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The Emperor's New Coins

Venture quality signals in Initial Coin Offerings

ABSTRACT

Entrepreneurs are raising billions of dollars through an emerging funding mechanism called initial coin offering (ICO). ICOs take place on blockchains, outside the traditional financial system, allowing rapid fundraising without friction. Amount of investment in ICOs have surged—$5.6 billion was invested in 2017. Some argue that this surge of investment is irrational, and that the ventures raising funds have no intrinsic quality. This study aims to examine this by investigating signals of venture quality that entrepreneurs send to investors in ICOs. A quantitative study is performed by collecting data on 136 Initial Coin Offerings that took place in September 2017–November 2017. Regression analysis is then used to find causality between ventures' quality signals and ICO funding. The empirical findings are that signals of human capital, social alliance capital and signals related to product and business artefacts are valued in an ICO setting.

Keywords: initial coin offering, entrepreneurship, venture capital, growth, blockchain

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Our warmest, and toughest critic

(...) you could do it without going to a bunch of venture capitalists [...] and here's who we are and here's our plan, and here's our bitcoin address, and anybody who sends coins to this address owns a piece of our new protocol. Anybody could do that. (...)

–J.R. Willett, before he launched Mastercoin, the first ICO

1. Introduction

H.C. Andersen's "The Emperor's New Clothes" tells the story of two swindling weavers that promise an Emperor a dress made out of the highest quality fabric. The fabric is not only claimed to be of utmost quality, but also has a special feature: it is invisible to anyone who is unusually stupid. When the Emperor parades with his new dress in procession for his subjects, no one dares to acknowledge that they cannot see the dress, in fear of being considered stupid.

Some argue that entrepreneurs promising investors great returns through Initial Coin Offerings (ICOs) are the swindlers, weaving together an invisible dress of buzzwords and false promises to cover the lack of intrinsic quality in their venture. The subjects in this story are investors, afraid to be considered stupid for missing out on the booming market, ready to invest in anything. In essence, it is argued that the 2017's boom of $5.6 billion in ICO funding should be called "The Emperor's New Coins", remembered as a cautionary tale on what happens when investors disregard searching for quality signals out of fear for missing out.

In this thesis, it will be examined what, if any, entrepreneurial signals of venture quality ICO investors value. We will find out whether the ICO investors are attentive to traditional cues of venture quality, or if this story in fact will go down in history as "The Emperor's New Coins".

1.1 Background

Although venture capital (VC) has long dominated the entrepreneurial equity financing landscape, new mechanisms have emerged (Drover et al, 2017). One of the new mechanisms, equity crowdfunding, changed the landscape and democratized equity investments by opening up the markets to a broader crowd of investors (Ahlers, Cumming, Günter & Schweizer, 2015). Owing to the development of blockchains, a new funding mechanism, similar to equity crowdfunding has surfaced, known as an ICO (Conley, 2017). In an ICO, a venture raises funds by offering digital tokens on a blockchain to a crowd of online investors in exchange for Bitcoin or Ether[1].

Since 2013, hundreds of ICOs have been attempted and it has quickly become a popular funding mechanism (Marks, 2018). In 2017, $5.6 billion was raised in ICOs by blockchain entrepreneurs, almost six times the amount they raised from VC (Fabric Ventures, 2018). The most successful ICO in 2017 raised $232 million, 30 times more than that year's most successful equity crowdfunding campaign (Williams–Grut, 2017).

[1] At the time of writing, the two most valuable cryptocurrencies by market cap

ICOs are announced on social platforms such as Reddit, executed on blockchains, and the tokens offered are later traded on cryptocurrency-exchanges with low to none transparency (Rohr & Wright, 2018). No traditional gatekeepers, such as national securities exchanges or financial supervisory authorities control the access to ICOs.

Unsurprisingly, as a result of the enormous amounts raised outside the traditional financial system ICOs have caught regulators attention. Chinese and South Korean authorities banned ICOs in 2017 (Zetzsche, Buckley, Arner & Föhr, 2017). US authorities issued an alert indicating that companies may use ICOs to manipulate investors, but they also mentioned the potential in the new funding mechanism (SEC, 2017).

Regardless of its controversial reputation, the ICO phenomenon has given rise to a new way for entrepreneurs to secure funds. Securing funds is vital for the expansion and survival of young ventures (Nicholls–Nixon, 2005). Because of its importance, the pursuit of external financing for young ventures has a long history of research.

1.2 Research gap

For young ventures seeking external financing, Hall and Hofer (1993) emphasise the importance of knowing what signals of venture quality investors look for. VC has been studied since the early 80's, and vast research exists on which signals of venture quality investors are attentive to in traditional entrepreneurial equity financing, such as VC (Drover et al, 2017). Since the phenomenon of ICOs is recent, almost no research has been done to examine what signals of venture quality investors in ICOs look for, and whether or not those signals complement or challenge existing theories in the entrepreneurial equity financing literature. The discrepancy between what is known about signals of venture quality in traditional entrepreneurial equity financing literature, and what is known about signals of venture quality in ICOs is the research gap identified.

1.3 Purpose and relevance

The purpose of this thesis is to reduce the above-mentioned research gap by investigating quality signals of a large number of attempted—successful and unsuccessful—ICOs.

As new forms of entrepreneurial financing emerge, such as ICOs, greater attention need to be put on these sources to fully understand the financing of high-growth ventures. Drover et al (2017) urge scholars to build from what is already known and investigate if traditional theories of entrepreneurial equity financing can be used to understand the dynamics of new sources as well. For academics, it is important to understand if emerging financing mechanisms, such as ICOs, complement or challenge existing assumptions and value-adding dynamics for entrepreneurs in the entrepreneurial equity financing literature.

Because of the large fundraising potential in ICOs, it of importance for entrepreneurs to understand if they should, as a means to receive funding from this emergent mechanism, focus on developing and emphasizing the same quality signals towards ICO investors as they have been taught to do towards more traditional equity finance investors, such as VCs.

Further, there are lessons to be learned for policy makers developing regulations for ICOs. Instead of prohibiting ICOs entirely, they may consider requirements for disclosure, such as a more detailed whitepaper or better team transparency.

1.4 Research question

Following the above, we will in section 3 create hypotheses that will answer the following two research questions:

1. What signals of venture quality determine whether entrepreneurs will receive ICO funding?
2. What signals of venture quality determine how much venture funding entrepreneurs will receive?

1.5 Structure of the thesis

The remainder of the thesis is structured as follows. The next section provides an institutional background on funding for high-growth ventures, with focus on VC and ICO. Section 3 presents the theoretical framework from which hypotheses are deduced. Section 4 presents the methodology while section 5 describe the data-gathering process. Section 6 presents the study's empirical results. Section 7 concludes and discusses the research findings.

2. Institutional Background

In this section, we describe the importance of outside funds for high-growth ventures. We explain the VC model and give an overview of the market. We then describe innovations within the entrepreneurial finance setting that has allowed for ICOs to emerge. The concept of ICOs as a new method of fundraising for entrepreneurs is explained. This is followed by a brief overview of the ICO market and a description of how the mechanism works. Lastly, it is described describe why entrepreneurs might choose to pursue an ICO.

2.1 Expansion of start-ups

Every year, 700,000 new ventures are started in the United States. Only 3.5% manage to grow sufficiently to survive and eventually become a large firm (Barringer, Jones & Neubaum, 2005). Growth is more important for start-ups than it is for more established firms. Established firms have reached a level of viability and survival that is not dependent on high and continuous growth (Freeman, Carroll & Hannan, 1983). Start-ups on the other hand, are subject to newness, and in absence of growth, their likelihood of survival is reduced significantly. Gilbert, McDougall and Audretsch (2006) summarize it by saying

"The growth of established firms is about sustaining viability, new venture growth is about obtaining viability." (s. 927)

There are several key aspects influencing the growth of young ventures, and they help to understand why some experience higher growth than others. Gilbert et al (2006) argue that growth and expansion will be facilitated when the entrepreneur has a strategy enabling growth and operates in an attractive industry. However, for an entrepreneur to successfully execute strategies and undertake larger projects, they need resources. Financial management, and the availability of suitable financing, is therefore one of the core factors shaping entrepreneurial venture expansion (Nicholls-Nixon, 2005). It is possible that seed capital required to start the venture is attributable to the entrepreneur's personal funds, but the amount required to build the company further often exceeds the entrepreneurs' personal resources (Gilbert et al, 2006)

One of the greatest challenges facing entrepreneurs explained by Greene, Brush, Hart and Sparito (2001) is the endeavor to attract external funds. There are two primary forms of outside funds that can be obtained – debt and equity (Vanacker & Manigart, 2010).

2.1.1 Debt or equity

Vanacker and Manigart (2010) use the pecking order theory to explain the financing choices of high growth ventures. The theory explains a hierarchy of financing, where entrepreneurs want to avoid costs and excessive loss of control over the business. The theory suggests that ventures prefer to use internal funds first, followed by debt financing and lastly external equity. In many high-growth ventures the internal funds are insufficient to fuel upcoming endeavors, and they are dependent on outside financing, as mentioned earlier (Gilbert et al, 2006). The returns in these ventures are highly variable, they rarely have collaterals and the setting in which they operate is characterized by severe information asymmetries (Carpender & Petersen, 2002). Because of these reasons, young ventures' access to debt financing is poor (Carpender & Petersen, 2002; Gompers & Lerner, 2001). As a result, equity investment represents the key source of capital for many entrepreneurial ventures (Drover et al, 2017).

There are several mechanisms available when entrepreneurs decide to pursue equity financing, but the most acknowledged is VC (Drover et al, 2017). Drover et al (2017) argued that VC models are spilling over into other equity funding mechanisms, and to understand new mechanisms, it is vital to understand the most established one.

2.2 Venture capital (VC)

2.2.1 Definition and business model

Venture capital is the most recognized form of equity financing and the first VC firm was created in 1946 by the president of MIT (Gompers & Lerner, 2001). Isaksson (2006) describes the VC model as capital investments made by professional investors in small to medium-sized growth ventures. The VC firm is comprised of venture capitalists, also referred to as general partners (GPs). The GPs raise funds from wealthy individuals and institutional investors who are referred to as limited partners (LPs). The GPs seek to provide returns on these funds through selective investments in young and innovative ventures.

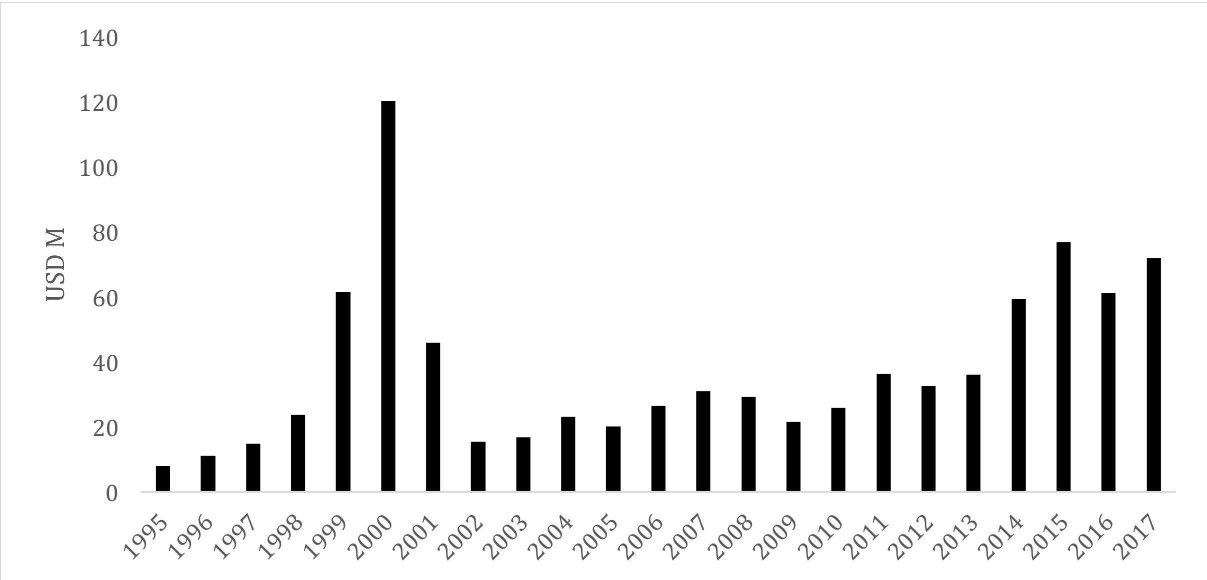
The work of the GPs consists of two main activities (1) identifying and investing in qualitative ventures, and (2) monitoring and assisting the acquired venture by providing value adding services. VCs provide resources to the entrepreneurs through active ownership, and they are more involved in the management of the business than debt providers. Venture capital investments average around ten years. After these years, the GPs exit the venture and distribute the returns to the LPs. The GPs are often compensated with a management fee and a performance based fee (Isaksson, 2006).

Further, VCs strive to lower the risks involved in investing in untested ventures, and overcome the problem with asymmetric information between the VC and the venture, by applying certain strategies. One practice is to use staged investments where VCs make investment decisions stage by stage. They initially provide the venture with small amounts of money and invest more conditional on the startups performance. This enables the VCs to evaluate the viability of the entrepreneur and his idea over time (Gompers, 1995).

2.2.2 The VC Market

As can be seen in Graph 1, the market gradually grew during the 90's, and reached a peak during the dot-com bubble in 2000 with $124 billion in VC investments. After 2000, VC investments fell drastically and reached its bottom in 2002, and since then the amount of VC investments has been growing steadily. As of today, VC investments amount to $75 billion annually (PwC, 2018).

Graph 1. Venture capital funding since 1995 in the US (PwC, 2018)



However, less than 1% of all young ventures receive VC financing as of 2015 (Drover et al 2017), and many entrepreneurs turn to other sources of financing to bridge their funding needs.

2.3 Developments in entrepreneurial financing

2.3.1 Equity Crowdfunding

One of the more prominent innovations is the phenomenon of equity crowdfunding. Drover et al (2017) define the mechanism as where “a large volume of online investors contributes smaller amounts for factions of company ownership.” (p. 1822) There are large crowdfunding platforms to which ventures submit funding proposals. If a venture is accepted, its funding campaign is launched and becomes available to a large number of investors (Belleflamme, Omrani & Peitz, 2015). The method initially met regulatory challenges, but the restrictions are currently being relaxed in many countries (Dover et al, 2017).

2.3.2 Blockchain technology

Blockchain technology was created in 2008 by a person under the pseudonym Satoshi Nakamoto (Nakamoto, 2008). The idea of a distributed network was first invented in 1964 by Baran (1964) who built a communication network based on nodes. In this network, the participants could communicate even if nodes were compromised. The main idea is that centralized networks expose a vulnerable “single point of failure” not present in decentralized networks (Kosner, 2014).

Blockchains leverage the same technology. Regardless of any node being compromised, the distributed network remains accurate (Nakamoto, 2008). A transaction on a blockchain is based on three main components: a sender address, a receiver address and a transaction unit (such as a bitcoin or ether). There is a determined number of transaction units on the blockchain, and they are all known to the blockchain. This enables people to transact anonymously without a centralized exchange. The centralized exchange is replaced by nodes that continuously evaluate and validate the transactions on the blockchain.

2.3.3 Equity crowdfunding meets blockchain

By combining the mechanics of equity crowdfunding with blockchain technology, you create an ICO (Li & Mann, 2018). In a crowdfunding campaign, the project is launched on a crowdfunding platform. In an ICO, the project is launched on a blockchain. The established crowdfunding platforms are centralized for-profit businesses that decide which projects can crowdfund, and charge high fees, typically 4-5% of the amount raised (Agrawal, Catalini & Goldfarb, 2014). ICOs are disruptive in the sense that they decentralize the funding model and are subject to close-to-zero fees, allowing entrepreneurs to seek funding on their own terms (Li & Mann, 2018).

The most striking difference between equity crowdfunding and ICOs is the amounts involved. The average amount raised in equity crowdfunding campaigns in the US was 2017 $264,000, compared to $12.7 million in ICOs the same year. The maximum amount raised 2017 in equity crowdfunding was $7 million, compared to $230 million in ICOs (Stradling, 2018; Fabric Ventures, 2018; Williams–Grut, 2017).

2.4 Initial coin offering (ICO)

2.4.1 Definition of ICO

The most recent way for entrepreneurs to seek funding is through an ICO. ICOs are taking many different forms, and it is therefore quite challenging to define the phenomena (Zetzsche et al, 2018). Nonetheless, the basic common structure of an ICO is the offer of digital tokens or coins that utilize blockchain technology. We propose a general definition of ICOs as an equity funding mechanism used by young ventures to raise capital through the sale of digital tokens to a broad crowd of online investors.

ICOs utilize the same dynamics as equity crowdfunding with one major difference, the medium that is offered in return for the investment. While the medium offered in equity funding is that, equity, the medium offered in an ICO is a blockchain based cryptocurrency—similar to Bitcoin or Ether (Conley, 2017). This blockchain based cryptocurrency can then be used in the venture's project, or traded on cryptocurrency exchanges.

Since the issued token is based on blockchain technology, ICO is not suitable for every venture. It can only be used by ventures building on blockchain technology. However, with the broad possible applications of this technology, ICOs are expected to become viable for more ventures going forward (Swan, 2015).

2.4.2 Mechanics of ICOs

Researchers Kaal & Dell'Erba (2017) are among the first that have attempted to formally define the mechanics of an ICO. They describe the ICO process as inconsistent, but that most projects follow a certain structure.

1. Before the ICO is launched, the project is announced on some fora such as bitcointalk.org or reddit.com to receive comments and input.
2. The comments and input are used by the ICO management team for drafting the whitepaper—equivalent of an offering memorandum and is similar to a business plan. The whitepaper contains

information about the project such as a roadmap and team information. Additionally, whitepapers often include details such as the funding amount to be raised and important technical information about the product.

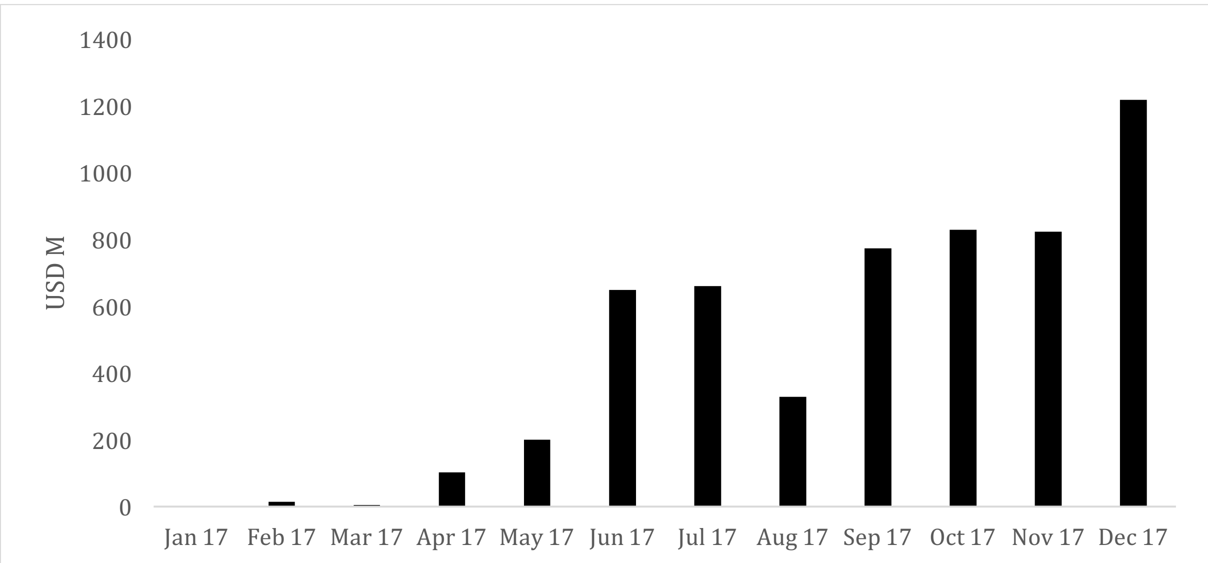
3. Sometimes a pre-ICO offer is made to selected investors.
4. The ICO is launched, and funds from investors—usually Bitcoin or Ether—are collected to a public cryptocurrency address. The ICO's tokens are sent to the investors' provided blockchain addresses.

Entrepreneurs conducting an ICO can choose to establish a maximum amount of funds that can be raised. The maximum amount is referred to as a hard cap and is mentioned in the whitepaper. When the hard cap is reached, no further tokens will be sold. Some ventures also offer protection in form of a soft cap. A soft cap is, in contrast, the lowest total amount a venture will accept in the ICO. If the soft cap is not reached, all funds will be returned to investors and the ICO will receive $0 in funding (Filipov, 2018).

2.4.3 The ICO market

After the first ICO in 2013, the activity was modest with only a few completed campaigns in 2014 and 2015. In 2016, entrepreneurs raised a total of $240 million through ICOs. The breakthrough came in 2017, with a total number of 913 ICOs, 435 of which regarded as successful, which means they met their minimum threshold—their soft cap—and kept the funds. The funds raised during 2017 amounted to $5.6 billion. The peak was in December 2017 where $1.2 billion was raised (Fabric Ventures, 2017).

Graph 2. ICO funding in 2017



2.4.4 Why entrepreneurs choose ICO

ICOs allows an easier entry for ventures to the capital markets to finance their ideas. Few ventures manage to raise funds from VC or banks (Drover et al, 2017), and many ideas become unrealized in absence of funding (Cassar, 2004). Through an ICO, anyone that believes in an idea can support it, and ideas that otherwise would have gone lost can survive.

Amsden and Schweizer (2018) mention four primary reasons why entrepreneurs might choose to ICO. The first reason is concerned with the weak regulatory body surrounding ICOs. Ventures conducting ICOs do not have comply to financial regulations since most ventures are not registered as tokenized securities. This means that the token does not confer any legal claim against the company, unlike with traditional equity ownership, and token holders are not secured against losses (Lipusch, 2018). For entrepreneurs, this is advantageous since they can collect funds more easily, to lower costs and with fewer obligations.

The second reason is related to the cost benefit associated with ICOs due to the absence of intermediaries, such as VCs (Amsden & Schweizer, 2018). As a result, ICOs are not only cost effective, but also a way for entrepreneurs to raise funds at a fraction of the time of more traditional sources, such as VC (Lipusch, 2018).

The third reason mentioned by Amsden and Schweizer (2018) is that entrepreneurs by doing an ICO build an investor base comprised of a large number of small investors that have no voting power in the company. Unlike when having an investor base comprised of classic institutional investors such as VCs, the entrepreneur now does not have to appease one or two investors' interests, but can instead focus on building the venture in the way it finds most suitable (Lipusch, 2018).

The fourth reason why entrepreneurs might choose an ICO as a means for fundraising is the large instant transaction volumes. ICOs allow ventures to raise large amounts rapidly, as opposed to in VC, where investments come in stages conditional on performance. In addition, ventures pursuing an ICO keep the option to raise more capital in a later stage, since they do not need permission from token holders to create and issue new tokens or equity. ICOs are also characterized by quick liquidity and exit opportunities. Once the ICO is completed and the tokens are listed on a crypto exchange, the tokens can be traded freely. The high liquidity creates exit opportunities for entrepreneurs as the tokens are not subject to any lock up periods, and can be sold in an anonymous manner, avoiding sending negative signals to stakeholders.

3. Theoretical framework and hypothesis development

In this section, the entrepreneurial equity financing literature on signals of venture quality is reviewed, with focus on human capital, social capital, products and business artefacts. Biases known in this literature are brought up to problematize. Throughout the section hypotheses are deduced for answering the research question.

3.1 Scope of theoretical framework

The blockchain movement is based on anonymity and decentralization. Participants transact outside the bounds of conventional systems, hiding behind blockchain addresses. It is within this anonymous, borderless and opaque world that ICOs emerged. Interestingly, in this anonymous world of blockchain, entrepreneurs conducting ICOs are surprisingly prone to step out of anonymity. In this world where the norm is to be anonymous, entrepreneurs opt to be visible and present detailed descriptions of themselves and their team members to investors. This might not make sense from a blockchain perspective, but it is very much in line with quality signaling in traditional entrepreneurial finance theory. The question arises whether these theories can bring explanatory value in an ICO setting as well.

In a review of the literature on entrepreneurial selection, Zacharakis and Meyer (2000) find that founder and team characteristics are the most frequently used selection criteria by VCs. In addition, VCs are attentive to characteristics of the venture's financials, its market and its product (Tyebjee & Bruno, 1984; Macmillan, Zemann & Subbanarasimha, 1987; Kollmann & Kuckertz, 2010; Kakati, 2003). However, all of these areas are not of interest in the ICO setting. Since most ventures conducting ICOs are in an early stage, they have few performance metrics, and rarely have financial figures to disclose. Measuring the financial stability and performance in ICO ventures as a proxy for venture quality is therefore not viable. Market characteristics, such as current market size and level of competition, are neither good bases for evaluating the quality of an ICO venture; many ICOs are held to decentralize existing markets and create new ones.

Left for ICO investors to evaluate is signals from the entrepreneurs and their team as well as characteristics of the product or service.

3.2 Asymmetric information and quality signaling

Asymmetric information separate entrepreneurial firms seeking funds from prospective investors (Ragozzino & Reuer, 2007). The problem is based on the assumption that the entrepreneur knows more about the ventures' true value than a prospective investor. Asymmetric information hinders investors from distinguishing between qualitative and less qualitative ventures, and startups seeking funds face problems in credibly portraying their true value (Ahlers et al, 2015).

To reduce the information gap, entrepreneurs must send credible signals of quality. While signals cannot eliminate the information asymmetry, they reduce the information gap substantially (Ragozzino & Reuer, 2007).

3.3 Entrepreneurial selection of VCs

To overcome information asymmetry, VCs have developed considerable expertise in identifying signals that indicate venture quality (Drover et al, 2017). VCs capture signals of quality through continuous meetings, the use of shared networks and through documents such as the business plan (Shane & Cable, 2002).

3.3.1 Human capital

One key factor signaling venture quality is the availability of human capital. Kirsch, Goldfarb and Gera (2009) mentioned that "VC invest in people as much as, if not more than, they invest in technology" (p. 494). Speaking in general terms, more human capital is associated with more capabilities and skills. Ventures with more human capital are subject to greater entrepreneurial success; they are better at capturing business opportunities, realizing strategies, attracting resources and building platforms for future learning (Ahlers et al, 2015).

3.3.1.1 Founders

Ventures founded by teams has shown to outperform individually founded ventures (Chandler, Honig & Wiklund, 2005). Kirsch et al (2009) argued that founding team size is positively correlated with revenue growth in new ventures. Baum and Silverman (2004) found that startups with larger founding teams obtain significantly more VC financing, signaling accumulation of human capital. It is expected that ICO investors value this attribute as well. This leads us to the first hypothesis. We hypothesize:

H1: A larger number of founders will lead to greater ICO fundraising success

Except for the count of founders, VCs are especially attentive to founders with previous experience (Colombo, Delmastro & Grilli, 2004). Kaplan and Strömberg (2004) found in their study that over 60% of VCs investigated valued founders with previous experience highly. In the same study, an inexperienced founder was perceived as negative. Even non-entrepreneurial work experience has shown to positively correlate with receiving funding (Colombo et al, 2004). Taken together, we hypothesize:

H2: A larger count of total years of experience among the co-founders will lead to greater ICO fundraising success

Founders with previous venture founding experience are viewed upon as a good sign, regardless if the venture was successful or not (Flynn, 1991; Gimmon & Levie 2009). MacMillan (1986) was amongst the first scholars to study VCs entrepreneurial selection, and argued that entrepreneurs with prior funding experience have had “the opportunity to learn how to efficiently and swiftly overcome the stumbling blocks they encountered in their first efforts.” (p. 242) Another important aspect of start-up experience brought up by Kirsch et al (2009) is that experienced entrepreneurs may be better connected to VC networks, which serves as a positive cue for VCs. We hypothesize in the affirmative:

H3: A co-founder with previous venture founding experience will lead to greater ICO fundraising success

The literature acknowledges another form of founder experience beyond previous entrepreneurship, being those who found ventures in a parallel manner (Wright, Robbie & Ennewcr, 1997). Apart from having been involved in previous startups, it is argued that the founders with involvement in several ventures simultaneously, referred to as portfolio entrepreneurs, are subject to greater VC fundraising success (Gottschalk, Greene, Höwer & Müller, 2014). It is also acknowledged that founders with industry experience are valued by VCs (MacMillan, 1986; Colombo et al, 2004; Kaplan & Strömberg, 2004). Hence, we hypothesize that portfolio entrepreneurship and industry experience may be cues for ICO investors as well. We hypothesize:

H4: A co-founder that is a portfolio entrepreneur will lead to greater ICO fundraising success

H5: A co-founder that is involved in another ICO will lead to greater ICO fundraising success

Except from having work related experience, VCs value founders with advanced education. Bates (1997) put forward education as being the most used measure of human capital and having advanced degrees signal quality to VCs (Colombo et al, 2004). Roure and Maidique (1986) also found higher education among founders positively correlated with VC funding. The same conclusion was drawn by Hsu (2007) who argued that founders with a PHD or MBA are more likely to receive funding. We expect the presence of advanced degrees in the founding team to have high cue validity in the ICO scene as well. We hypothesize:

H6: A co-founder that has a Master's degree will lead to greater ICO fundraising success

H7: A co-founder that has MBA will lead to greater ICO fundraising success

H8: A co-founder that has a PhD will lead to greater ICO fundraising success

If the venture has a high technology business model, it is perceived positive to have a technical degree. Also, if there are several founders, Franke, Gruber, Harhoff and Henkel (2008) showed that founders with mixed educations—i.e. both managerial and technical skills—were valued higher than founders with only one area of expertise. Since ICOs utilize blockchain technology, we hypothesize:

H9: A co-founder that has a technical Master's degree will lead to greater ICO fundraising success

H10: Founders with mixed managerial and technical education will lead to greater ICO fundraising success

As previously mentioned, VCs perceive signals of quality partly through personal meetings and shared networks. Because of this personal approach, there are biases in the way VCs make decisions. Several scholars have acknowledged a VC gender bias, where VC to a lesser extent fund female founders than male (Greene, Brush, Hart & Saparito, 2001; Ruef, Aldrich & Carter 2003; Harrison & Mason, 2007). There are several potential explanations to this. Greene et al (2001) presented a structural barriers approach suggesting that ventures led by women face either institutional or social network barriers, preventing them access to institutional VCs. Ruef et al (2003) confirmed the existence of network barriers, but also introduced homophily on the side of VCs as a potential explanation. Harrison and Mason (2007) emphasized that VC gender bias is due to shared networks, and not a result of homophily, since female VCs favor male entrepreneurs, just as their male colleagues. However, it is not assumed that gender bias will prevail in the ICO selection process. For investors in an ICO, cues of venture quality are not collected through personal meetings and shared networks, eliminating structural network barriers. Thus, we hypothesize:

H11: Having at least one female founder will not affect ICO fundraising success

3.3.1.2 Team

Attributes of the management team are also related to VC funding success, and serve as cues of human capital for VCs (Kirsch et al, 2009). A large management team signals an overall confidence in the project. As mentioned earlier, larger founding teams signal a greater accumulation of human capital to VCs. The same logic applies to the size of the management team. We expect large management teams to serve as a quality cue for ICO investors as well. We hypothesize:

H12: A larger team will lead to greater ICO fundraising success

In addition to team count, there are other characteristics of the venture team valued by VCs. Performance of entrepreneurial ventures was found to be positively correlated with organizational structure, and greater specialization in management teams influence revenue growth (Sine, Mitsuhashi & Kirsch, 2006). Beckman, Burton and O'Reilly (2007) brought up the concept of functional heterogeneity, and suggest that having diversity in functional backgrounds lead to greater capabilities. In the same study, the importance of team completeness is brought up and the authors underline the importance of organizational structure for funding success. By having functional specialization within the management team, team members can focus on specific tasks and gain task-specific knowledge (Kirsch et al, 2009). Taken together, a more detailed organizational structure and task specialization within the management team is associated with greater VC fundraising success. Ventures conducting ICOs are often characterized by complex and technical business models, and a management team with great specialization is expected to be valued in an ICO setting as well. We hypothesize:

H13: A greater role specialization in the team will lead to greater ICO fundraising success

The described gender bias in VCs selection of ventures will be tested with focus on the management team as well. As argued earlier, we do not expect this bias to be present in the ICO setting. We therefore hypothesize:

H14: The number of females mentioned in the management team will not affect ICO fundraising success.

3.2.2 Social alliance capital

In addition to signals of human capital, VCs are attentive to cues of social alliance capital. Social alliance capital is largely concerned with the existence of network connections. Ventures with access to external networks and alliances attract more VC funding, since external networks and acquaintances ease the information asymmetry between the venture and the VCs. Organizations benefit from network connections in general, and young organizations in particular. Alliances give access to complementary resources and knowledge, which is essential for the development of start-ups (Baum & Silverman, 2004).

Moreover, alliances signal legitimacy. Stuart, Hoang and Hybels (1999) mentioned that ventures endorsed by prominent actors performed better than ventures without network and alliances. Duchesneau & Gartner (1990) reached the same conclusion and underlined the importance of outside professionals and advisors for venture success. Positive endorsements from knowledgeable actors serve as signals of quality for VCs (Fried & Hisrich, 1994). We expect social alliance capital to signal quality to ICO investors as well. Teece (1992) found that when investors evaluate ventures that use complex technologies, they tend to turn towards social capital indicators to judge venture quality. Due to the technical nature of blockchains, this behavior is expected to be found in an ICO setting as well. In fact, many ICOs have advisors mentioned in their whitepapers, usually prominent blockchain experts. Prominent actors listed as advisors ought to serve as a signal of quality in an ICO setting as well. Taken together, we hypothesize:

H15: Having a larger number of advisors will lead to greater ICO fundraising success

3.2.3 Product and artifacts

Another area of inquiry for VCs is the product. According to Ford, Bornstein and Pruitt (2007), the product is often carefully described in the business plan, and Kirsch et al (2009) mentioned the business plan as being a standard artifact that must be available to VCs. Kirsch et al (2009) also brought up the importance of having a complete business plan, and mentioned that an incomplete plan might signal strategic withholding of information. As mentioned before, a person associated with a venture is indirectly endorsing the proposed project. This is even more true if the person is mentioned in the business plan. Kirsch et al (2009) stated that business plans that do not refer to any individuals might suffer from omission effects. In the ICO setting, the whitepaper is equivalent to a business plan. We believe that it is of the same importance for ventures conducting an ICO to state founders in the white paper to bridge information asymmetries, expose themselves and mitigate investment risk. We hypothesize:

H16: Having co-founders described in the whitepaper will lead to greater ICO fundraising success

A signal of quality related to VCs funding decision has to do with venture preparedness, which could be demonstrated in the form of working prototypes and products (Mollick, 2013). This is expected to serve a cue of quality for ICO investors alike. To measures these concepts, we make a holistic assessment of the product and preparedness of ICO ventures using attributes in their whitepapers as measures. We hypothesize:

H17: Having a roadmap or having milestones presented in white paper will lead to greater ICO fundraising success

H18: A larger word count in the white paper will lead to greater ICO fundraising success

All 18 hypotheses are summarized in Table 1 below.

Table 1. Hypotheses

Human capital, founders	
H1	A larger number of founders will lead to greater ICO fundraising success
H2	A larger count of total years of experience among the co-founders will lead to greater ICO fundraising success
H3	A co-founder with previous venture founding experience will lead to greater ICO fundraising success
H4	A co-founder that is a portfolio entrepreneur will lead to greater ICO fundraising success
H5	A co-founder that is involved in another ICO will lead to greater ICO fundraising success
H6	A co-founder that has a Master's degree will lead to greater ICO fundraising success
H7	A co-founder that has MBA will lead to greater ICO fundraising success
H8	A co-founder that has a PhD will lead to greater ICO fundraising success.
H9	A co-founder that has a technical Master's degree will lead to greater ICO fundraising success
H10	Founders with mixed managerial and technical education will lead to greater ICO fundraising success
H11	Having at least one female founder will not affect ICO fundraising success
Human capital, team	
H12	A larger team will lead to greater ICO fundraising success
H13	A greater role specialization in the team will lead to greater ICO fundraising success
H14	The number of females mentioned in the management team will not affect ICO fundraising success.
Social alliance capital	
H15	Having a larger number of advisors will lead to greater ICO fundraising success
Product and artefacts	
H16	Having co-founders described in the white paper will lead to greater ICO fundraising success
H17	Having a roadmap or having milestones presented in white paper will lead to greater ICO fundraising success
H18	A larger word count in the white paper will lead to greater ICO fundraising success

4. Method

In this section, we describe the methods used for sampling, collecting, and analyzing the data in order to test the hypotheses summarized on the previous page (in Table 1).

4.1 Research Approach

Considering that hypotheses are deduced from theory and put subject to empirical scrutiny, a deductive approach was used. However, once the hypotheses had been tested under empirical scrutiny, the approach turned inductive as research findings from those tests are fed back to the theory of which the respective hypotheses were originally deduced (Bryman & Bell, 2015). Although this entails that the research has features of inductivism, it is primarily deductive in nature and Bryman & Bell (2015) argues that this should place the research within the doctrine of positivism. Further, as the research examined venture teams and investors as tangible objects, and did not examine the social actors that the objects are comprised of, it takes an objectivist ontological position (Bryman & Bell, 2015).

4.2 Research Strategy

Since the research followed a deductive approach, is within positivism, and views the examined venture teams and investors as objects, the research strategy for this study was quantitative (Bryman & Bell, 2015).

4.3 Research Design and Research Method

A cross-sectional design was the starting point for this thesis' research design. The research method consisted of manually encoding data about the entrepreneurs, their team, their whitepaper, and their ICO funding outcome into a dataset, for it to later be analyzed. This method has been used in multiple other studies (Dimov & Shepherd, 2005; Zarutskie, 2015).

4.4 Sample selection

4.4.1 Population and Sampling frame

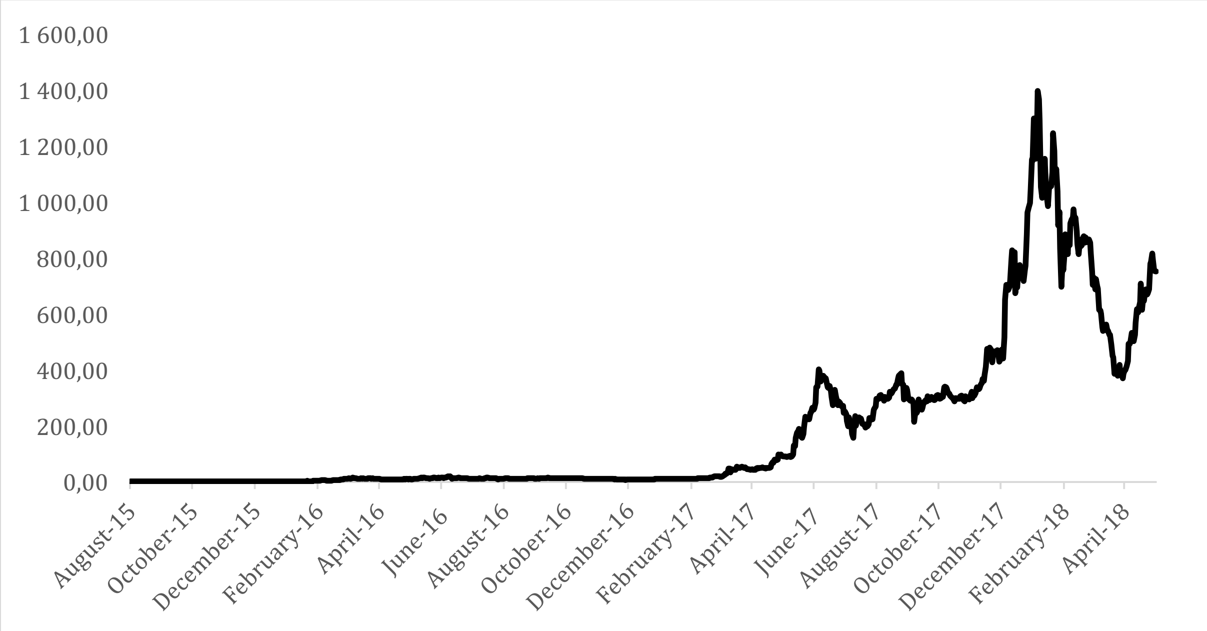
The population for this study consisted of all ICOs—successful and unsuccessful—from three databases: TokenData, Coinschedule and ICObench.[2] When designing the sampling frame, two considerations were made.

First, survivorship bias—successful ventures become overrepresented over time—as discussed by Cassar (2004) was addressed by restricting the sampling frame to ICOs that took place close in time. As a result of this consideration, it was decided that only ICOs from September 2017–December 2017 would be part of the sampling frame.

Second, since ICOs take place on blockchains, the funds raised are blockchain based currencies. In order to ensure data consistency, the ICOs' raised blockchain based currencies were converted into the currencies' corresponding USD value at the time of the ICO. Although this ensured that a consistent unit of measure is used later in the analysis, fluctuations in the price of the blockchain based currency would affect the measure in an unwanted way. It was decided to limit the sampling frame to a time period when the price of Ether—one of the main currencies—fluctuated as little as possible, while still maintaining a large dataset. Therefore, because of the extreme Ether price fluctuation in December 2017 (see Graph 3), it was decided to exclude ICOs that took place in December 2017 from the sampling frame.

[2] Three databases that have been featured in e.g. Business Insider, Bloomberg, Chicago Evening Post, and Forbes

Graph 3. Ether price August 2015–May 2018



4.4.2 Sample selection

When deciding on method for sample selection, both probability and non-probability based approaches were considered. Although a probability based approached reduces the sampling error (Bryman & Bell, 2015), the authors opted for a non-probability based approach. The approach entailed selecting ICOs that had a hard cap. A hard cap is the maximum amount of funds the ICO will raise. The authors believed the hard caps might have an anchoring effect that could affect ICO fundraising, and therefore chose to exclude all ICOs that did not have hard caps (Jacowitz & Kahneman, 1995). 136 ICO projects had hard caps, and were selected for investigation.

4.5 Data collection

For testing the hypotheses, quantitative data had to be collected about ICO outcome, the entrepreneurs doing the ICO, their team and their whitepaper. This was done through a method similar to content analysis, and a coding manual and a coding schedule (see Appendix 4 and 5) were created, as described in Bryman & Bell (2015).

4.5.1 Creating the dataset

A dataset based on the discussion in 4.4.1 was created by combining data from three established ICO databases: TokenData, Coinschedule and ICObench. This dataset contained the ICO project name, ICO date, amount of funds raised, and hard cap of 487 ICOs. The sample selection in 4.4.2 is then done, limiting the number of ICOs to 136.

4.5.2 Using whitepapers to expand the dataset

No central authority collects the white papers, they had to be found on the internet. One important consideration was that the whitepapers used in this study had to be the same ones that were available to investors prior to the ICO. In order to ensure this, the publication date of the whitepaper had to be an earlier date than that of the ICO. To ensure the authenticity of the whitepapers missing a publication date, a tool—Internet Archive's Wayback Machine—was used.[3] The coding schedule was completed according to the coding manual, and the dataset was expanded further. Now, only information about the ICO project founders was missing.

4.5.3 Using Linkedin profiles to complete the dataset

Using the names of the founders as stated in the whitepapers, the Linkedin profiles of the founders were found and data was added to the dataset according to the coding schedule. If their names were not in in the whitepaper, no further data was collected. This was not judged to be a problem, as this means that investors neither could access information about the founders. The dataset was now complete.

A weakness in the data collection was prevalent at this stage: data from founders' Linkedin pages were collected during the 25th of February–28th of March, and therefore not at the time of the ICO. Because of the technical design of Linkedin, the Wayback Machine did not have reliable data on Linkedin profiles. However, similar methods have been used by many other studies (e.g. Dimov & Shepherd, 2005; Courtney, Dutta & Li, 2017).

4.6 Statistical methods

Once the dataset was completed, the hypotheses were tested using regression models. In order to ensure internal validity, a 5% significance level was required for a hypothesis to be supported. Two different regression models were used for testing: a binary logistic, and an ordinary least square (OLS).

4.6.1 Binary Logistic Regression

A binary logistic regression is well suited for testing hypotheses about relationships between a binary outcome—in our case whether or not a venture received ICO funding—and predictor variables (Peng, Lee, & Ingersoll, 2002). Based on the predictor variables, this model will return a probability on how

[3] Internet Archive's Wayback Machine is an open source software program that allows any individual to go back in time on the internet. In this study, it was used to download the pre-ICO whitepaper.

well they can predict whether an ICO will get funding or not. This regression analysis will be used to answer research question 1.

4.6.2 Ordinary Least Square (OLS) Regression

An OLS regression will be used for testing hypotheses about relationships between a continuous variable—in our case how much ICO funding a venture received—and predictor variables (Newbold, 2013). This model is used to see which variables affect the amount of funds raised, and how big the effect is. This regression analysis will be used to answer research question 2.

To ensure quality in the OLS regression analysis, the dataset was cleared of ventures that received $0 in ICO funding. This measure was taken because of ICO soft cap. As explained before, an ICO's soft cap is the minimum amount of funds the venture will accept, below which funds will be returned to investors. Therefore, a venture in the dataset that raised $0 might have raised more, but not sufficiently to reach the soft cap. Because of this, we cannot with certainty know the actual amount raised and therefore excluded those ICOs from the analysis.

4.7 Method discussion

The research question could also have been answered through an inductive approach, collecting data to generate theory about what factors determine ICO funding for entrepreneurs (Bryman & Bell, 2015). However, since factors that determine funding in other entrepreneurial financing methods were well known, and since no study was found to have tested if those factors apply in an ICO funding setting, it was decided that entrepreneurial financing theory should be the starting point for answering the research question, and therefore the approach is deductive.

An alternative to the research method selected was self-completion questionnaires (sent to ICO investors). This method was dismissed because of two reasons. First, Bryman & Bell (2015) stated that not knowing who answers the questionnaire is a disadvantage of the method, especially for internet administered self-completion questionnaires. Given the anonymous nature of the blockchain space, the authors believed this disadvantage to be further exacerbated as it is impossible to validate that an online self-proclaimed ICO investor actually is an ICO investor. Second, Podsakoff & Organ (1986) brought up problems with ensuring validity of self-reported data, especially when the requested data requires higher-order cognitive process in order for the respondent to report it. Asking investors to rate the factors they considered when they invested in an ICO—i.e. recall past investment behavior—is a typical higher-order cognitive process (Podsakoff & Organ, 1986); therefore, it was deemed difficult to establish the validity of that type of measure and the idea of a self-completion questionnaire method was dismissed.

4.7.1 Ethical aspects

One ethical consideration was that no venture founder, nor their team, had given consent to participate in this study. However, the study was nonetheless deemed ethical by the authors since, although requiring significant effort to hand-collect the data, all data collected was accessible on the open web. Further, to ensure not infringing on the privacy on any examined founders or their teams, no personal data is presented in the thesis.

4.7.2 Research quality criteria

4.7.2.1 Reliability

For a quantitative study such as this, reliability of the measures used is of high importance (Bryman & Bell, 2015). Although not using identical phrasing of the measures, previous studies have tested the concepts used in this study with similar measures, with well documented reliability (e.g. Ahlers et al, 2015; Kirsch et al, 2009). Therefore, the reliability of measures used was concluded to be sufficient.

Another aspect of reliability, inter-rater reliability, was given a great deal of consideration as two individuals performed the variable encoding. Bryman & Bell, (2015) described inter-rater reliability as becoming a problem when a subjective judgement is involved in translating data into categories and when two or more raters are involved. As suggested by Bryman & Bell (2015), there is a need for consensus in the data encoding, and the authors ensured to both encode all variables for all observations in the sample, and investigated differences in coding. As a result of a clear coding manual (see appendix 5), the number of times the authors differed in their encoding were very few (below 10 instances). Differences in the encoding were discussed by the authors and consensus were after discussion reached without any issues.

4.7.2.2 Validity

Even though other studies have tested the same concepts with similar measures, the authors wanted to meet the minimum requirement for establishing validity from Bryman & Bell (2015): face validity. Bryman & Bell (2015) mentions that one way of determining face validity is to have people, preferably people with experience in the field, to judge whether or not the measure actually represents the concept that is tested. The authors have presented the measures to Doctorates or Professors at the authors' institution, and it was confirmed that the measures in a good manner reflect the concepts tested.

Internal validity, concerned with the issue of causality (Bryman & Bell, 2015), was addressed in this study by having requirements on statistical significance for a hypothesis to be supported, i.e. for a causal relationship to be supported.

Since no control variables are used, and the selected sample is not selected with a probability based method, the results from the study cannot be generalized (Bryman & Bell, 2015). However, given the large sample size used—136 out of the 913 ICOs attempted in 2017—the results from testing the hypotheses are still believed to contribute to the existing theory base on entrepreneurial equity financing.

The study examined directly what has happened in the real world, and avoided the unnaturalness of a questionnaire, and is therefore deemed to have high ecological validity (Bryman & Bell, 2015).

4.7.2.3 Replicability

It has been attempted to describe the chosen methods as detailed possible in this section to enable replicability. Together with the appendices, the authors believe the information given is sufficient for replicating the study.

5. Data

Under this section the dependent variables and independent variables that will be used for testing the hypotheses are presented and statistical tests have been used to guarantee the reliability of data are discussed. Lastly, possible biases in the data are discussed.

5.1 Measures

5.1.1 Dependent variables

Two dependent variables were investigated: *ICO funding received*, operationalized as whether or not an ICO reached its soft cap, and *funds raised*, operationalized as the amount of funds in USD million raised.

5.1.2 Independent variables

5.1.2.1 Founders

The names of the co-founders were presented in the whitepaper, and the *number of co-founders* was counted and coded. Using their names, the co-founders' Linkedin pages were visited and their total *years of working experience*, along with whether they had *previous venture founding experience,* if any of them was a *portfolio entrepreneur* and the *number of ICOs involved in* was coded. It was also coded whether at least one of them had attained any of the following educational degrees: *Master's*, *MBA*, *PhD*, *technical Master's*, and if they had a *mixed managerial and technical educational background*. Lastly, it was coded whether there was at least one *female co-founder*.

5.1.2.2 Team

In the whitepaper, the *team size* and *number of different roles* were found and coded into two seperate variables. The *number of females* mentioned in the team was also coded.

5.1.2.3 Social alliance capital

Also in the whitepaper, the *number of advisors* was counted and coded.

5.1.2.4 Product and artefacts

Lastly, it was coded whether *descriptions of co-founders* were present in whitepaper, if it had a *roadmap,* and the total *number of words* in it.

For a summary of the variables and their minimum values, maximum values, means, standard deviations and expected coefficient sign, see Table 2.

Table 2. Descriptive statistics

	N	Min.	Max.	Mean	Std. Dev.	Expected coefficient sign
Dependent variables						
ICO funding received	136	0	1	0.82	0.38	N/A
Funds raised (USD M)	136	0.00	86.54	11.63	16.63	N/A
Independent variables						
Human capital, founders						
Number of co-founders	136	0	4	1.61	1.24	+
Years of working experience	136	0	78	15.10	16.92	+
Previous venture founding experience	136	0	1	0.60	0.49	+
Portfolio entrepreneur	136	0	3	0.34	0.52	+
Number of ICOs involved in	136	0	7	0.38	1.10	+
Master's degree	136	0	1	0.43	0.50	+
MBA degree	136	0	1	0.14	0.35	+
PhD degree	136	0	1	0.06	0.24	+
Technical Master's degree	136	0	1	0.29	0.46	+
Mixed managerial and technical education	136	0	1	0.17	0.38	+
Female co-founder	136	0	1	0.08	0.27	No sign
Human capital, team						
Team size	136	0	33	5.15	5.70	+
Number of females	136	0	12	0.90	1.91	No sign
Number of different roles	136	0	29	4.75	5.35	+
Social alliance capital						
Number of advisors	136	0	31	2.68	4.543	+
Products and artefacts						
Descriptions of co-founders	136	0	1	0.43	0.50	+
Roadmap	136	0	1	0.71	0.46	+
Number of words	136	0	40777	6865.08	5390.90	+

5.2 Data review

5.2.1 Assumptions for quantitative data analysis

5.2.1.1 Assumptions for Logistic Regression analysis

In a logistic regression analysis, 10-15 observations per predictor variable is deemed to be statistically sound in order to avoid overfitting of data (Babyak, 2004). This means that this study, if using all 18 predictor variables, had a risk of overfitting data. This risk was countered by reducing the number of predictor variables in the model one by one until it only includes statistically significant ones.

5.2.1.2 Assumptions for OLS Regression analysis

To ensure that the results of the OLS regression were statistically sound, a number of assumptions were tested (Newbold, 2013).

First, the residuals had to be normally distributed. This was tested by a Jarque–Bera test, and the Jarque–Bera test statistic was found to be below the critical value, meaning the residuals are normally distributed (see Appendix 1).

Second, the data had to be tested for multicollinearity to ensure no perfect multicollinearity—i.e. that no dependent variable correlates perfectly with another one. No perfect multicollinearity was found, as can be seen in the correlation matrix (see Appendix 2).

Third, it had to be ensured that the residuals had constant variance—i.e. that the residuals are homoskedastic. A test described in Newbold (2013) was used (see Appendix 3a), and the result was that the residuals were heteroskedastic. This violated the assumptions for an OLS regression. To counter this, five outliers—the largest observations—were removed from the dataset. The test was applied again, and the residuals were now homoscedastic (see Appendix 3b).

Fourth, Newbold (2013) also recommended testing the data for autocorrelation if the dataset concerns time series data. As time series data is not what was analyzed, a test for autocorrelation was not performed.

5.2.2 Possible biases in the data

Four possible causes of bias are identified, rooted primarily in the sampling process but also in the technical design of Linkedin.

First, although the study used multiple databases to ensure that the population included all ICOs attempted in 2017, it is possible that ICOs that should have been included in the population were not, as they were not listed in any of the three databases used. This could be considered a non-sampling error, as it would result in a disparity between the population defined by this study, and the actual population (Bryman & Bell, 2015).

Second, the sampling frame was limited to ICOs that took place in September 2017–November 2017 because of reasons discussed in 4.4.1, and there is a risk that this sampling frame was inadequate, meaning that it does not represent the population in an adequate manner (Bryman & Bell, 2015).

Third, as previously discussed, a non-probability based sampling method was used. This means that human judgement interfered, and therefore some members (ICOs) of the population might be more likely to be selected than others (Bryman & Bell, 2015).

Fourth, the time lag between the time of Linkedin data collection and the ICO is a possible source of bias. There is a risk that the Linkedin profiles have changed during that time period, and no way was found to counter this issue as the Internet Archive's Wayback Machine did not work on Linkedin profiles, nor was any other tools found.

6. Results

Two methods for testing the hypotheses and ultimately answer the two research questions are used in this section: logistic regression and OLS regression. For both analyses, an initial model that included all 18 independent variables was created. The initial model was then revised by removing all non-statistically significant independent variables and independent variables that had coefficients with the wrong expected sign. This process was done by removing independent variables one at a time until a final model with only statistically significant variables with the correct expected sign was reached. This process was done to ensure that any causal relationships found were not illusions caused by overfitting the model.

The logistic regression analysis was used to see if the predictors can determine ICO success at all, and returns a probability on how well it can predict whether an ICO will get funding or not. After the logistic regression is completed, the dataset will be cleared both of the unsuccessful ICOs in order to ensure data quality, and of the large outliers to ensure that the OLS assumptions are met (see section 4.6.2 and 5.2.1.2). The OLS regression is then used to see which variables affect the amount of funds raised, and to what extent they affect it.

6.1 Binary Logistic Regression Analysis

6.1.1 First model

The initial binary logistic regression model (see Tables 4 and 5) showed that the independent variables could predict whether an ICO will be a success or not in more than 90 percent of the cases (91.7% for unsuccessful ICOs, and 92% for successful ICOs), and three of the dependent variables were significant. However, recall that we had too many predictors compared to our number of observations, and the model risked overfitting. The model was therefore revised by excluding non-significant variables and variables with the incorrect sign coefficient.

Table 4. Binary Logistic regression first model classification results

		Predicted		
		ICO funding received		
		No	Yes	% Correct
Observed	No	22	2	91.7
ICO funding received	Yes	9	103	92.0
	Overall			91.9

a. The cut value is .600

Table 5. Binary logistic regression first model variable table

	B	S.E.	Wald	df	Sig.	Exp(B)
Human capital, founders						
Number of co-founders	-0.69	0.61	1.28	1	13%	0.50
Years of working experience	0.09	0.08	1.22	1	14%	1.10
Previous venture founding experience	0.99	1.58	0.39	1	27%	2.69
Portfolio entrepreneur	1.06	1.67	0.41	1	26%	2.90
Number of ICOs involved in	-0.28	0.78	0.13	1	36%	0.76
Master's degree	4.47	1.92	5.45	1	1%	87.65
MBA degree	17.44	6606.66	0.00	1	50%	37622828.04
PhD degree	18.29	12321.35	0.00	1	50%	87936111.01
Technical Master's degree	-4.50	1.98	5.14	1	1%	0.01
Mixed managerial and technical education	-1.14	1.85	0.38	1	27%	0.32
Female co-founder	0.28	2.09	0.02	1	89%*	1.32
Human capital, team						
Team size	12.81	3217.78	0.00	1	50%	364821.82
Number of different roles	-12.40	3217.78	0.00	1	50%	0.00
Number of females	-0.51	0.35	2.16	1	14%*	0.60
Social alliance capital						
Number of advisors	0.46	0.38	1.46	1	11%	1.59
Products and artefacts						
Descriptions of co-founders	-1.57	1.66	0.89	1	17%	0.21
Roadmap	-1.18	0.80	2.16	1	7%	0.31
Number of words	0.00	0.00	4.87	1	1%	1.00
Constant	-0.50	0.55	0.83	1	36%*	0.61

*Two-tailed test

6.1.2 Final model

After reducing the model, three statistically significant variables are left: *years of working experience*, *number of advisors*, and *number of words* (see Table 7). This final model has a lower overall classification rate (see Table 6), 87.5% (still 92% for predicting successful ICOs, but 66.7% for predicting unsuccessful ones), but does now not overfit to the data as the number of independent variables used has been reduced greatly.

Table 6. Binary Logistic regression final model classification results

		Predicted		
		ICO funding received		
		No	Yes	% Correct
Observed	No	16	8	66.7
ICO funding received	Yes	9	103	92.0
	Overall			87.5

The cut value is .600

Table 7. Binary logistic regression final model variable table

	B	S.E.	Wald	df	Sig.	Exp(B)
Human capital, founders						
Years of working experience	0.067	0.034	3.74	1	3%	1.069
Human capital, team						
-						
Social alliance capital						
Number of advisors	0.372	0.212	3.07	1	4%	1.451
Products and artefacts						
Number of words	0.000	0.000	7.25	1	0%	1.000
Constant	-0.716	0.457	2.45	1	12%*	0.489

* Two-tailed test

6.1.2.1 Final model results

To answer the first research question, the binary logistic model found statistical support for *co-founders years of experience*, *number of advisors* and *number of words* being used as quality signals by investors for deciding whether or not they invest in the an ICO at all.

6.2 Ordinary Least Square Regression

6.2.1 First model

The initial OLS regression model (see Tables 8, 9 and 10) was found to have an R-square of 32.5%, i.e. the 18 dependent variables explained 32.5% of the variance in the independent variable. Further, two dependent variables had statistical significance. Although the risk for this model overfitting was not as prominent as in the Binary Logistic Regression model, the model was revised to only include significant variables and variables with the correct coefficient sign in order to isolate the causal relationships.

Table 8. OLS regression first model summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.570	0.325	0.187	11.29

Table 9. OLS regression first model ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	5407	18	300.37	2.358	0.4%
Residual	11208	88	127.36		
Total	16614	106			

Table 10. OLS regression first model coefficients overview

	B	Std. Error	Beta	t	Sig.
Constant	6.41	3.08		2.08	4%*
Human capital, founders					
Number of co-founders	-1.62	1.56	-0.16	-1.03	15%
Years of working experience	-0.13	0.10	-0.19	-1.37	9%
Previous venture founding experience	6.48	3.17	0.24	2.04	2%
Portfolio entrepreneur	0.02	2.64	0.00	0.01	50%
Number of ICOs involved in	0.69	1.09	0.07	0.63	26%
Master's degree	1.41	3.35	0.06	0.42	34%
MBA	2.87	3.88	0.08	0.74	23%
PhD	6.72	5.03	0.13	1.34	9%
Technical Master's degree	6.99	3.58	0.26	1.95	3%
Mixed managerial and technical education	5.44	4.17	0.16	1.31	10%
Female co-founder	3.48	4.02	0.08	0.87	39%*
Human capital, team					
Team size	0.96	0.92	0.41	1.04	15%
Number of different roles	-1.31	0.96	-0.54	-1.36	9%
Number of females	0.76	1.38	0.09	0.55	58%*
Social alliance capital					
Descriptions of co-founders	3.17	3.06	0.13	1.04	15%
Roadmap	-2.51	2.80	-0.09	-0.90	19%
Number of words	0.00	0.00	0.14	1.32	9%
Number of advisors	-0.28	0.35	-0.11	-0.80	21%

* Two-tailed test

6.2.2 Final model

Reducing the model decreased the explanatory power from 32.5% to 17.8% (see Table 11). However, this meant that two out of 18 variables could explain 17.8% of the variance in *funds raised.* The two statistically significant variables in the final model were *previous venture founding experience* and *technical Master's* (see Table 13). When examining the coefficients, it could be concluded that having a co-founder with *previous venture founding experience* increased the amount of *funds raised* by \$5.22 million. Having a co-founder with a *technical Master's degree* increased *funds raised* by \$8.85 million.

Table 11. OLS regression final model summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.422	0.178	0.163	11.46

Table 12. OLS regression final model ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2965	2	1482.33	11.29	0
Residual	13650	104	131.25		
Total	16614	106			

Table 13. OLS regression final model coefficients overview

	B	Std. Error	Beta	t	Sig.
Constant	5.27	1.97		2.68	0.00%
Human capital, founders					
Previous venture founding experience	5.21	2.44	0.20	2.14	2.00%
Technical Master's degree	8.85	2.48	0.33	3.58	0.00%
Human capital, team					
-					
Social alliance capital					
-					

6.2.2.1 Final model results

To answer the second research question, the OLS regression model found that *previous venture founding experience* and having a *technical Master's degree* are used as quality signals by investors for deciding how much to invest. Table 14 summarizes the results of both regression analyses.

Table 14. Summary of hypotheses testing results

Human capital, founders		Research Question 1	Research Question 2
H1	A larger number of founders will lead to greater ICO fundraising success		
H2	A larger count of total years of experience among the co-founders will lead to greater ICO fundraising success	Supported	
H3	A co-founder with previous venture founding experience will lead to greater ICO fundraising success		Supported
H4	A co-founder that is a portfolio entrepreneur will lead to greater ICO fundraising success		
H5	A co-founder that is involved in another ICO will lead to greater ICO fundraising success		
H6	A co-founder that has a Master's degree will lead to greater ICO fundraising success		
H7	A co-founder that has MBA will lead to greater ICO fundraising success		
H8	A co-founder that has a PhD will lead to greater ICO fundraising success.		
H9	A co-founder that has a technical Master's degree will lead to greater ICO fundraising success		Supported
H10	Founders with mixed managerial and technical education will lead to greater ICO fundraising success		
H11	Having at least one female founder will not affect ICO fundraising success		
Human capital, team			
H12	A larger team will lead to greater ICO fundraising success		
H13	A greater role specialization in the team will lead to greater ICO fundraising success		
H14	The number of females mentioned in the management team will not affect ICO fundraising success.		
Social alliance capital			
H15	Having a larger number of advisors will lead to greater ICO fundraising success	Supported	
Product and artefacts			
H16	Having co-founders described in the white paper will lead to greater ICO fundraising success		
H17	Having a roadmap or having milestones presented in white paper will lead to greater ICO fundraising success		
H18	A larger word count in the white paper will lead to greater ICO fundraising success	Supported	

7. Conclusion and Discussion

In this section, the results of the study will be discussed in relation to the purpose, research question and theoretical gap.

7.1 Summary of Results

The purpose of this study has been to reduce the research gap regarding entrepreneurs' signals of venture quality used by ICO investors. The research questions asked were:

1. What signals of venture quality determine whether entrepreneurs will receive ICO funding?
2. What signals of venture quality determine how much venture funding entrepreneurs will receive?

The first research question has been answered in section 6.1.2.1, and the answer is summarized in Table 14. Out of the 18 hypotheses tested, three were supported by data. It was shown that *cofounders years of experience*, *number of advisors* and *number of words* in the whitepaper were used as venture quality signals by investors for deciding whether or not to fund entrepreneurs at all.

Table 14. Results research question 1

Human capital, founders		
H2	A larger count of total years of experience among the co-founders will lead to greater ICO fundraising success	Supported
Human capital, team		
	-	
Social alliance capital		
H15	Having a larger number of advisors will lead to greater ICO fundraising success	Supported
Product and artefacts		
H18	A larger word count in the white paper will lead to greater ICO fundraising success	Supported

The second research question was answered in section 6.2.2.1, and the answer is summarized in Table 15. Out of the 18 hypotheses tested, two were supported by data to have causal relationships with increased venture funding for entrepreneurs: *previous venture founding experience* and having a *technical Master's degree*.

Table 15. Results research question 2

Human capital, founders		
H3	A co-founder with previous venture founding experience will lead to greater ICO fundraising success	Supported
H9	A co-founder that has a technical Master's degree will lead to greater ICO fundraising success	Supported
Human capital, team		
	-	
Social alliance capital		
	-	
Product and artefacts		
	-	

7.2 Academic Contribution

The study has so far been deductive: we deduced hypotheses from entrepreneurial financing theory that were then tested with data. Now, it is time to reverse the direction of reasoning to induction, and infer implications of our findings back to the stock of theory. This is in line with Drover et al (2017) that urge scholars in this field to build from what is already known and investigate if traditional theories of entrepreneurial finance can be used to understand the dynamics of new sources as well.

7.2.1 Human capital

As mentioned, the blockchain movement is based on anonymity and decentralization. In this world where the norm is to be anonymous, entrepreneurs chose the spotlight. This did not make sense from a blockchain perspective, but was in line with traditional theories on quality signaling. We wanted to investigate if traditional signals of human capital work an ICO setting.

Interestingly, multiple venture signals of quality related to human capital were found to have causal relationships with ICO fundraising success, both in terms of whether the ICO raised any funds at all, as well as with how much was raised. It can therefore be concluded that the concept of human capital, prominent in the entrepreneurial financing theory, can be extended to ICOs as well.

We found that more work experience correlated with whether entrepreneurs received ICO funding, in line with findings of Colombo et al (2004). Few signals of human capital are as prominent in previous research as venture founding experience (Flynn, 1991; Gimmon & Levie 2009; Macmillan, 1986). Our findings confirm this for the ICO setting as well, and further expands the empirical base.

In addition to signaling human capital through work experience, educational credentials are valued by previous research (Maidique, 1986; Bates, 1997; Colombo et al, 2004; Hsu, 2007). ICOs are built on technically complex blockchains, and, perhaps unsurprisingly, we found that a technical Master's degree had a causal relationship with the amount of ICO funding a venture received.

7.2.2 Social Alliance capital

In addition to signals of human capital, the literature suggests that VCs are attentive to cues of social alliance capital (Baum & Silverman, 2004). Social alliance capital is concerned with the existence of network connections.

Teece (1992) found that investors, when evaluating a venture built on complex technology, tend to turn away from the actual product and instead turn towards social capital indicators to judge the quality of the venture. Interestingly, this also seems to apply to an ICO setting; causality was supported between the number of external advisors and whether the venture received ICO fundraising. Given that companies seeking funding through an ICO are built on complex emerging technology, it is perhaps unsurprising that external advisors have a causal relationship with successful ICO fundraising. Whether the causal relationship is due to investors valuing the availability of advisors because of the external technical advice they can bring, or because of endorsements, or both, is not possible to discern. However, the findings are clear: ICO investors value signals of social alliance capital, just as investors have been found to do in the entrepreneurial financing literature.

7.2.3 Product and artefacts

Although there is a tendency for investors to resort to other signals of quality when evaluating technically complex products, our findings suggest that the product itself still is important in an ICO setting.

The literature states that the product is often carefully described in the business plan, and mentions the business plan as being a standard artifact that must be available (Ford et al, 2007; Kirsch, 2009). Kirsch et al (2009) brought up the need to have a complete business plan, and given the unstandardized nature of ICO whitepapers, a measure used to evaluate this was the whitepaper's word count. A causal relationship was found between longer whitepapers—i.e. higher word count—and successful ICO fundraising. It is acknowledged that the length of a whitepaper is a rough measure for a number of concepts—product quality, standard artefacts, and preparedness—and therefore the causality found cannot be derived to a specific concept. However, we believe it to be of value for academia to know that the causality is there, and that ICO investors value quality signals from concepts beyond human and social capital.

7.3 Practical implications

7.3.1 Entrepreneurs

An increasing number of entrepreneurs turn to ICOs to fund their ventures. It is of crucial importance for these entrepreneurs to understand if they should, as a means to receive funding from this emergent mechanism, focus on developing and emphasizing the same venture quality signals towards ICO investors as they have been taught to do towards traditional equity financing investors.

This research shows that in order to receive ICO funding, entrepreneurs should ensure they have many years of work experience, attract a lot of external advisors, and present a lengthy whitepaper. Further, once above factors are addressed, two quality signals have been found to increase amounts raised drastically. Having at least one founder with previous venture founding experience increases funds raised with $5.22 million. Ensuring to have at least one founder with a technical Master's degree resulted in an average of $8.85 million more funds raised.

7.3.2 Policymakers

Given the potential of ICOs as a funding mechanism, we deem it unwise by authorities to ban ICOs; they could instead use this research's findings to build a foundation of required disclosures that are of value to investors and thereby mitigate risk.

7.4 Relevance of the study

Although the results cannot be scientifically generalized due to a non-probability sampling method used, the sample size was relatively large in contrast to the population, and should therefore be considered relevant to the academic discussion. By answering the research questions, we contributed to reduce the research gap in a new and evolving area. The study has both important academic conclusions, as well as practical implications for both entrepreneurs and policymakers. Taken together, we consider the study to have high relevance.

7.5 Limitations

A number of limitations of this study need attention. To begin with, entrepreneurial equity financing was chosen as the theoretical framework from which hypotheses were deduced. Another theory base could have been used, for instance theory related to Initial Public Offerings. However, as the research question takes the perspective of the entrepreneur, and not of a more mature company, it was decided that entrepreneurial equity financing theory was most applicable.

Also, as discussed in section 4.7, an inductive approach could have been used to generate theoretical insights about what signals of quality ICO investors value. It is possible, even likely, that this study did not create hypotheses related many important quality signals valued by ICO investors. This could have been avoided through conducting interviews with ICO investors to generate new theory, not currently in the entrepreneurial equity financing literature.

7.6 Suggestions for future research

As one of the first studies to investigate ICOs from an entrepreneurial financing perspective, we hope to encourage future research within this area. Building upon the previous section, we suggest future research to attempt to uncover signals of quality used in an ICO setting that are not currently in the entrepreneurial financing literature through using an inductive approach. This would create new theory that later can be tested deductively to ensure statistical validity by studies such as this.

Also building upon the previous section, entrepreneurial equity financing theory is not the sole area that can be used for deducing hypotheses, and we encourage other researchers to explore the potential in this further.

Two specific findings in the study invite to further research. The causal relationship between a lengthy whitepaper and successful ICO fundraising. Although it was statistically supported that a longer whitepaper led to higher chance of receiving ICO funding, this finding could not be derived to a specific concept. The same situation applies to the casual relationship between more advisors and a greater probability of raising funds in an ICO. Future research could explore these two findings by formulating more specific measures, and try to discern and isolate the underlying concept that cause the causality.

7.7 Concluding reflection

In addition to answering the research questions and to close the research gap we gave you a promise: to give an answer on whether the story of ICOs will be remembered as “The Emperor’s New Coins”. Five acknowledged signals of venture quality from entrepreneurial financing research have been found in this research on ICOs. Entrepreneurs and investors involved in ICOs seem to have more in common with their colleagues in other entrepreneurial financing settings than argued by some.

Instead of ending this thesis, and the story of “The Emperor’s New Coins”, as H.C. Andersen did, with a little child crying out: “But he hasn't got anything on!”, we propose another ending regarding the ventures attempting ICOs:

“But they look fully dressed!”

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9. Appendix

Appendix 1. JB Test Calculation

		Skewness		Kurtosis	
		Statistic	Std. Error	Statistic	Std. Error
Unstandardized Residual	112	0.758	0.228	1.342	0.453

JB test statistic:	**-2.114554478**
Critical value	5.991
	2df and p =
Critial value based on:	5%

Appendix 2. Correlation table

Appendix X. Correlations

	Funds raised	Number of co-founders	Years of working exp	Previous venture founding experience	Portfolio entrepreneur	Number of ICOs inv	Master's degree	MBA degree	PhD degree	Technical Master's degree	Mixed managerial and technical education	Female co-founder	Number of different roles	Team size	Descriptions of co-founders	Number of advisors	Roadmap	Number of females	Number of words	ICO funding received
Pearson correlations																				
Funds raised	1																			
Number of co-founders	0.151	1																		
Years of working experience	.196*	.700**	1																	
Previous venture founding experience	.372**	.576**	.536**	1																
Portfolio entrepreneur	0.098	.424**	.417**	.538**	1															
Number of ICOs involved in	0.047	.265**	.304**	.282**	.269**	1														
Master's degree	.382**	.440**	.399**	.438**	.269**	0.139	1													
MBA degree	.289**	.315**	.434**	.289**	.228**	.210*	.339**	1												
PhD degree	.250**	0.104	0.089	0.142	0.078	-0.028	.290**	-0.101	1											
Technical Master's degree	.353**	.308**	.330**	.302**	.202*	-0.044	.683**	.205*	.387**	1										
Mixed managerial and technical education	.325**	.459**	.372**	.292**	.198*	0.132	.484**	.497**	0.054	.441**	1									
Female co-founder	0.046	0.137	0.073	0.025	0.015	-0.003	0.017	0.114	0.040	-0.014	0.010	1								
Number of different roles	0.142	.174*	0.072	.203*	0.017	0.109	0.052	0.091	-0.041	0.030	-0.012	-0.001	1							
Team size	0.165	.177*	0.093	.224**	0.053	0.105	0.046	0.102	-0.056	0.009	-0.022	-0.003	.977**	1						
Descriptions of co-founders	0.164	.404**	.220*	.317**	0.097	.193*	.188*	0.167	-0.026	0.031	-0.032	.180*	.489**	.511**	1					
Number of advisors	0.097	.198*	.209*	.179*	0.059	.258**	.190*	0.076	0.052	.175*	0.110	0.027	.640**	.642**	.407**	1				
Roadmap	0.057	.214*	0.139	.224**	-0.015	0.118	0.132	0.074	-0.044	0.063	0.076	0.014	.415**	.386**	.361**	.293**	1			
Number of females	0.130	-0.069	-0.054	-0.010	-0.154	-0.081	-0.082	-0.036	-0.020	-0.010	-0.091	0.100	.725**	.725**	.223**	.507**	.248**	1		
Number of words	.365**	.321**	.373**	.274**	0.153	.203*	0.149	.217*	0.083	0.122	0.098	0.028	.300**	.339**	.260**	.298**	.176*	.314**	1	
ICO funding received	.325**	.322**	.313**	.405**	.265**	0.141	.282**	.187*	0.116	0.129	0.106	0.067	.257**	.273**	.243**	.244**	0.125	0.048	.336**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix 3a. Heteroscedasticity calculation, 1 / 2

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	.476a	0.227	0.220	278.64763

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-125.2396	589.8869	174.7555	150.23810	112
Residual	-464.85748	1664.43726	0.00000	277.38962	112
Std. Predicted Value	-1.997	2.763	0.000	1.000	112
Std. Residual	-1.668	5.973	0.000	0.995	112

a. Dependent Variable: Res_kvadrat

Hetero:	112*0.227	=	25.424
	n * R^2		

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

Appendix 3b. Heteroscedasticity calculation, 2 / 2

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	.236a	0.056	0.047	166.67913

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	39.3183	196.0751	104.7462	40.29205	107
Residual	-183.09001	998.14484	0.00000	165.89104	107
Std. Predicted Value	-1.624	2.267	0.000	1.000	107
Std. Residual	-1.098	5.988	0.000	0.995	107

a. Dependent Variable: Res_kvadrat

Hetero calculation:	107*0.056	=	5.992
	n * R^2		

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

Appendix 4. Coding Schedule (for all 136 ICOs)

Number	Variable	Variable value
1	Number of co-founders	
2	Years of working experience	
3	Previous venture founding experience	
4	Portfolio entrepreneur	
5	Number of ICOs involved in	
6	Master's degree	
7	MBA degree	
8	PhD degree	
9	Technical Master's degree	
10	Mixed managerial and technical education	
11	Female co-founder	
12	Team size	
13	Number of females	
14	Number of different roles	
15	Number of advisors	
16	Descriptions of co-founders	
17	Roadmap	
18	Number of words	

Appendix 5. Coding Manual

Variable	Type	Instruction
Number of co-founders	Continuous	Count the total number of co-founders as listed in the whitepaper. If no co-founders are mentioned, set value to 0
Years of working experience	Continuous	Go to the linkedin profiles of the co-founders mentioned in the whitepaper and count the total number of years of work experience since graduating university
Previous venture founding experience	Binary	If any of the co-founders on linkedin has the title of Co-founder or Founder as job description for a previous employment, set value to 1, else 0.
Portfolio entrepreneur	Binary	If any of the co-founders on linkedin has the title of Co-founder or Founder as job description for an employment still active set value to 1, else 0.
Number of ICOs involved in	Continuous	On the linkedin profiles of the founders, count the number of other ICO projects that the founder is active in, in any capacity
Master's degree	Binary	If any of the co-founders on linkedin has a recorded Master's degree, set value to 1, else 0.
MBA degree	Binary	If any of the co-founders on linkedin has a recorded MBA degree, set value to 1, else 0.
PhD degree	Binary	If any of the co-founders on linkedin has a recorded PhD degree, set value to 1, else 0.
Technical Master's degree	Binary	If any of the co-founders on linkedin has a recorded technical Master's degree, set value to 1, else 0.
Mixed managerial and technical education	Binary	If any of the co-founders on linkedin has a recorded technical Master's degree, and one of the other co-founders has an MBA degree or similar business degree BSc or above, set value to 1, else 0.
Female co-founder	Binary	If any of the co-founders are female, set value to 1, else 0.
Team size	Continuous	In the whitepaper, count the number of team members mentioned.
Number of females	Continuous	In the whitepaper, count the number of female team members mentioned.
Number of different roles	Continuous	In the whitepaper, count the number of different roles mentioned.
Number of advisors	Continuous	In the whitepaper, count the number of advisors mentioned.
Descriptions of co-founders	Binary	If the co-founders are described in more than one sentence in the whitepaper, or similar, set value to 1, else 0.
Roadmap	Binary	If the whitepaper has a roadmap or milestone, or similar mentioned, set value to 1, else to 0.
Number of words	Continuous	Count the total number of words by importing the whitepaper into Microsoft Word.