final model with a coefficient ranging from 0.183 ($p < 0,.5$) to 0.124 ($p < 0.05$).

Model 2 shows that *Duration (days) (log.), Pre-sale (dummy), Ether price (log.), Location: US (dummy)* and *Location Singapore: (dummy)* do not have a significant influence on the funding amount.

The variables *Soft cap (log.)* and *Valuation approx. (log.)* are both significant at $p < 0.01$ (0.401 and 0.403 respectively) . The token-related control variables are both significant in Model 2, where *Tokens distributed (share)* shows positive effects on the funding amount at $p < 0.05$ (0.013) while *Token supply (log.)* has a negative effect at a significance level of $p < 0.1$ (-1.02).

Moreover, Model 2 shows that ICOs build on Ethereum achieve a higher funding amount than other ventures ($p < 0.1$; 0.658). The variable *KYC (dummy)* shows that also a KYC process on place prior the ICO has positive effects on funding ($p < 0.05$; 0.695).

The only location control variable that remains in the final model is *Location: EU (dummy)* which shows a significant negative effect on funding (-0.312; $p < 0.1$).

Table 5. OLS Regression - Final Model

This table presents stepwise regressions with backwards elimination, analyzing the determinants of funds raised in completed ICOs (dependent variable = Funds raised (log.)).
 * p < 0.10
 ** p < 0.05
 *** p < 0.01

	Model 1		Model 2	
Variable	Coeff.	(SD)	Coeff.	(SD)
Independent variables: cheap signals				
Human Capital				
Nr. of team members (log.)	0.302	(0.166)*	-	-
Network				
Nr. of advisors (log.)	-	-	-	-
Project Elaboration				
Whitepaper (dummy)	-1.422	(0.842)*	-1.172	(0.697)*
Whitepaper score	0.550	(0.228)**	0.529	(0.194)**
Github (dummy)	-	-		
Social Media				
Reddit followers (log.)	-	-	-	-
Facebook followers (log.)	-	-	-	-
Twitter followers (log.)	-	-	-	-
Telegram followers (log.)	0.183	(0.062)**	0.124	(0.053)**
Control variables				
Soft cap (log.)			0.401	(0.103)***
Valuation approx. (log.)			0.403	(0.113)***
Duration (days) (log.)			-	-
Pre-sale (dummy)			-	-
Tokens distributed (share)			0.013	(0.007)**
Token supply (log.)			-0.102	(0.057)*
Ethereum-based (dummy)			0.658	(0.366)*
Ether price (log.)			-	-
KYC (dummy)			0.695	(0.286)**
Location: US (dummy)			-	-
Location: EU (dummy)			-0.312	(0.212)*
Location: Singapore (dummy)			-	-
R^2 (R^2 adjusted)	0.145	(0.124)	0.441	(0.405)
N	168		168	

5. Discussion

In this section, the results of the final regression model are discussed in relation to the hypotheses as well as the implications for practices and theory.

Hypothesis H1 states that the communicated number of team members should not be related to amount of ICO funding of completed ICOs. Model 1 shows there is a low but significant impact on funding. However, the coefficient is insignificant when taking the control variables into account. This suggests that hypothesis H1 should be accepted - the communicated number of team members itself does not positively influence the funding amount of an ICO. This finding is in line with previous research on signaling theory which suggests that signals should be sent by trusted third parties or be costly to mimic. Since this is not true for the communicated number of team members, it is classified as a cheap signal and should not be taken into account by investors. However, the findings are at odds with existing research on ICOs, that has found a positive effect of number of team members on funding success (Ante et al., 2019, Amsden & Schweizer, 2018).

I do not find a significant impact of the communicated numbers of advisors on ICO funding. Hence it seems to be an ineffective signal in the ICO context which provides evidences for hypothesis H2 such that it is accepted. These findings do not correspond with Amsden & Schweizers (2018) study on ICOs where they find a positive impact of number of advisors on ICO success. However, it corresponds to Ante & Fiedler’s (2019) research on STOs where they do not find a significant impact and conclude that citing external advisors does not necessarily represent a costly signal.

In terms of project elaboration, publishing a whitepaper have a negative effect on funding amount. However, this negative effect should not be overstated since 98% of the ICOs published a whitepaper, making the variable highly skewed. When testing the whitepaper score, representing the length of the whitepaper, the analysis shows a positive and significant coefficient across both models. With other words, investors in the ICO context seem to interpret the length of the whitepaper as an important signal when investing in ICOs. Since this variable say nothing about whitepaper quality - a longer whitepaper does not necessary have to be more informative - it is not necessarily a costly signal and these findings do hence challenge previous signaling studies.

Model 1 and 2 both show that releasing the source code publicly on Github prior to an ICO do not influence the funding amount. The coefficient is not statistically significant, indicating that H3 cannot be rejected. These findings are against the findings of Adhami et al. (2018), Amsten and Schweizer (2018) and Jong et al. (2018), who all find a positive effect in terms of ICO funding success. Releasing the source code may be a way for ventures to signal the quality and future prospects of their tokens with the intent to differentiate themselves from lower-quality projects. However, the variable says nothing about the quality of the source code, hence the findings in this study is not surprising when building on signaling theory.

When it comes to social media signals, Telegram followers shows a significant positive effect in both models, while number of followers on Reddit, Facebook and Twitter do not end up in any of the final models. A positive effect of number of Telegram followers is in line with studies in the context of ICOs (Howell et al., 2018), and my findings further point to the importance of establishing a social media presence to increase ICO capital raise. The fact that social media network size is cheap and quite simple for ventures to fake makes it a cheap signal according to signaling theory. With other words, these findings imply that social media network size can act as a cheap signal of quality for ICO projects, and I accept hypothesis H4.

5.1. Implications for Theory

By exploring the role of cheap signals in ICO funding, the study shows that signaling theory is only able to explain some of the dynamics of the ICO market.

One of the basic assumptions of signaling theory is that costless signals do not generate an equilibrium, hence rational investors should ignore them. However, this study challenges this rationality and finds that cheap signals of project elaboration and social media have a positive effect on funding amount in completed ICOs. This is at odds with the effect of different signaling types shown in previous studies on more mature markets and indicates that ICO market participants behave differently.

It is clear that due to the unregulated and decentralized context, the market suffers from serve information asymmetries and is far from being information transparent. Following this, even cheap signals might be important for ICO investors since the information is so scarce and investors may not have any other choice than relying on unaudited information provided by the ventures themselves, which could be problematic since it creates incentives for ventures to dishonestly signal quality through cheap signals. One could argue that this inefficiency should diminish over time, as the market learns to disregard the signal. However, there are already several examples of fraud and scams. Overall, this opens up for further research on the key mechanisms underlying signaling theory.

Moreover, a further investigation of the casual relationships found in this study would be valuable. For example, I suggest testing these variables with different definitions of funding success, e.g. token and coin tradability (Amsden & Schweizer, 2018), as well success in terms of different time horizons. To include ICOs that did not manage to receive any funding at all would also be interesting.

Further research should also explore the qualitative part of each signal to test models that involve both cheap and costly signals of quality. It is also possible that ventures employ alternative ways to signal quality in ICOs, so further research could try to operationalize the variables in a more nuanced way.

5.2. Implications for Ventures

Overall, the findings in this study could help to improve communication strategies of ventures. Firstly, they indicate that ventures should focus on growing their presence on their Telegram social channel at the time of the ICO. That I did not find any relevant effects for the size of other social media channels, might be explained by the fact that Telegram is often seen as the leading channel for people interested in crypto and ICOs (Amsden & Schweizer, 2018). Moreover, social media channel networks may have different effects in different states of funding. A suggestion for future research would be to control for the characteristics of social networks before, during and after the campaign, and also in terms of size and activity.

The results that publishing a whitepaper are negatively correlated with funding success, but whitepaper length is positive correlated may indicate that ventures are better off not releasing a whitepaper than releasing a short one, which is in line with the conclusion of Fisch’s study on ICO success (2019). However, as mentioned before the correlation between publishing a whitepaper and funding amount should not be given to much focus since the variable is highly screwed. Altogether, the results suggest that ventures should make sure to communicate a lot of information in their whitepapers since investors seem to asses them to infer the ventures quality and take it into account in their investment decisions.

5.3. Implications for Investors and Regulators

This study implies that investors seem to consider different signals than other domains of entrepreneurial finance. These signals may not have any direct association with a venture's underlying quality, but nevertheless seem to influence investors' decision-making. Identifying these factors and their influence on the amount of funding raised, makes it possible for investors to more accurately evaluate ICOs, despite the considerable uncertainty that surrounds them.

Due to the findings that cheap signals of project elaboration and social media have a positive effect on funding amount, ventures have incentives to boost these to attract funding. This, in combination with the largely unregulated environment, implies that ICOs investors face big challenges in finding reliable information. Since the market has suffered from fraud and scams (Chohan, 2017), investors should exercise a high degree of caution and diligence when researching and investing in ICOs.

However, little is known about ICO investors. This is a crucial part in a comprehensive understanding of the dynamics in the ICO market. further research should study the phenomenon from this perspective, but also from the perspective of regulation, society and platform providers and develop models that test for both cheap and costly signals of quality.

I argue that the findings wake the debate on ICO regulation and provide initial insights for policy makers interested in regulating ICOs. The market frictions found in this study should speak for a regulation framework that address information asymmetry by, for example, imposing disclosure requirements.

5.1. Limitations

Some of the foremost severe limitations in this study pertain to data accessibility and quality. Due to the lack of a central database of ICOs, the data is manually collected from several different secondary sources, many of which do not collect their data in a standardized way. Despite the fact that several actions are performed to counteract a potential bias, e.g. choosing established tracking sites and cross-referencing data between various sources, this highly limits the generalizability of the results.

The limited data accessibility also results in a final dataset that only represent a fraction of the total number of ICOs, which further makes it impossible to exclude the presence of some selection bias.

Moreover, several factors that could have an effect on funding amount are left out from the study since I was unable to collect this information. I especially want to emphasize these limitations in terms of costly versus cheap signals. It would have been highly valuable to have proxies for costly signals and put these against the cheap signals to investigate the different effects on funding success. However, this was not possible due to data limitations.

Also, the term cheap signal is somewhat undefined and not fully established in previous literature. In this study, I use the term in a similar way as Ante & Fiedler (2019) - as a way to describe signals that could also be faked by ventures for a low cost.

5.2. Conclusion

The results in this study imply that ICO investors take some cheap signals into account when investing in ICOs. While cheap human capital and network signals do not affect the funding amount, cheap signals related to project elaboration and social media show significant effects on the amount raised. More precisely, for ventures seeking to raise money in an ICO, a longer whitepaper and established presence on Telegram may serve as quality signals to investors, even though these are factors the ventures could cheaply influence themselves.

These results implicate that ICO markets behave differently than other, more researched markets such as IPOs or VC investments, where research based on signaling theory shows that signals should be costly in order to create separating equilibrium. The differences can possibly be explained by ICOs being much freer in terms of structure due to their decentralization and lack of regulation. In a largely unregulated environment with large information asymmetries, investors may have to rely on unaudited information provided by ventures themselves.

I want to highlight that there are several limitations in this study pertains to data accessibility and quality that challenge the generalization of my findings. With this said, the results are still believed to contribute to existing theory by bringing new insights to a still rather unexplored market and motivate further research regarding the particularities of ICOs. Additionally, my findings could be relevant for ventures seeking to raise funding through an ICO, as well as current and potential investors. Finally, the results should open up for a regulatory discussion that addresses the market frictions found in this study.

6. References

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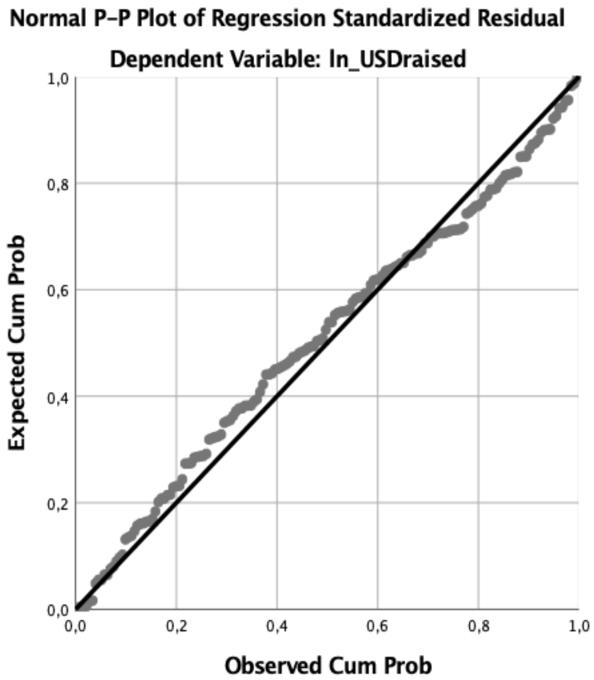
7. Appendix

Appendix 1. P-P Plot



Appendix 2. Breusch-Pagan Test

Model		Sum of Squares	df	Mean Square
1	Regression	237.5733773	21	11.31301797
	Residual	268.3116365	146	1.837750935
	Total	505.8850138	167	

a. Dependent Variable:

ln_USDraised

b. Predictors: (Constant), singapore_dummy, github_dummy, ln_team, ln_etherprice, USA_dummy, ln_valuation, whitepaper_dummy, ln_duration, ln_reddit, preICO_dummy, ln_advisors, tokensshare, ethereumbased_dummy, ln_tokensnr, ln_telegram, KYC_dummy, ln_fb, ln_twitter, EU_dummy, Wpscore, ln_softcap

Model		Sum of Squares	df	Mean Square	F
1	Regression	8.937399838	1	8.937399838	3.30177 4
	Residual	449.3367798	166	2.706848071	
	Total	458.2741797	167		

a. Dependent Variable: RES_2 = (residual*residual) / (268.3116365/168)

b. Predictors: (Constant), Unstandardized Predicted Value

Hetero calculation:	8.937 / 2	=	4.469

- Below critical value following $n{\cdot}R$^2<χ1;0.01 = 6.635