The determents of the failure of Icos

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Année académique : 2021-2022
URI/URL : http://hdl.handle.net/2268.2/15679

THE DETERMENTS OF THE FAILURE OF ICOS

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For a Master in Management, with a specialization in Financial Analysis and Audit
Academic year 2021/2022

Contents

1 Abstract

Initial coin offerings are a new and innovative form of corporate financing, in which a venture finances itself through the sale of digital tokens to a crowd of investors. This new approach is enjoying increasing popularity since investments can promise extremely high profits. Recently however, accusations of a lack of transparency, high levels of uncertainty, risk, and fraud have increased. This thesis considers the phenomenon of the ICO from the perspective of the investor and asks the question: Which determents lead to the failure of ICOs? What does the investor have to consider avoiding a loss of his investment?

This thesis argues that ICOs initiated by high-quality ventures with a skilled team and a serious business model have a lower likelihood of failure. Building on Signaling Theory (Spence, 1973) it suggests that these high-quality ventures can demonstrate their superiority to investors via specific signals. The lack of such signals can thus be considered as “red flags” and therefore as determents for the failure of ICOs.

Using a binary logistic regression based on a dataset of 1,288 ICOs, some of these determents could be identified. It was found that the lack of activity on certain niche social networks forms such a determent of failure. The same goes for missing activity on the source code platform Github and the aggregated ICO rating of different websites. For low ratings, a low number of team members could be found as an additional indicator for failure. The same goes for low ratings itself. The host country of an ICO being a tax haven, surprisingly, has been identified not positively, but rather negatively related failure. Finally, the existence of a KYC whitelist, in which token buyers can identify themselves to gain preferential access to token sales, was found to be significantly negatively related with the failure of ICOs.

The results of this study contain important information for investors but also regulators. They help to identify and better understand important determents of the failure of ICOs. This reduces the great uncertainty associated with ICOs. It helps ICO investors make better investment decisions and regulators to better understand the risks of ICOs.

2 Introduction

The objective of this thesis is to identify the determents of the failure of Initial Coin Offerings (ICOs). ICOs are a new, innovative form of corporate financing: A company sells digital tokens to investors, who can then participate in the company's future development. Intermediaries like banks are no longer required. ICOs have been enjoying a lot of popularity lately. However, the market suffers from high uncertainty and asymmetric information. ICO investments can generate very high profits but are also subject to high risk. There is a lack of regulation, of disclosure verifiability, and the entrepreneur often has a limited track record (Howell et al., 2020). Concerns are rising, from investors, but also from governments and regulators (Shrestha, Thewissen and Torsin, 2022, p. 2) To reduce this uncertainty and to determine the factors of failure for ICOs, further research is needed.

The determents of the success of ICOs have already been the subject of previous studies. However, the term "success" can be viewed from different angles. Ante, Sandner and Fiedler (2018), differentiate between "the perspective of (1) startups; (2) individual investors; and (3) social welfare" (Ante, Sandner and Fiedler, 2018, p. 1 et seq.). Previous works mostly look on the ICOs success from the startup's perspective, defining it by the amount of money that is raised during the ICO. This thesis aims to go a different way. Building on the work of Conlon and McGee (2021), Liebau and Schueffel (2019) and Pastwa et al. (2021/18), it analyses the success of ICOs from the investor's perspective. Investors can consider their participation in an ICO as successful if they receive a positive return on investment (ROI). However, the exact ROI of an ICO is often difficult to quantify and might vary between the different investors. Conlon and McGee, (2021, p. 6) deal with this by concentrating on fraud. They argue that, for a successful investor, it is particularly important to avoid ICOs that turn out to be fraudulent. However, fraud depends on moral intensions, and it is often difficult to examine weather the ICO-initiator initially had good intentions or not. Therefore, this thesis concentrates on the overall quality of the ICO-initiating venture, to explain its failure. It argues that from the investor's perspective it is immaterial whether the ICO fails is due to intentional fraud, incompetence of the venture team, a poor business model or just bad luck. The investor will just want to know whether the ICO he invests in will fail or succeed. Therefore, this thesis aims to answer the following question: What are the determents of the failure ICOs?

To answer this question, this thesis is building on signaling theory (Spence, 1973). It argues that ICOs initiated by high-quality ventures with competent teams and serious business models can send signals of their superiority to investors. ICOs of low-quality ventures with incompetent teams and poor or fraudulent business models instead, are not able to do so. Good signals are characterized by the fact that they are cheap to communicate for high-quality ICOs, but very costly to fake for low-quality ICOs. The absence of such signals should therefore be interpreted by investors as a "red flag" indicating a low-quality venture. This thesis argues that the avoidance of investments in low quality ventures decreases the likelihood of failure.

ICOs are a technology-intensive form of corporate financing, often used by innovative and tech-focused companies. Therefore, it is assumed that high-quality ventures initiating ICOs must have a high competence in technology, an innovative business model and a very skilled workforce. It is additionally assumed that high-quality ventures strive to reduce the high information asymmetry between them and the investor to communicate their superiority. Low-quality ventures, on the other hand, do not have this interest and try to hide their inferiority behind the low transparency of the ICO-process.

Based on these assumptions, this thesis proposes different factors as signals for high-quality ICOs. Their absence will be considered as a determent for the failure of ICOs.

It is argued that the activity on certain social media can work as a signal for high-quality ventures. Through social media activity, ventures directly connect with potential investors. This can reduce information asymmetry and thus increase the likelihood of investments in ICOs that will be successful in the long term.

This argumentation is based on the literature. Fisch (2019) e.g. identifies an increased Twitter activity as a positive factor to explain the amount raised by the venture (compare: Fisch, 2019, p. 3). Amsden and Schweizer (2018) found that "not being on [...] Telegram" correlates negatively with the tradability of the issued token, which is how they define the ICO' success (Amsden and Schweizer, 2018, p. 1). The "Additional Indicators from websites and ICO Rating Sites" collected by Conlon und McGee, (2021) strongly advise the investor to consider the "sentiment of the community in social media" and "the level of engagement from the team with members of the ICO community online" (Conlon and McGee, 2021, S. 16).

However, this thesis argues that not all social networks are equally suitable for this purpose. The decisive factor is the cost of this signal for low-quality ventures. Therefore, only the activity on certain niche social networks in which a close communication with an ICO-interested community is required is suggested as a signal.

The white paper is the central document explaining the ventures business model to be implemented through the ICO. This thesis argues that high-quality ventures can signal their superiority by writing a technical, accurate and high-quality white paper, while low-quality ventures are not able to do so. Writing such a paper requires the detailed description of an ingenious business model. This brings low costs for high-quality ventures that just have to describe their developments. Low-quality ventures however cannot describe what they did not develop. And faking of the detailed description of a high-quality business model would mean to actually develop one what would make them a high-quality venture. The lack of a high-quality white paper is thus proposed as a determent for the failure of ICOs

The suitability of the white paper as such a determent is also based on the literature. Fisch (2019) found out, that a technical white paper was leading to a higher amount of funding. (compare: Fisch, 2019, p. 3). Conlon and McGee (2021) as well as Howel et al. consider the fact whether the white paper provides a budget (Conlon and McGee, 2021, p. 16) as important determent.

The source code of an ICO forms a significant indicator of the programming skills of the ICO team. Investors with computer science knowledge can deduce a lot about the ICO-venture and its quality from the source code. This thesis argues that a high-quality source code is a signal for a skilled workforce and thus a high-quality ICO-venture that is unlikely to fail. Inferior or unpublished source codes instead are a sign of an unskilled workforce and thus a low-quality ICO-venture that is likely to fail. The importance of the source code is mentioned by various authors. Fisch (2019) found out, that a high-quality source code was leading to a hinger amount of funding (compare: Fisch, 2019, p. 3). Conlon and McGee (2021) consider whether the project code is publicly available (e.g., on Github) as an important success factor (Conlon and McGee, 2021, p. 16). Also, they advise the investor to check the "activity on the source code repository, if available (as a measure of adoption)" (Conlon and McGee, 2021, p. 16). And Amsden and Schweizer (2018) argue that "not being on **Github**" where ICO source codes are generally published, leads to a lower tradability of tokens (Amsden and Schweizer, 2018, p. 1).

Great importance can also be attached to the team behind the ICO. The source code and the business plan, which can be found in the white paper, have already been mentioned as important factors. Both depend on the quality of the team. This thesis argues that the experience, the human capital and the knowledge of computer science in the ICO team are important factors for the overall quality of the venture and have great influence on whether the ICO will be a failure. Various sources emphasize the importance of the ICO team. Ante, Sandner and Fiedler (2018) found out, that "human capital characteristics, […] [have] a positive influence on the collected amount of capital (Ante, Sandner and Fiedler, 2018, p. 1). Conlon and McGee (2021) advise the ICO investor to verify whether "the issuing team include significant experience in computer science" (Conlon and McGee, 2021, p. 16), to check “the background and experience of the leadership of the project” and “the background and experience of the development team (as a measure of their capability but also signals commitment from knowledgeable industry people)” (Conlon and McGee, 2021, p. 16).

This thesis argues that high-quality ventures with a serious business model are more likely to attract a skilled workforce. Additionally, they also are more in need of a big and smart team to implement their strategy. Low-quality ventures are less attractive for highly skilled programmers and technology experts. Also, there is no need for them to develop a simple, poor or even fraudulent business model. And if the business model actually is fraudulent, the founders can have no interest in a big team that might talk, and with them they might have to share their profit with. Therefore, it is suggested that the team size serves as a signal for the overall quality of the venture. This is why ICOs initiated by ventures with small teams are assumed not to be of high-quality and thus more likely to fail.

Soft cap refers to the minimum amount that must be achieved in the sale of tokens during the ICO for the venture’s business model to be carried out. Hard cap refers to the maximum number of tokens that can be issued during the ICO. This thesis argues that the implementation of soft caps and hard caps shows that the venture has very exact plans of how much they have to raise for implementing their business model. That shows the serious intentions of the venture and reduce uncertainty in the ICO process. As argued before, only high-quality ventures can have an interest in reducing this uncertainty. Also, the implementation of hard caps and soft caps causes additional effort and costs. Costs that are not worth incurring for low-quality ventures with poor business models that benefit from uncertainty. This argument is also based on findings in the literature. Amsden and Schweizer (2018) found out, that “a hard cap in a pre-ICO [is able to] […] help investors […] to measure success in the pre-sale. (Amsden and Schweizer, 2018, p. 1).

Various websites issue ICO ratings in which they evaluate ICOs (and the initiating ventures) according to different criteria. These websites are usually run by crypto enthusiasts who have a certain standing in the crypto community. This thesis argues that these crypto-enthusiasts have the knowledge and experience to distinguish high-quality ventures with a highly skilled team and a serious business model from low-quality ventures with a low-skilled team and a poor business model. It is assumed that this will be reflected in the ratings accordingly. A high ICO rating can therefore be perceived as a positive "seal of approval" by the crypto community. The ICO initiating ventures have no influence on the rating. It is not assumed that they do manipulate the rating via bribery or similar. High-quality ventures on the one hand have no need to do this. They can assume that the website operators recognize their superiority and provide them with a positive rating. For low-quality ventures on the other hand, influencing the rating would involve immense costs. In addition, there is a large number of rating websites. To change the community's mind on an ICO, it would be necessary to influence most rating websites, which seems unlikely. Therefore, this thesis proposes an aggregated high ICO rating from different websites as a signal for high-quality ventures. A low ICO rating, on the other hand, would indicate a low-quality venture whose ICO will probably lead to failure. This approach is also based on the work of Pastwa et al. (2021/18), who created an aggregated ICO rating based on various websites.

The country in which the ICO is held can also be considered an important feature. This thesis takes this into account by building on the work of Shrestha et al. (2021). “Drawing on psychological theories on cognitive bias, […] [they] propose […] one heuristic by which investors [can] assess an ICO’s trustworthiness […] [via] the reputation of the ICO’s country of origin, which [they] proxy as institutional strength.“ (Shrestha et al., 2021, p. 1). Based on this approach, this thesis argues that countries with a higher reputation and stronger institutions tend to be preferred by high-quality ventures. Since they are characterized by a serious business model, they have nothing to fear from the strong institutions in strong countries. On the contrary, these countries good reputation can help signal the seriousness of the business model to investors. Moreover, high-quality ventures depend on highly skilled employees. It can be assumed that they are more likely to be found in countries with a high reputation. Also, for high-quality ventures, the choice of a country with a high reputation does not represent an additional cost factor. It is assumed that the venture will settle in such a country anyway to carry out the ICO.

Low-quality ventures with a poorly trained workforce and a poor business model have more of an interest in hiding their weaknesses. Therefore, it seems more attractive for them to operate in a country with weak institutions. So, this thesis suggests an ICO host country with a high reputation as a signal for high-quality ventures, countries with a low reputation thus as a sign for low-quality ventures, that are likely to fail. The host country is thus suggested as a determent for the failure of ICOs. Building on the work of Pastwa et al. (2021/18) the Human Development Index and whether the country is considered as a tax haven is used as indicators of the country's reputation.

Also building on Shrestha et al. (2021) the regulation of ICOs is examined. Here, the idea is not to regard the reputation of the country as a proxy for the strength of its institution. Instead, the existing regulation by the institutions itself is examined. The idea is that high-quality ventures are more likely to be regulated. They pursue a serious business model and are (as shown above) more likely to be active in strong countries where regulation is present. Also, they have nothing to fear of the regulation. Thus, being regulated can serve as a signal of high-quality to investors. low-quality ventures, on the other hand, will be strongly tempted to circumvent regulation to hide their inferiority. This is why it is assumed that ICOs held by ventures with no regulation are likely to fail.

If ICOs have been regulated, however, the result of the regulation must also be taken into account. It can be assumed that the regulating institutions correctly recognize low-quality ventures. A restricted or banned ICO is therefore considered a strong indication of a low-quality venture, that is likely to fail.

Again, to verify these assumptions, this thesis adapts the dataset by Pastwa et al. (2021/18) that provides detailed information on the regulation of ICOs.

Finally, the Whitelist KYC is proposed as a signal for high-quality ventures. The Whitelist forces investors to register and to provide personal data before they can participate in the ICO. This increases transparency and reduces the uncertainty in the ICO process. As argued before, only high-quality ventures can have an interest in the reduction of this uncertainty. The implementation of such a Whitelist brings additional costs that low-quality ventures are unlikely to want to incur. Therefore, this thesis regards a KYC Whitelist as a signal for high-quality ventures. A lack of a Whitelist is thus regarded as a signal for a low-quality venture and therefore proposed as a determent for the failure of ICOs.

The hypotheses listed above will be transformed into a data set and tested with statistical methods. In addition to the determinants proposed based on signaling theory (Spence, 1973), control variables are included in the study. These were derived from the dataset of Pastwa et al. (2021/18). In detail, variables concerning the token issued during the ICO, the circumstances of the ICO and whether a video was published are considered.

The listed factors are to be tested with the help of a multivariate data analysis in order to verify whether the failure of an ICO can actually be determined with these factors. For this purpose, a binary logistic regression was performed, where the dependent variable is a binary dummy variable that indicates whether the ICO was a success or not. The factors listed above were examined using various independent variables. The multivariate model was run on a dataset of 1,288 ICOs, building on the work of Pastwa et al. (2021/18). It only includes data from ICOs that were conducted before December 31, 2017. This was done in order to decide ex post which of the ICOs carried out at that time can be classified as a failure today. In this thesis, an ICO is considered a failure if the venture financed by it no longer exists at the time of the study (March 2022). This was determined by the objective criterion of the tradability of the token issued in the ICO.

Based on this binary multivariate regression, it was found that the activity on a certain niche social network actually is negatively related with failure of ICOs. Approx. 70% of all ICOs have a Facebook account, however Facebook could not be found as a good indicator. Instead, the activity on the niche network Reddit was found as a determent significantly negatively related with the failure of ICOs. This is explained by Reddit being a social network strongly used by experts and enthusiasts of certain topics. Thus, ICO investors should particularly consider to inform themselves via Reddit before investing into ICOs. The same goes for the activity on the source code platform Github. Investors with good knowledge in computer science should consider to check the quality of the source code on Github. However, investors with no such skills can still regard the presence of a Github account for the ICO as a positive signal. This is the case since it only makes sense to publish high quality source codes. Regulators may want to require the publication of the source code in the future. The ICO ratings of different websites can also be found as a good indicator for the ICOs becoming or not becoming a failure. For low ratings additionally, the number of team members could be found as an indicator. The smaller the team the higher the likelihood of failure. The ICO host country being a tax haven interestingly decreases the likelihood of failure. However, this can possibly be attributed to the fact that the tax havens in the sample studied are primarily very highly developed countries such as Singapore and Switzerland. Finally, the existence of a KYC whitelist, in which token buyers can identify themselves to gain preferential access to token sales, was also found to be significantly negatively related with the failure of the ICO. This seems very logical, as the whitelist forces token investors to disclose their identity. This increases transparency and reduces the uncertainty of ICO investments. ICO investors should therefore consider reducing their exposure to ICOs with KYC whitelists. Regulators may want to require them in the future.

3 Literature review

3.1 Objectives and introduction

This chapter introduces the reader into the subject of ICOs. To do so, it will discuss the definitions of different key terms in crypto technology, explain the phenomenon of the ICO and give an overview over the current literature on this topic. It will start by discussing the phenomenon of cryptocurrencies in a broader sense, explain and differentiate the terms of Distributed Ledger and blockchain technology as well as the difference between a token and a crypto coin. It will then continue by providing a general overview of the ICO, explaining the function, the challenges, and threads in this new way of corporate financing. Finally, an overview and a summary of different the different analyses and findings of the current literature will be given.

3.2 What is Distributed ledger technology (DLT)?

ICOs are a new and innovative way of financing companies by selling crypto tokens to the public. It allows the token holders to participate in the company's future development and allows the company to gather funds without a costly intermediary. To understand this new way of financing, it is firstly crucial to get familiarized with the concept of a token. Therefore, the differentiation between a token and a cryptocurrency must be made. Both the token and the coins of cryptocurrencies are based on a disruptive new technology, the blockchain. And the blockchain itself is widely considered as a sub-form of a broader technology, the so-called Distributed Ledger Technology (DLT). This is why this literature review first tries to clarify the concept of DLT.

A general and universally accepted definition of DLT has not yet been found. Different actors and researchers have delt with the phenomenon and have come to different approaches. The following abstract gives an overview of the multiple definitions and aims to summarise its possible similarities.

In its 2017 report "Distributed Ledger Technology (DLT) and Blockchain", **the World Bank** describes DLT as a "novel and fast-evolving approach to record and sharing data across multiple data stores (ledgers), which each have the exact same data records and are collectively maintained and controlled by a distributed network of computer servers, which are called nodes" (Natarajan et al., 2017, p. 1). It is further explained, that DLT "allows for transactions and data to be recorded, shared, and synchronized across a distributed network of different network participants" (Natarajan et al., 2017, p. IV). To give an even simpler approach, the report states, that "One way to think about DLT is that it is simply a distributed database with certain specific properties (see section 3)" (Natarajan et al., 2017, p. 1).

The European Central Bank describes DLT as a technology, that "allow[s] their users to store and access information to a given set of assets and their holders in a shared database of either transactions or account balances. This information is distributed among users, who could then use it to settle their transfers of e.g. securities and cash, without needing to rely on a trusted central validation system" (Pinna and Ruttenberg, 2016, p. 8).

It can be noted that both the World Bank and the European Central Bank are having a quite general view on DLT, namely as a technology for decentralised data storage.

The Bank of England (BOE) additionally differentiates between distributed ledger technology and distributed ledgers (DL). It refers to DLT as „a database architecture which enables the keeping and sharing of records in a distributed and decentralized way, while ensuring its integrity through the use of consensus-based validation protocols and cryptographic signatures" (Benos et al., 2017, p. II). Here, the BOE is particularly addressing to the potential of DLT, namely "the potential to reduce costs and increase the efficiency of securities settlement, the ultimate step of every security transaction" (Benos et al., 2017, p. II).

While the BOE generally regards DLT as a database architecture, it defines DL as "a distributed database, in the sense that each node has a synchronized copy of the data". (Benos et al., 2017, p. II) But it also states, that DL "departs from the traditional distributed database architectures in three important ways:

1. *Decentralisation:* The control of the database (read/write access) is decentralized; that is, it is performed by multiple (or all) network participants. There is no need for a central administrator to ensure the integrity of the data or its consistency across nodes. Instead, this is achieved through some consensus mechanism or validation protocol.

2. It is reliable in trust-less environments: The consensus mechanism ensures the consistency and integrity of the database even if the parties involved do not fully trust each other.

3. Cryptographic encryption: The ledger uses cryptographic encryption tools to deliver (1) and (2) above" (Benos et al., 2017, p. 5).

The researchers **Davidson et al. (2016)** describe DLT as „a distributed, cryptographically secure, and crypto-economically incentivized consensus engine" (Davidson et al., 2016, p. 2).

And **Tasca and Tessone (2018)** describe DLT as "community consensus-based distributed ledgers where the storage of data is not based on chains of blocks" (Tasca and Tessone, 2018, p. 3).

As indicated, DLT is generally regarded as the generic term for the more specific blockchain technology. This can also be substantiated by statements such as, for example, by Rauchs (2018) who states that DLT "has established itself as an umbrella term to designate multi-party systems that operate in an environment with no central operator or authority, despite parties who may be unreliable or malicious ('adversarial environment'). Blockchain technology is often considered a specific subset of the broader DLT universe that uses a particular data structure consisting of a chain of hash-linked blocks of data" (Rauchs, 2018, p. 15).

However, there are also few researchers who equate or "do not differentiate between 'DLT and blockchain" (Rauchs, 2018, p. 20).

Cong and He (2018), for example describe the blockchain as a "distributed database that autonomously maintains a continuously growing list of public transaction records in units of "blocks," secured from tampering and revision" (Cong and He, 2018, p. 7) without referring to the broader concept of DLT.

However, most of the literature differentiates between DLT and blockchain, with blockchain being viewed as a sub-are of DLT. This thesis will also follow this approach. The exact functionality of the blockchain and how it differs from the broader concept of DLT is discussed in the next chapter.

Although a general definition for DLT has not yet been established in the literature, the general function can be summarized as follows:

It is a technology used for the documentation of (transaction) data. It characterized by the non-existence of a central ledger. Instead, the data are stored decentralized in as many ledgers with as many identical copies as desired. The technology is designed in such a way, that new (transaction) data are immediately registered by all ledgers. Additionally, it is insured that the entries in the decentralized ledgers are identical at a given time.

At this point, it should also be mentioned, that DLT can be further subdivided in "open/permissionless or permissioned [systems], and there are fundamental differences between these two types, which lead to very different risk profiles" (Natarajan, 2017, p. IX). Permissionless DLs are characterized by the fact, that "there is no central owner who controls network access. All that is needed to join the network and add transactions to the ledger is a computer server within the relevant software" (Natarajan et al., 2017, p. IX) "permissionless DLs […] [are] achieved through cryptographic and algorithmic solutions which ensure that anonymous network participants are incentivized to enforce accuracy of the ledger, without the need for barriers to entry or trust among participants" (Natarajan et al., 2017).

In permissioned DL systems however, "network members are pre-selected by an owner or administrator of the ledger who controls network access and enforces the rules of the ledger" (Natarajan et al., 2017). They "are better at resolving issues related to identify verification and data privacy but they require a central entity that regulates access, which creates a potential target for cyberattacks. Permissioned systems can also potentially fit more easily into existing legal and regulatory frameworks and institutional arrangements" (Natarajan et al., 2017, p. X).

3.3 The Blockchain

3.3.1 Introduction to the Blockchain

The blockchain is generally considered as "The most common type" (Fisch 2019, p. 3) of distributed ledger technology. While the idea of DLT has its roots in the system theory, that goes back to the 1940s (compare: Rauchs, 2018, p. 17 et seq.) (but could not really be applied until the advanced development of the computer) the blockchain-based DLT is a very recent phenomenon, that was "first applied as the underlying technology of the cryptocurrency Bitcoin" (Natarajan et al., 2017, p. IX) in the year 2008. This section seeks to explain the function of the blockchain technology and tries to draw the connection between DLT and blockchain.

DLT is characterized by the fact that the sequence of (transaction) data is stored identically in several decentralized ledgers. In addition, a system must be introduced, that prevents subsequent changes of the data. Therefore, the data in the ledgers must compared with each other regularly, to ensure that no manipulation has taken place. If the data in one or more ledgers derivate from another, it must be determined which data sequence is now considered as the true one. Only if this is the case, a third, central authority, is no longer required. However, the DLT itself does not deliver an answer or technology to solve this problem. This is the point where blockchain comes into play.

While there is no universally accepted definition for DLT, the blockchain phenomenon can be narrowed down very precisely. It was firstly described in "a landmark paper was written by an yet unidentified person using the pseudonym Satoshi Nakamoto, "Bitcoin: A Peer-to-peer Electronic Cash system" (Natarajan et al., 2017, p. IX) in the year 2008. It "proposed a novel approach of transferring "funds" in the form of "Bitcoin" in a P2P manner. The Underlying technology for Bitcoin outlined in Nakamoto's paper was […] [the] Blockchain" (Natarajan et al., 2017, p. IX).

As illustrated, the origin of the blockchain can be traced back very precisely to the paper of Satoshi Nakamoto. It explains in a very detailed manner, how this technology works. However, it is written very technically and the term "blockchain" itself is not mentioned in the paper (Compare: Nakamoto, 2008, p. 1 et seq.) Therefore, there have been numerous attempts in the literature to describe or define the phenomenon of the blockchain more precisely.

The World Bank describes blockchain as "a particular type of DLT, [that] uses cryptographic and algorithmic methods to create and verify a continuously growing, append-only data structure that takes the form and a chain of co-called 'transaction blocks' – the blockchain – which serves the function of a ledger" (Natarajan et al., 2017, p. 1) or as " a particular type of data structure used in some distributed ledgers which stores and transmits data in a package called "blocks" that are connected to each other in a digital ‘chain’. Blockchains employ cryptographic and algorithmic methods to record and synchronize data across a network in an immutable manner” (Natarajan et al., 2017, p. IV).

Rauchs (2018) also considers “Blockchain technology […] [as] a specific subset of the broader DLT universe that uses a particular data structure consisting of a chain of hash-linked blocks of data” (Rauchs, 2018, p. 6).

The Bank of England refers to blockchain as “a particular architecture of a DL [=distributed ledger] whereby data are batched into a sequence of blocks linked to each other using cryptographic tools. This dependence of the various blocks of data on the previous blocks makes it extremely difficult to retroactively alter the database [This is because of one wanted to alter data in a block, one would also alter all the subsequent blocks]. Thus, the blockchain forms a perpetual chain od immutable blocks” (Benos et al., 2017, p. 6).

The European Central Bank defines the blockchain as the “basis for the virtual currency Bitcoin”, that “combines the idea of sequentially records in an immutable “hash-chain” with anti-spam algorithms and novel economic incentives, in a way that allows users (who are authenticated by means of pseudonyms) to transfer tokens between themselves while avoiding central authorities and censorship tools. (Compare: Nakamoto, 2008, p. 1 et seq.)”

Tasca and Tessone (2018) write, that “Blockchain allows new forms of distributed software architecture to be developed where networks of untrusted (and sometimes corrupted) participants can establish agreements on shared states for decentralised transactional data in a secure way and without a central point of control or regulatory supervision. Blockchain ensures trust among anonymous counterparties in decentralised systems without the need of central supervisor authorities in charge of verifying the correctness of the record in the ledger” (Tasca and Tessone, 2018, p. 2).

Ghiro et al. (2021) point out, that there are primarily three elements “that distinguish […] [the blockchain] from other distributed ledger technologies: *immutability, transparency* and *anonymity*” (Ghiro et al., 2021, p. 1) *Immutability* means, that the blockchain has to rely “on a STRONG DISTRIBUTED CONSENSUS PROTOCOL” (Ghiro et al., 2021, p. 1) that secures it from “attacks, and further frees the system from cenztralized trusted authorities (e.g., banks)” (Ghiro et al., 2021, p. 1). *Transparency* means, that “ a FULL and PUBLIC HISTORY OF TRANSACTIONS, which permits their distributed and completely transparent validation” (Ghiro et al., 2021, p. 1) is guaranteed. And *Anonymity* means, that the blockchain is “OPEN TO ANONYMOUS USERS […] [and therefore] preserve[s] users privacy” (Ghiro et al., 2021, p. 1).

As we have seen above, the literature largely agrees on the point, that the blockchain is a special sub form of DLT. DLT itself however, as described above, gives no answer to following two questions: How does the system of decentralised ledgers protect itself against manipulation of its data. And if the data in the decentralised ledgers differ, how is it determined which ledgers contain the true data. The blockchain solves these problems by storing the series of data in smaller entities, so called blocks. These blocks are protected with so-called hashes, whereby the hash code of the previous code always becomes part of the next block. This creates a chain of blocks, a blockchain. The function of this blockchain is based on a strong distributed census protocol, enables a full and transparent overview of the whole data series and guarantees the anonymity of its users (compare: Ghiro et al., 2021, p. 1).

Based on the work of Brownworth (2016), the exact function of the blockchain will be explained in more detail below.

3.3.2 Hash function

The very basis for the blockchain is the so-called hash-function (compare: Nakamoto, 2008, p. 1). A hash function (also hash algorithm) is "a major tool in cryptography" (Merkle, 1990, p. 1). It has the property, that it can cover any data set into a unique hash. A hash is a code that consists of a series of numbers and letters with a certain length.

If the same data set is entered into the same hash function, the generated hash will always be identical. However, if only a minor thing at the data set is changed, a completely different hash is created. Therefore, it can also be described as the fingerprint of a data set. The form of the data set thereby is not relevant, it is both applicable to a single character or document of hundreds of pages. Also, the length of the data set does not influence the length of the hash. Hash functions only work in one direction. Thus, the hash value cannot be used to regenerate the original data set. Good hash functions are also characterized by the fact, that the same hash value can never be generated from two different data set (compare: Merkle, 1990, p. 1 et seq.)

3.3.3 Block

A block is a unit in which data can be stored. It consists of the block's number, a so-called nonce, the data unit, the hash of the data unit and the hash of the previous block. In principle, all possible data can be stored in a block. In the case of Bitcoin or other cryptocurrencies, it contains the data of payment transactions. From these transaction data, a hash value is generated, which forms the hash value from this block. In order to release a block and the transactions it contains; the hash of the block must take a certain form (e.g. a certain number of zeros at the beginning). This is achieved with the nonce. The nonce is the separate block's number, that flows into the hash function in addition to the data set. Therefore, it is necessary to calculate the nonce which, together with the data set, generates the desired hash. This process of calculating the appropriate nonce is called mining.

3.3.4 Blockchain

A blockchain is basically a string of multiple of the data blocks described above. However, the blocks are now described by the fact that the hash of the previous block flows into its hash (in addition to the nonce and its data set). This creates a chain of blocks, a blockchain.

If the data set of a block is subsequently changed, this has the following consequences: The hash is changed. It no longer has the desired form (e.g., the zeros at the beginning). The mining process must therefore be repeated and a nonce must be calculated. However, since the hash of the current block also flows into the following block, its hash also has been changed. Therefore, if an entry in a block is to be changed, it is necessary to repeat the mining process in all subsequent blocks.

3.3.5 Distributed blockchain

A distributed blockchain is created, when blockchain technology and DLT are linked together. A network of several distributed ledgers is created, with the individual ledgers being structured as a blockchain. Every transaction made in the network is simultaneously saved on all distributed blockchains.

It is therefore possible to verify the correspondence of all blockchains by comparing the last hashes of the last blocks in each case. If they are identical for all blockchains in the network, no manipulation has occurred.

If an already recorded transaction is to be subsequently manipulated, not only the block and all subsequent blocks of the blockchain, but 51% of all the distributed blockchains in the network had to be changed and re-mined. As soon as the blockchain network reaches a certain size, subsequent manipulations become virtually impossible. In this way, the security questions of the DLT are solved and a central authority in the network can be avoided (compare: Nakamoto, 2008, p. 1 et seq.).

3.4 Tokens and Cryptocurrencies

In the previous section, it was explained how a distributed blockchain network works. Distributed blockchains form the basis for Bitcoin (compare: Nakamoto, 2008, p. 1 et seq.) and other cryptocurrencies. While the units of cryptocurrencies are usually referred to as coins, regarding ICOs, we normally use the term token. In this section, the phenomenon of the token is to be examined in more detail. Also, they will be distinguished from the concept of the coin and the cryptocurrency.

The literature has suggested various definitions of a token.

Fisch (2019) for instance describes them as "units of value intended to provide utility or to function as securities (Sameeh, 2018, p. 1 et seq.)" (Fisch, 2019, p. 3).

The World Bank refers to them as "a representation of a digital asset […] [that] typically does not have intrinsic value but it is linked to an to an underlying asset, which could be anything of value" (Natarajan et al., 2017, p. IV).

In summary, they can be referred to as a digital unit of value, which can take very different forms. It can serve as a bond, a share, another form of profit participation right or as a representation for a physical asset. If these tokens are part of a distributed blockchain network that is used for monetary transactions, "these tokens are cryptocurrencies, that are meant to function as a currency (in the ventures own ecosystem)" (Fisch, 2019, p. 3).

3.5 What is an ICO?

After the basic concepts of cryptofinance have been explained in the previous sections, the focus should now be on the main topic of this thesis: the ICO. The term ICO (=Initial Coin Offering) is based on the term IPO (Initial Public Offering). An IPO is the process in which the shares of a company are offered for sale on a stock exchange for the first time. The company can gather funds through the sale of its shares and the shareholders can participate in the future economic development of the company.

An ICO is very similar to an IPO. It differs in the fact, that the company does not sell shares, but instead tokens to the investors. Additionally, the sale does not take place via a central instance (a stock exchange) but via a decentralized network of distributed blockchains.

Fisch (2019) describes an ICO "(also referred to as "crowd sale" or "token sale"), [as a process in which] ventures [can] raise capital by issuing and then selling tokens to investors" (Fisch 2019, p. 3). In this way Fisch (2019) points out, that ICOs are particularly by young and technology intensive companies (ventures).

This is also affirmed by **Shrestha, Thewissen and Torsin (2022)**, who defies ICOs as "an innovative blockchain-based funding mechanism, and have become prominent in the venture capital market" (Shrestha, Thewissen and Torsin, 2022, p. 1). The Venture capital market is the part of the financial market through which ventures usually gain financing. It is dominated by so-called venture capital companies, which are ready to finance the still young and very risky ventures. For this, however, the VCs demand large shares and an extensive influence over the venture. By carrying out an ICO, ventures are able to finance themselves without VCs.

Fisch (2019) also emphasizes the relatively recency of ICOs. As he states, "The first ICO was conducted in July 2013 by Mastercoin, a digital currency built on Bitcoins blockchain (Shin, 2017, p. 1 et seq.). Since then, hundreds of ICOs have followed. As of September 2018, CoinShedule reports that 366 ICOs took place in 2017, raising a combined USD 6.2 bn. The 2017 funding volume was already surpassed in the first quarter of 2018 alone, where 254 ICOs raised USD 7.8 bn. By contrast, the premier crowdfunding platform Kickstarter has raised a total of USD 3.9 bn since its inception in 2009 (Kickstarter, 2018)" (Fisch, 2019, p. 3). He refers to ICOs as "a mechanism through which new ventures raise capital by selling tokens to a crown of investors. Often, this token is a cryptocurrency, a digital medium of value exchange based on distributed ledger technology (DLT)" Also, he points out that „While DLT, blockchain technology, and cryptocurrency are potentially revolutionary innovations within the monetary and technological fields (e.g., Elnaj, 2018, p. 1 et seq.; Swan, 2015, p. 1 et seq.), ICOs represent an innovation in entrepreneurial finance. In an ICO, investors buy tokens directly from a new venture; these tokens are intended to become functional future units of the venture's project (e.g., utility function, right to ownership, royalties). ICOs enable startups to raise large amounts of funding with minimal effort while avoiding compliance and intermediary costs (Kaal and Dell'Erba, 2018, Sameeh, 2018)" (Fisch, 2019, p. 4).

Hahn and Wons (2018) state, that "An Initial Coin Offering (or Initial Public Coin Offering [IPCO]) enables startup companies a new form of financing that quickly achieves large reach of potential investors and is purely digital. It is based on the concept of Initial Public Offering (IPO) - that is, an IPO - since so-called "tokens" are issued here instead of shares, but which have a different function and structure than conventional shares. The sale of tokens gives potential interested parties access to the startup's future product or service. In contrast to an IPO, however, an ICO largely takes place within the early stages. It is usually used by companies whose business model is based on cryptocurrencies. Since an ICO is regularly aimed at an indefinite number of potential investors, it is very close to crowd investing" (Hahn and Wons, 2018, p. 1 et seq.*).

And **Hönig (2020)** explains, that "An Initial Coin Offering (ICO), sometimes also called (IPCO) Initial Public Coin Offering, more simply said "first offer of a coin", combines blockchain technology with the financing model of crowdfunding or crowd investing and serves as a financing option in the world of cryptocurrencies for projects based on blockchain technology (see Sesterhenn 2018). It is a swarm financing in which the issuer exchanges a self-programmed crypto token for cryptocurrencies, rarely also FIAT currencies. The term FIAT currency is used to describe classic physical currencies such as euros or US dollars. These are legal currencies that are issued by the central banks of the respective country and represent an officially recognized means of payment" (Hönig, 2020, p. 1 et seq.*).

3.6 Determents of Corporate Financing via ICOs

3.6.1 Introduction to Corporate Financing via ICOs

In this section, the current state of the scientific research of ICOs will be examined.

As stated above, ICOs are a relatively recent way of corporate financing. But since the first ICO carried out in 2013, this new and innovative way of financing became more and more popular. In particular, the Bitcoin hype of 2017 has contributed to its increasing popularity. Despite this development, very little is known about the dynamics of ICOs as a tool for corporate financing. Since the market is still barely regulated, there are great uncertainties on the part of the ventures, investors, and public authorities (compare: Fisch, 2019, p. 1 et seq.). The aim of current research is therefore to better understand the phenomenon of ICOs and to overcome these uncertainties.

ICOs can be viewed from three different perspectives: First from the perspective of the venture, that aims to gather funding via the ICO. Then from the perspective of the investor, who hopes that his participation in the ICO generates a positive return. And finally, from the perspective of social welfare, which judges the ICO according to its contribution to the society (compare: Ante, Sandner and Fiedler, 2018, p. 1 et seq.).

3.6.2 Determents from the venture's perspective

In the following, the literature that concentrates on the perspective of the venture will be presented.

Fisch (2019), for example, follows this approach. In his research, he focusses on the "factors [that] determine the amount of funding [the venture raises during the] […] ICOs" (Fisch, 2019, p. 3) "To explore this question, […] [he is drawing] on signalling theory" (Fisch, 2019, p. 3) by Spence (1973). It states, "that high-quality ventures can attract higher amounts of funding" (Fisch, 2019, p. 3) by convincing potential investors of their technical superiority. Ventures, that finance themselves through ICOs are usually very technology driven companies. Therefore, Fisch (2019) assumes that high technology ventures can signal their technological superiority through the following indicators: technical white papers, that explain the business model, a high-quality source code and the number of patents the venture has filed for. Based on a multivariate data analysis, which was carried out based on a random sample of 423 ICOs from 2016 – 2018, it was found out, that both the technical white paper and the high-quality source code were leading to a hinger amount of funding. Patents, however, did not have the same effect. Instead, an increased Twitter activity of the venture could be identified as a positive factor. (compare: Fisch, 2019, p. 3)

The approach of **Shrestha, Thewissen and Torsin (2022)** is very similar. In its paper "What's the name? The case of initial coin offerings", they explain the amount of funding by the fluency of the name of the ventures. Based on "prior literature in psychology" (Shrestha, Thewissen and Torsin, 2022, p.1), they argue, that "fluent stimuli[are] more favourable than information that are difficult to process" (Shrestha, Thewissen and Torsin, 2022, p.1) By analysing a sample of 3,500 ICOs via a multivariate data analysis, they indeed found out, that "the fluency of the name of […] [ICOs] positively affects the funding outcome" (Shrestha, Thewissen and Torsin, 2022, p.1)

Amsden and Schweizer (2018) instead define the success of an ICO as the tradability of the token or coin issued by the venture. To identify factors that lead to a successful ICO, they use a data set of "1,009 ICOs from 2015 to March 2018" (Amsden and Schweizer, 2018, p. 1). Using a multivariate data analysis, they were able to determine that the "venture uncertainty (not being on Github and Telegram, […])" (Amsden and Schweizer, 2018, p. 1) was negatively, and "higher venture quality (e.g. better-connected ICOs)" (Amsden and Schweizer, 2018, p. 1) were positively correlated to the ICOs success. In addition, they were able to find out, that "a hard cap in a pre-ICO [is able to] […] help investors […] to measure success in the pre-sale.

Ante, Sandner and Fiedler (2018) define the success of ICOs just like Fisch (2019) and Shrestha, Thewissen and Torsin, (2022) as the "amount of capital a project could raise." (Ante, Sandner and Fiedler, 2018, p. 1) In their study, they analyze a "dataset of 278 projects, that finished their ICOs by August 2017" (Ante, Sandner and Fiedler, 2018, p. 1). By carrying out a multivariate data analysis, they found out, that certain "human capital characteristics, business model quality, project elaboration, and social media activity" have a positive influence on the collected amount of capital.

3.6.3 Determents from the investor's perspective

Some studies look at the ICO from an investor's perspective. For them, the success of their investment is particularly important. Due to the low level of regulation of the market, many papers target the subject of fraud in the ICO market.

Conlon and McGee (2021) for example give a general overview of fraud and regulation in the ICO market. They note that this new and innovative, but also unregulated market offers many opportunities. However, it "also bring(s) increased risk of fraud and manipulation" (Conlon and McGee, 2021, p. 1). Thereby they concentrate on fraud in from of a "fake ICO' Ponzi scheme" (Conlon and McGee, 2021, p. 2) where the ICO just aims to gather funds for the scammer, who did not develop any business model. After the reviewing a series of past ICO scams they present "a set of rules, informed both by the academic literature and online rating community, to assist investors in avoiding ICO scams" (Conlon and McGee, 2021, p. 6). Due to their review of the academic literature on this topic, they find the following indicators as significant for the success (= no scam) of ICOs:

"1. Utility tokens have more successful firm outcomes, 2. Institutional investor/ VC involvement in the ICO is significant in forecasting success of the project, 3. Does the white paper provide a budget for the use of ICO proceeds, 4. Is there a lockup (vesting) period for sale of insider ICO tokens? 5. Does the issuing team include significant experience in computer science? 6. Is the project code publicly available (e.g., on GitHub)?" (Conlon and McGee, 2021, p. 16)

Also, they present a list of "Additional Indicators from websites and ICO Rating Sites (:) 1. Check the state of the project website (as an indicator of investment by the team and computing experience). 2. Check the background and experience of the leadership of the project. 3. Check the background and experience of the development team (as a measure of their capability but also signals commitment from knowledgeable industry people). 4. Consider the technical feasibility of the whitepaper. 5. Check activity on the source code repository, if available (as a measure of adoption). 7. Consider the sentiment of the community in social media. 8. Observe the level of engagement from the team with members of the ICO community online" (Conlon and McGee, 2021, p. 16).

Liebau and Schueffel (2019) research on the question of how many ICOs can be classified as fraud. They note that, although ICOs obviously seam to become an "increasingly popular way to raise capital for Blockchain technology startups" (2, p. 2), "its performance lacks behind expectations" (ICO Market Research, Q3 2018). "A recent industry study went as far as to maintain that 80% of all ICOs are indeed scams" (compare Dowlat, 2018) However, they argue that "poor economic performance cannot automatically be equated with a scam" (Liebau and Schueffel, 2019, p. 1) and that "high failure rates are [not] idiosyncratic to […] ICOs. Therefore, they propose another definition of fraud. They draw on Principal Agent Theory (PAT) arguing the investor/ token holder is the principal and the token issuer/ ICO team is the agent. Due to the lack of control mechanisms in ICOs, the principal is hardly able to control the agents actions. According to Liebau and Schueffel (2019), this favours conflict of interest in the form of fraud, which the classify as "acts throughout the scammer purposefully deprives the trustful investor of his or her funds to advantage to the scammer" (Liebau and Schueffel, 2019, p. 2). This differentiates them from other authors, who already regard the mere failure of the venture after the ICO as a fraud. Liebau and Schueffel (2019), however, were able to show that the failure rate of ICO-funded ventures is not higher than that of other comparable young companies. Using a data set of 45 ICOs, which were all concluded in 2016, Liebau and Schueffel (2019) investigated against which of these so financed ventures legal actions for fraud were taken. It could be shown that only one of the 45 investments could actually be classifies as fraud.

3.6.4 Determents from the social welfare perspective

Finally, the ICO can also be viewed in terms of its contribution to social welfare. In this context, the following work should be mentioned.

Howell et al. (2020) has presented kind of a hybrid study in his paper. He examines a sample of 1,500 ICOs, looking both for the survival of the ventures and for the employment. His study takes up the perspective of the investor as well as that of social welfare. The investor focusses on the long-term success of his investment, and thus also in the venture. An increasing level of employment instead is particularly important for the level of social welfare. Interestingly, Howell et al. (2020) come to the conclusion that both sides are favoured by identical factors: "whether a token had utility value […] whether […] the issuer's executive team has a lockup (vesting) period for sale of its ICO tokens […] whether […] the white paper provides a budget for the use of ICO proceeds […] whether […] the issuer has successfully raised Venture Capital funding in the past" (Conlon and McGee, 2021, p. 6).

4 Decision for a failure-based model

In the following section, it will be discussed why this thesis focuses on the identification of determents for failure of ICOs. This is based on two approaches that this thesis represents. On the one hand, the consideration of the phenomenon of the ICO from the perspective of the investor. On the other hand, the way in which it defines the success of an ICO. These two factors are interrelated and will be examined in more detail below.

As Ante, Sandner and Fiedler (2018) noted before, “There are three ways of looking at ICO financing: From the perspective of (1) startups; (2) individual investors; and (3) social welfare” (Ante, Sandner and Fiedler, 2018, p. 1 et seq.). Further, they remark that when the topic is approached “from the perspective of startups, the main questions are how ICOs can help finance business ventures and how they are best applied. Individual investors [instead,] focus on success rates and on the return on their invested capital. From the social welfare perspective, the angle of analysis is on the benefits and costs that ICOs entail for society, how much market value they help create, and how they could be regulated“ (Ante, Sandner and Fiedler, 2018, p. 2).

Reviewing chapter 3.6 - Determents of Corporate Financing via ICOs, it can be found that most papers state that they aim to identify factors for the success of ICOs. However “The term “success” is somewhat misleading, as it can be applied to funding success, venture success, secondary market access, or return on investment“ (Ante, Sandner and Fiedler, 2018, p. 2). Most papers (Ante, Sandner and Fiedler, 2018; Fisch (2019); …) “define success as the amount of funding that a project is able to gather“ (Ante, Sandner and Fiedler, 2018, p. 2). So, they actually focus on the startups’ perspective.

This thesis however argues that this definition of success says nothing about whether the startup that was financed will be successful in the long term.

Therefore, this thesis aims to follow the approach of Conlon and McGee (2021), Liebau and Schueffel (2019) and Howell et al. (2020) and considers the ICO from the investor’s perspective. The success should therefore not be described as the amount of funding raised by the startup, but instead by the success of the startup (venture) itself.

However, this still does not explain at what state a startup can be considered as a success. While (ICO Market Research, Q3 2018) argues, that 80% of all ICOs are scams, Liebau and Schueffel (2019) could only identify one of 45 as an actual fraud. This thesis argues that it makes no difference for the investor whether he loses his money due to fraud, incompetence, or simply bad luck. The ultimate economic success of a venture (and thereby also the success for the investor) can be better described by the likelihood of the venture’s mortality (compare: Liebau and Schueffel, 2019). Therefore, it was decided to simply focus on the survival rate of the venture, financed by the ICO. Considering, that the survival rate of new technology ventures (NTVs) is quite low (36% after four years and 21.9% after five years, (compare Song et al., 2008, p. 7 et seq.), this can be considered as an interesting benchmark for the also high-technology intensive ICO-financed ventures that are object to this study. This is also in line with the findings of Shrestha, Thewissen and Torsin (2022). Building on Amsden and Schweizer (2018), they define (among other criteria) an ICO as successful if the issued token is tradable on a secondary exchange. After examining a dataset of 3,560 ICOs, 20% can be identified as successful according to this criterion (Shrestha, Thewissen and Torsin, 2022, p. 2 et seq.) This thesis aims to find the corresponding results by its own definition of success and failure.

Building on the approach of examining the existence of a venture after an intermediate period of time, this thesis argues that success is not necessarily the opposite of failure. A venture that ceases to exist after a certain period clearly is a failure. A venture that still exists at that time, however, may go bankrupt a short time later. Or, despite its long-term existence, it can be so weak that it never brings a positive return for the ICO investor.

This thesis therefore considers failure as the cleaner criterion to examine the ICO from an investor's perspective.

To explain the failure of ICOs, it argues that high-quality ICO-ventures with a competent team and a serious business model have a high likelihood of long-term survival. Low-quality ventures instead with an incompetent team and a poor or no business model are likely to go bankrupt soon. Building on signaling theory (Spence, 1973), this thesis argues that high-quality ventures can show their superiority via specific factors in advance, while low-quality ventures cannot. By identifying these factors, this thesis helps investors and regulators to identify ICO-financed ventures that are likely to fail in advance.

The following chapter shows how the failure of ICOs presented here can be explained by determents developed based on signaling theory. For this purpose, a dataset is created to empirically examining the described approach.

5 Sample and Method

To collect a sample for the empirical analysis, this thesis builds on the work of Pastwa et al. (2021/18). For their analysis, they screened “seven third party ICO tracking websites” (Pastwa et al., 2021/18, Appendix p. 1) (ICOHolder, ICOBench, ICOMarks, ICORating, FoundICO, CryptoCompare and ICODrops) and merged their findings into a single combined data set. It provides valuable information about a sum of 9.159 ICOs that took place between 2015 and 2021 (Compare Pastwa et al., 2021/18, Appendix p. 3). Due to Pastwa et al. (2021/18) this data set covers “a large share of the [entire] ICO population” (Pastwa et al., 2021/18, Appendix p. 1) and therefore forms an excellent research basis. To adapt this data set for this thesis however, it had to be modified and extended.

The aim of this thesis is to make out determents of the failure of ICOs. To do so, it was decided to consider ICOs a failure if the ventures they fund cease to exist after a certain period. To verify that, a sufficient interval between the end of the ICO and the implementation of the analysis must be defined. Therefore, it was decided to only consider ICOs that were completed by December 31st, 2017. Since the final data modification was carried out in March 2022, this makes for a minimum period of four years and two months after the ICO. An even longer distance would be desirable (A typical period for the survival rate of startup’s after a certain time is five years (compare Song et al., 2008, p. 7 et seq.) However, this could result in a very small sample (compare Liebau and Schueffel, 2019, p. 4). As mentioned, ICOs are a relatively new method of corporate financing and 2017 used to be the first year they experienced a real boom. Therefore, it makes sense to include the ICOs of this boom into the data set. After the deletion of the data of all ICOs that ended after December 31st 2017, the data set still provided information about 1,288 Initial Coin Offerings. This amount can be considered as large enough to provide significant results.

In the next step, the dependent variable for the data set was computed. This was done in the form of a dummy variable, which takes the value 1 in case of a failed ICO and 0 if the ICO was no failure. The failure or not-failure of the individual ICO was again determined with the help of various sub-variables, on which the final dependent variable is based. As mentioned before, from an investor's perspective, we consider an ICO to be a failure if the startup financed by it no longer exists. On the other hand, the ICO cannot be considered a failure if the startup is still active at the time of the analysis. The sub-variables mentioned above are indicators of whether the startup is still active. Hereby, the databases of the two websites 99bitcoins.com (https://99bitcoins.com/deadcoins/) and coinopsy.com (https://www.coinopsy.com/dead-coins/) were used as a basis. They provide information about crypto coins- and tokens that were issued during ICOs but are no longer active and can therefore considered as “dead”.

The “deadcoin” database of **99bitcoins.com** uses the following “Death Indicators” to check whether a token can be considered as “dead”:

> <u>Inactive Development</u>
>
> “The coins Github repository hadn’t been updated in the past 6 months, suggesting the team has abandoned its development” (https://99bitcoins.com/deadcoins/).
>
> <u>Inactive Twitter</u>
>
> “The coins channel has not been active in the past 12 months. While this is not a “clear death indicator”, it’s a big warning sign that the project is no longer being maintained” (https://99bitcoins.com/deadcoins/).
>
> <u>Low Volume</u>
>
> “The coin has no substantial trading volume which means that only a handful of people use it as an asset” (https://99bitcoins.com/deadcoins/).

Not indexed

"The coin was delisted or never existed on major indexes such as CoinGecko or CoinMarketCap, indicating it did not pass their quality tests" (https://99bitcoins.com/deadcoins/).

Not listed on exchanges

"The coin is listed on 3 or less exchanges which means it did not gain any significant adoption. The quality of exchanges it trades on is also examined, as some exchanges will list any coin, in exchange for payment" (https://99bitcoins.com/deadcoins/).

Website down

"The coins official website is either down, broken or hacked for an extensive period of time, suggesting no one is actively maintain it" (https://99bitcoins.com/deadcoins/).

Coinopsy.com on the other hand works with the following rules to decide whether they consider a token as "dead":

Instant dead coin listing

"Ranked below 1000* for over 3 months.

Volume under $ 1000 USD for 3 months.

Website dead and no traces of updates.

No nodes or similar problems"

(https://www.coinopsy.com/dead-coins/).

Possible dead coin listings

"Scamming the top 1000*.

Low volume in the top 1000*.

No updates and neglect.

Less than 3 exchange listings.

Related to past scams.

Wallet issues.

Premine"

(https://www.coinopsy.com/dead-coins/).

The data bases of these two websites were compared with the data set of the 1,288 ICOs. However, only 121 (9.39%) of these 1,288 tokens were mentioned as "dead coins" in the list of 99bitcoins.com. The result of coinopsy.com was only slightly higher, 217 of the 1,288 coins (16.83%) were considered as "dead" due to their database. In turn, this would mean that 90.61% and 83.17% of ICOs can be considered as no failure. A comparison with the analyses mentioned above (compare Song et al. 2008, p. 7 et seq., ICO Market Research, Q3 2008) shows that this is not realistic. Therefore, it cannot be assumed that 99bitcoins.com classifies 1,167 and coinopsy.com 1,071 of the 1,288 ICOs as not "dead" based on the above criteria. Rather, it can be assumed that the lists are incomplete and that a large portion of the 1,288 ICOs have never been checked against these criteria.

Therefore, the entire dataset was compared manually based on a selection of the above-mentioned criteria. After a thorough review of these criteria, the following two were found to be the most meaningful and therefore used to compute the sub variables:

Low Volume

Not listed on exchanges

In favour of this selection was the fact that these can be checked very objectively and were also used as criteria in both databases (99bitcoins.com and coinopsy.com). In addition, it seems to make sense from the investor's perspective to consider an ICO as no failure if he can still trade the token acquired in the process. Also, this is in line with the work of Amsden and Schweizer (2018), who defined the ICOs success by the tradability of the token or coin issued by the venture.

To make the criterion low volume even more objective, it was decided to consider this criterion as fulfilled for a token if the trading volume is below 10,000 US-Dollar (USD). The sub variable derived from this criterion takes the value 1 if the USD 10,000 is not reached and takes the value 0 if it is exceeded. After comparing the dataset with this sub variable, low volume was detected for 1,104 of 1,288 tokens (85.71%).

The definition of the criterion not listed on exchanges could be taken from 99bitcoins.com. According to this, the sub variable takes the value 1 if the token is only traded on 3 or less crypto exchanges. If it is traded on more than 3 exchanges, the variable takes the value 0. After comparing the dataset with this sub variable, it was determined that 1,104 of 1,288 tokens (85.71%) were listed only on three or fewer crypto exchanges.

It was decided that an ICO should be considered a failure overall if these two sub-variables were met. In addition, the fact that the token of an ICO is considered "dead" by 99bitcoins.com and coinopsy.com was also captured in two sub-variables (the value 1 in case the token is considered "dead" and 0 if not). For the cases where the ICO was not classified as failure overall by the variable low volume and not listed on exchanges, this classification was still made if both 99bitcoins.com and coinopsy.com classified the token in question as "dead". However, this was only the case in two instances.

The finally derived dependent binary variable ICO_Fail takes the value 1 if the ICO is to be classified as a failure according to the above criteria and the value 0 if it is not to be classified as a failure. It can be deduced that of the 1,288 ICOs, a total of 1,106 are to be classified as failures. This corresponds to a failure rate of 85.87%. If this is compared with the studies cited above (compare Song et al., 2008, p. 7 et seq.; ICO Market Research, Q3 2018; Shrestha, Thewissen and Torsin, 2022, p. 2 et seq.), this can be regarded as realistic.

Building on signaling theory (Spence, 1973) and based on the literature, several determents for the failure of ICOs were proposed. These determents are verified by transforming them into independent variables.

To test the determents of social media activity, a series of dummy variables from Pastwa et al. (2021/18) was used. They take the value 1 if these is an account for the ICO on the corresponding social media, and 0 if not. This thesis proposes that activity on niche social networks is a signal for high-quality ventures. In particular Reddit, Bitcointalk and Bitcoinwiki come into consideration. The idea is that activity on these networks (or online forums) requires close networking with very interested crypto enthusiasts. They can be assumed to have a high level of competence in the crypto field, as well as a critical attitude. Activity on these networks therefore only appears to make sense for high-quality ventures. There, they can present their superiority to a group of interested and informed potential investors, reducing the information asymmetry in their ICO. Low-quality ventures on the other hand are likely to be recognized as such by the community if they are active on these niche networks. This would correspondingly result in "bad press". In addition, the exchange with the community is associated with high time costs. It therefore makes no sense for low quality ventures to be active on these niche networks. For them, it makes more sense to address a broad mass of uninformed people on networks like Facebook. Therefore, the activity on other social networks is also examined for monitoring purposes. The activity on these niche networks is thus suggested as a signal for high-quality ventures. Non-activity instead would indicate low-quality ventures, which are likely to fail. With the help of the individual dummy variables, it will be examined if the activity of these social media is actually suitable as an indicator for the failure of ICOs. The following is an overview of the variables used to examine social media activity:

Table 1.1 – Variables for the determent social media activity

Variable	Definition
SM_twitter	Dummy for twitter account (SM = social media)
SM_facebook	Dummy for facebook account (SM = social media)
SM_reddit	Dummy for reddit account (SM = social media)
SM_medium	Dummy for medium account (SM = social media)
SM_telegram	Dummy for telegram account (SM = social media)
SM_vk	Dummy for vk account (SM = social media)
SM_bitcointalk	Dummy for bitcointalk account (SM = social media)
SM_bitcoinwiki	Dummy for bitcoinwiki account (SM = social media)
SM_slack	Dummy for slack account (SM = social media)
SM_discord	Dummy for discort account (SM = social media)
SM_linkedin	Dummy for linkedin account (SM = social media)
SM_instagram	Dummy for instagram account (SM = social media)
SM_youtube	Dummy for youtube account (SM = social media)
SM_blog	Dummy for a blog (SM = social media)

The determent white paper is a very complex factor. The suggestions in the literature refer to very specific contents of the white paper. Its technical complexity and whether it contains a budget have been suggested as signals for high-quality ventures. For a high-quality venture, the preparation of such a white paper does not present high difficulties or costs. Its team has the necessary technical skills and only needs to describe the innovative business model it has developed. Low-quality ventures, on the other hand, (by definition) do not possess appropriate skills and have a poor business model. To write a high-quality white paper, they would have to improve in these points, which in turn would make them a high-quality venture. Therefore, a technical white paper is suggested as a signal for high-quality ventures. Their absence thus forms a sign for low-quality ventures and therefore a determent for the failure of ICOs. However, with a data set of 1,288 ICOs, such a precise assessment would require an enormous amount of time. In addition, an objective classification seems difficult. This thesis focuses on factors for the failure of ICOs. From the sources mentioned, it can be deduced that a "bad" white paper is more likely to be considered a sign for a low-quality venture than a good one. From this, it can be deduced that the complete absence of a white paper can be seen all the more as an indicator of it. Moreover, this is a clearly objective criterion. Therefore, the determent white paper will be examined with the help of a dummy variable, which indicates the presence or absence of a white paper in the context of an ICO.

Table 1.2 – Variable for the determent white paper

Variable	Definition
WhitepaperDummy	Indicates whether a white paper was published for the ICO.

For the determent of the source code, the situation is similar to the one of the white paper. A more complex and technically superior source code requires an ICO team with high technical skills. A highly skilled workforce is considered as a sign of a high-quality venture. And a high-quality source code is thus considered as a signal for a high-quality venture. A simpler, poor or low-quality source code instead would be a sign for a low-quality venture that is likely to fail in the medium term. However, the exact assessment requires a high level of technical understanding and an objective assessment in a quantitative variable appears difficult. This also must be taken into account in the sources considered. For example, Conlon and McGee (2021) and Amsden and Schweizer (2018) suggest checking the general public availability of the source code. The theory is that technically savvy investors can recognize the quality of the source code, which is why it only makes sense to publish high-quality code. The public availability of the code can be identified by the activity on the platform Github, where ICO source codes are usually published. If there is no Github account for an ICO, it can be assumed that the source code is so inferior that it would not make sense to publish it. Not having a Github account would therefore be an indicator for a low-quality venture and thus a determent for the ICO's failure. This factor can also be modelled very objectively with the following dummy variable.

Table 1.3 – Variable for the determent source code

Variable	Definition
SM_github	Dummy for github account (SM = social media)

In the determent of the ICO team, its "human capital characteristics" (Ante, Sandner and Fiedler, 2018, p. 1), background and experience, respectively, especially in computer science (Conlon and McGee, 2021, p. 16) are considered particularly important. This thesis argues that high-quality ventures with a serious business model are more likely to attract a workforce that possesses these characteristics. Additionally, they also are more in need of a big and smart team to implement their strategy. Low-quality ventures instead are less attractive for highly skilled programmers and technology experts. Also, there is no need for them to develop a simple, poor or even fraudulent business model. And if the business model actually is fraudulent, the founders can have no interest in a big team that might talk, and they have to share their profit with. However, the assessment of these “human capital characteristics” is very subjective. Also, for many ICOs, there is no precise information about the team. And for those where this is the case, extensive research on the background of the team members, e.g. on LinkedIn, would be necessary. Therefore, it is suggested that the team size serves as a signal for the overall quality of the venture. ICOs initiated by ventures with small teams would be less likely to be of high-quality and thus more likely to fail.

Table 1.4 – Variable for the determent ICO team

Variable	Definition
Fin_Team	Number of team members during the ICO (after quality check)

By initiating a soft cap, the venture determines the minimum amount that must be raised during the ICO so that the business model can be implemented. The hard cap, on the other hand, represents the upper limit of tokens that can be sold in an ICO. This thesis suggests that setting soft- and hard caps indicates that the venture has precise plans on how much money is needed. In this way, the venture can also communicate its initial intentions to potential investors. This speaks for the seriousness of the venture, which is why the presence of soft- and hard caps is suggested as a signal for high-quality ventures. Low-quality ventures are assumed to simply want to raise as much money as possible. Therefore, they may not be interested in incurring these additional costs. The lack of hard or soft caps is thus suggested as a determent for the failure of ICOs. To test this determent, we can directly refer to the data set of Pastwa et al. (2021/18). With a dummy variable for soft cap and a dummy variable for hard cap, this data set already contains the appropriate data for a quantitative evaluation.

Table 1.5 – Variables for the determent hard cap/soft cap

Variable	Definition
Fin_hardcapDummy	Indicates whether a hard cap was specified during the ICO (after quality check)
Fin_softcapDummy	Whether a soft cap was specified during the ICO (after quality check)

For the determent of the ICO rating, this thesis argues that a high rating can be considered as a positive "sign of approval" for the ICO-venture by the crypto community. Thus, it can be considered as a signal for a high-quality venture. A low rating instead forms a sign for a low-quality venture that is likely to fail. To make sure that the opinion of the broad crypto community is considered (and that the ICO-venture did not influence the rating on single websites), an aggregated rating of several websites is considered. Therefore, this thesis builds on the work of Pastwa et al. (2021/18) They have done a valuable work by calculating the aggregated variable Rating. The problem in examining the ratings of ICOs is that "the rating across sources may not only be inconsistent (see Rhue, 2021, p. 44 et seq.; Boreiko and Viduso, 2019, p. 67 et seq.), but can also follow different rating schemes and scales. For instance, rating scores are available in six […] sources, and [the] websites ICOBench, ICORating, ICOHolder, and ICODrops use scales of 5, [the websites] FoundICO and ICOMarks use scales of 10[1]. To operationalize an aggregate rating score, […] [Pastwa et al., (2021/18)] take the average of the standardized scores (i.e., […] [they] subtract the source-specific mean from each value and divide by the source-specific standard deviation, and take the mean score across sources)" (Pastwa et al., 2021/18, Appendix p. 6 et seq.). In this way, a uniform rating with a scale of 5 is created for all sources, whereby a higher rating represents a better assessment of the ICO and vice versa. Accordingly, a poor rating would indicate that the ICO is likely to fail.

Table 1.6 – Variable for the determent ICO rating

Variable	Definition
Rating	Overall rating quality of the ICO

Building on the work of Shrestha et al. (2021), this thesis has proposed the country in which the ICO is held as a determent for the failure of ICOs. Shrestha et al. (2021) argue that investments in ICOs held in stronger countries with stronger institutions are perceived as less risky. This thesis argues that high-quality ventures are more likely to be present in stronger countries. The benefit from the strong institutions and the good reputation of these countries helps them to signal their superiority. Low-quality ventures instead are likely to prefer countries without strong institutions in order to hide their inferiority. It is assumed that they are likely to fail in the medium term.

To quantitatively assess the determent of the country on the failure of ICOs, this thesis again builds on the work of Pastwa et al (2021/18). Their dataset provides detailed information about the host countries of the ICOs. The collection of these data was done very thoughtfully, when there were "inconsistencies in the reported host-country across the various sources, […] [they] consider[ed] the countries with the highest frequency across sources. […] [In] most cases, […] [they identified] a single mode country, [However] there are cases where more than one country is specified. In such instances, […] [they took] the average aggregate score for continuous variable, Institutions, and for the [dummy variable] […], TaxHaven […] [they] take the value '1' if at least one country corresponds to the criteria" (Pastwa et al. 2021/18, Appendix p. 6). This thesis adopts the variable TaxHaven and used it as an

[1] Note that ICODrops ratings are represented as one the five categories: 'very low', 'low', 'medium', 'high', and 'very high'. We convert these categories to values 1 to 5.

indicator for the reputation of the country. The idea is that tax havens have a lower reputation and weaker institutions. Based on Pastwa et al. (2021/18)'s variable Country, the variable Country_HDI is created. It indicates the value of the Human Development Index (HDI) of the host country in the year the ICO was implemented. Here the idea is that a low HDI value also serves as a sign for a lower reputation and weaker institutions of this country. To verify the determent of the ICO host country it is thus evaluated whether this country being a tax haven or having a low HDI value has an impact on the failure of the ICOs held there.

Table 1.7 – Variables for the determent country

Variable	Definition
Fin_TaxHaven	Indicates whether the ICO was issued in a country that is considered as a tax haven (after quality check)
Country_HDI	Human development index of the country and year the ICO was issued.

HDI: https://hdr.undp.org/en/indicators/137506#

Also building on Shrestha et al. (2021) the determent regulation of ICOs is examined. Here, the idea is not to regard the reputation of the country as a proxy for the strength of its institution. Instead, the existing regulation by the institutions itself shell be examined. To do so, this thesis adopts the dataset by Pastwa et al. (2021/18) that also provides detailed information on the regulation of ICOs. The Fin_Regulated variable contains information about whether an ICO is REGULATED, UNREGULATED or BANNED. Based on this variable, the two dummy variables Fin_RegulatedDummy and Fin_BannedDummy were derived. The idea behind is that high-quality ventures can benefit from regulation as a signal for their superiority. Low-quality ventures instead will seek to avoid regulation to hide their inferiority. It is suggested that ICOs initiated by these ventures are likely to fail. This assumption is to be verified with the variable Fin_RegulatedDummy. It takes the value 1 in case it is a regulated ICO. For unregulated and banned ICOs it takes the value 0. Additionally, it is assumed, that if an ICO is regulated, the institutions are likely to recognize and restrict or ban low-quality ventures. ICOs initiated by these ventures are expected to be a failure. To verify this, the variables Fin_BannedDummy and Fin_USRestrict were used. The variable Fin_BannedDummy takes the value 1 for banned ICOs. For both regulated and unregulated ICOs it takes the value 0. Additionally, the variable Fin_USRestrict was adopted from Pastwa et al. (2021/18), which indicates whether the ICO is restricted from selling coins in the US.

Table 1.8 – Variables for the determent regulation

Variable	Definition
Fin_RegulatedDummy	Indicates whether the ICO was regulated (after quality check)
Fin_BannedDummy	Indicates whether the ICO was banned (after quality check)
Fin_USRestrict	Indicates whether the ICO is restricted from selling coins in the US (after quality check)

By initiating a whitelist, the venture forces investors to register and to provide personal data before they can participate in the ICO. This increases transparency and reduces the uncertainty during the ICO process. As argued, only high-quality ventures can have an interest in the reduction of this uncertainty. The implementation of such a Whitelist brings additional costs that low-quality ventures are unlikely to want to incur. Therefore, this thesis suggests a KYC Whitelist as a signal for high-quality ventures. A lack of a Whitelist is thus regarded as a sign for a low-quality venture and is therefore proposed as a determent of the failure of ICOs. Pastwa et al. (2021/18) also provides Information regarding the presence of a KYC whitelist during the ICO.

Table 1.9 – Variables for the determent whitelist

Variable	Definition
Fin_WhitelistKYCDummy	Indicates whether the ICO is whitelist KYC compliant (after quality check)

Finally, the control variables derived from Pastwa et al. (2021/18) are listed below. Their objective is to control for potential effects not explained by the determents derived from signaling theory. It was decided to include control variables regarding the token issued during the ICO, the circumstances of the ICO and whether a video was published for the ICO.

Table 1.10 – Control variables: Token

Variable	Definition
Fin_EthereumBlockDummy	Indicates whether the token is using the Ethereum blockchain (after quality check)
Fin_TokenDistributedDummy	Indicates whether there are information about the number of tokens (after quality check)
Fin_FiatAcceptingDummy	Indicates whether the token can be purchased using a fiat currency (after quality check)

Table 1.11 – Control variables: ICO circumstances

Variable	Definition
Fin_MinInvestDummy	Indicates whether there is a minimum investment amount to partake in the ICO (after quality check)
Fin_PreICODummy	Indicates whether a pre-ICO was held before the ICO (after quality check)
Fin_BonusDummy	Indicates whether a bonus could be obtained during the ICO (after quality check)
Fin_NumCurrencies	Number of currencies that the ICO accepts to purchase (after quality check)

Table 1.12 – Control variable: Video

Variable	Definition
Fin_VideoDummy	Indicates whether the company has published a video (after quality check)

6 Regression Analysis

Table 2 shows the descriptive statistics of the data set analysed in this thesis. Again, we see that approx. 86% of the 1,288 ICOs carried out before 31.12.2017 ICOs can be considered as a failure by March 2022. Consequently, the rate of no failure is quite low at around 14%, but this is in line with data in similarly risky ventures (compare Song et al., 2008, p. 7 et seq., ICO Market Research, Q3 2018) and further research on ICOs (Shrestha, Thewissen and Torsin, 2022, p. 4). The description of the distribution of the independent variables will be given in the respective sections below.

Table 2: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Q25%	Median	Q75%	Max
ICO_Fail	1288	0,86	0,348	0	1	1	1	1
SM_twitter	1214	0,85	0,353	0	1	1	1	1
SM_facebook	1214	0,7	0,457	0	0	1	1	1
SM_reddit	1214	0,36	0,479	0	0	0	1	1
SM_medium	1214	0,39	0,489	0	0	0	1	1
SM_telegram	1214	0,47	0,499	0	0	0	1	1
SM_vk	1214	0,03	0,167	0	0	0	0	1
SM_bitcointalk	1214	0,61	0,488	0	0	1	1	1
SM_bitcoinwiki	1214	0	0,064	0	0	0	0	1
SM_slack	1214	0,29	0,452	0	0	0	1	1
SM_discord	1214	0,01	0,118	0	0	0	0	1
SM_linkedin	1214	0,06	0,239	0	0	0	0	1
SM_instagram	1214	0,02	0,155	0	0	0	0	1
SM_youtube	1214	0,08	0,266	0	0	0	0	1
SM_blog	1214	0	0,064	0	0	0	0	1
WhitepaperDummy	1143	0,92	0,276	0	1	1	1	1
SM_github	1214	0,37	0,484	0	0	0	1	1
Fin_Team	890	7,91	5,866	1	4	7	10	49
Fin_hardcapDummy	1254	0,48	0,5	0	0	0	1	1
Fin_softcapDummy	1254	0,42	0,494	0	0	0	1	1
Rating	1061	2,5101	0,76239	0,45	2	2,5	3	5
Fin_TaxHaven	894	0,21	0,406	0	0	0	0	1
Country_HDI	886	0,8835	0,7251	0,47	0,82	0,924	0,926	0,98
Fin_RegulatedDummy	891	0,1021	0,30299	0	0	0	0	1
Fin_BannedDummy	892	0,0202	0,14069	0	0	0	0	1
Fin_USRestrict	1254	0,04	0,205	0	0	0	0	1
Fin_WhitelistKYCDummy	1254	0,19	0,394	0	0	0	0	1
Fin_EthereumBlockDummy	1254	0,64	0,479	0	0	1	1	1
Fin_TokenDistributedDummy	1254	0,71	0,455	0	0	1	1	1
Fin_FiatAcceptingDummy	1254	0,08	0,271	0	0	0	0	1
Fin_MinInvestDummy	1254	0,13	0,336	0	0	0	0	1
Fin_PreICODummy	1254	0,24	0,427	0	0	0	0	1
Fin_BonusDummy	1254	0,32	0,468	0	0	0	1	1
Fin_NumCurrencies	936	1,84	1,741	1	1	1	2	28
Fin_VideoDummy	1254	0,56	0,497	0	0	1	1	1

Note: This table shows the summary statistics of the variables used to test the suggested determents. This inculdes the dependent variable ICO_Fail as well as the independent variables. Auxiliary variables created to create sub datasets are not inculded. In detail, the summary statistics show (from left to right) the number of observations for this variable, the mean, the standard deviation, the smallest value observed, the 25% quantile, the median, the 75% quantile, and the largest value observed.

In order to find out which determents actually have a significant influence on the failure of ICOs, a binary Slogistic regression was performed. This involved regressing the independent variables listed above against the dependent variable ICO_Fail. The following table gives an overview of the output of the regression.

Table 3.1: Regression results

Determent	Variable	B	S.E.	Sig.
Social Media Activity	SM_twitter	0,009	0,775	0,990
	SM_facebook	**0,897**	**0,348**	**0,010*******
	SM_reddit	**-0,519**	**0,279**	**0,063***
	SM_medium	0,313	0,292	0,285
	SM_telegram	0,328	0,271	0,226
	SM_vk	0,35	0,802	0,663
	SM_bitcointalk	**0,705**	**0,306**	**0,021****
	SM_bitcoinwiki	-0,65	1,219	0,594
	SM_slack	-0,091	0,267	0,733
	SM_discord	-0,717	1,010	0,478
	SM_linkedin	-0,527	0,903	0,559
	SM_instagram	18,787	13999,554	0,999
	SM_youtube	0,727	1,186	0,540
	SM_blog	-21,83	40192,970	1,000
White Paper	WhitepaperDummy	-18,758	17768,184	0,999
Source Code	**SM_github**	**-0,806**	**0,277**	**0,004*******
ICO Team	Fin_Team	-0,024	0,020	0,224
Hard Cap/Soft Cap	Fin_hardcapDummy	-0,106	0,318	0,738
	Fin_softcapDummy	0,325	0,301	0,281
ICO Rating	**Rating**	**-0,793**	**0,273**	**0,004*******
Country	**Fin_TaxHaven**	**-0,485**	**0,289**	**0,094***
	Country_HDI	0,34	2,150	0,874
Regulation	Fin_RegulatedDummy	-0,492	0,381	0,196
	Fin_BannedDummy	0,052	0,936	0,955
	Fin_USRestrict	-0,602	0,416	0,148
Whitelist	**Fin_WhitelistKYCDummy**	**-1,299**	**0,281**	**<0,001*******
Control Variables	Fin_EthereumBlockDummy	0,374	0,445	0,401
	Fin_TokenDistributedDummy	-0,754	0,544	0,166
	Fin_FiatAcceptingDummy	-0,081	0,417	0,846
	Fin_MinInvestDummy	-0,148	0,309	0,633
	Fin_PreICODummy	0,109	0,274	0,960
	Fin_BonusDummy	0,394	0,276	0,153
	Fin_NumCurrencies	0,025	0,096	0,793
	Fin_VideoDummy	-0,279	0,377	0,459
(Intercept)	Constant	22,657	17768,184	0,999

Note: This table shows the output of the binary logistic regression that was performed to validate the determinants suggested. The individual variables are sorted according to the determents that are to be tested by them. Furthermore, the columns (from left to right) list the name of each variable, the beta, the standard error, and the significance based on a two-tailed t-test. Variables that have a significant impact on the failure of ICOs are marked in bold. *, ** and *** indicate a significance level at a 10%, 5% and 1% level, respectively.

3.2: Model Summary

Step	Cox & Snell R Square	Nagelkerke R Square
1	0,195	0,318

Regarding Cox & Snell R Square and Nagelkerke R Sqare (Table 3.2), the model can be granted a moderate explanatory quality. In the following, the output of the logistic regression (Table 3.2) will be interpreted in order to verify or falsify the original assumptions.

Social media activity

The descriptive statistics in Table 2 give us an overview of the ICO venture's activity on a total of 14 social networks. This data is available for 1,214 of the totals 1,288 ICOs. The first thing to note here is that the activity varies greatly depending on the social network. The most popular social network is Twitter. An active Twitter account was found for 85% of the 1,214 ICOs. Facebook (70%) and bitcointalk (61%) also seem very popular. This is followed by telegram (47%), medium (39%), reddit (36%) and slack (29%). The other social networks are all in the single-digit percentage range and do not seem to be very important.

A possible explanation here would be that Twitter and Facebook are two very popular social networks. The ICO team can therefore "hardly afford" not to be active on these channels if it wants to promote the ICO. At the same time, creating an account on these social networks is a relatively small effort. YouTube is also a very popular social network, but the production of high-quality videos is very costly. That seems to be an effort that approx. 92% of the ICO teams do not seem to want to take on. Remarkable is the low use of LinkedIn (approx. 6%). As a business and career network, it lends itself to advertising innovative corporate financing concepts such as ICOs. There may be further avenues for research here. On the other hand, the low use of the otherwise very popular social network Instagram (approx. 2%) does not surprise. As a very image-heavy network, it does not seem very suitable for ICO advertising. Additionally, it tends to appeal to the wrong target group.

On the other hand, niche social networks actually seem to play a special role in the ICO promotion. Here, Bitcointalk and Reddit are particularly noteworthy. Their popularity could be explained by the fact that the ICO tam does not only try to appeal to the broad masses. Rather, the aim is to draw the attention of people who are already highly interested in crypto technology to the ICO. The output of the binary logistic regression regarding the SM dummy variables shows that social media activity indeed has an impact on the success or failure of ICOs. However, we see that this only applies to the activity on certain social media. The activity on the social network Facebook (at a significance level of 0.01) and the niche network Bitcointalk (at a significance level of 0.05) has a significant influence on the failure of ICOs. The activity on the other niche network Reddit also seems to have a noticeable influence (0.063). Activity on the other social networks, on the other hand, does not seem to have any influence. This is particularly true of Twitter, which has a particularly low significance (0,990), what is at odds with the findings of Fisch (2019).

Surprisingly, we notice a positive correlation with the dependent variable ICO_Fail for both the large social network Facebook and the niche network Bitcointalk. The activity on these social networks therefore seems to favor the failure of ICOs. Only the variable SM_reddit behaves as expected (This is negatively correlated with ICO_Fail).

The results for the SM_facebook and SM_bitcointalk variables do not appear to make much economic sense. The effect of the variable SM_reddit, on the other hand, is more plausible and in line with the expectations. To better understand the relationships between these three variables, their correlation is examined below. Since these are nominally scaled binary dummy variables, crosstabulation, Chi-square test and symmetric measures are used.

Table 4.1 - 4.3 show us no very strong, but still clear relationship between SM_facebook and SM_reddit. The same applies to the relationship between SM_bitcointalk and SM_reddit (5.1 - 5.3) and SM_facebook and SM_bitcointalk (6.1 - 6.3).

Facebook and Reddit

Table 4.1: SM_facebook * SM_reddit Crosstabulation

		SM_reddit		
		0	1	Total
SM_facebook	0	271	88	359
	1	511	344	855
Total		782	432	1214

Table 4.2: Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	27,263[a]	1	<0,001		
Continuity Correction[b]	26,581	1	<0,001		
Likelihood Ratio	28,291	1	<0,001		
Fisher's Exact Test				<0,001	<0,001
Linear-by-Linear Association	27,24	1	<0,001		
N of Valid Cases	1214				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 127,75.
b. Computed only for a 2x2 table

Table 4.3: Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	0,150	<0,001
	Cramer's V	0,150	<0,001
	Contingency Coefficient	0,148	<0,001
N of Valid Cases		1214	

Bitcointalk and Reddit

Table 5.1: SM_bitcointalk * SM_reddit Crosstabulation

Count

		SM_reddit 0	SM_reddit 1	Total
SM_bitcointalk	0	366	110	476
	1	416	322	738
Total		782	432	1214

Table 5.2: Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	53,167[a]	1	<0,001		
Continuity Correction[b]	52,275	1	<0,001		
Likelihood Ratio	54,884	1	<0,001		
Fisher's Exact Test				<0,001	<0,001
Linear-by-Linear Association	53,123	1	<0,001		
N of Valid Cases	1214				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 169,38.

b. Computed only for a 2x2 table

Table 5.3: Symetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	0,209	<0,001
	Cramer's V	0,209	<0,001
	Contingency Coefficient	0,205	<0,001
N of Valid Cases		1214	

Facebook and Bitcointalk

Table 6.1: SM_facebook * SM_bitcointalk Crosstabulation

Count

		SM_bitcointalk 0	1	Total
SM_facebook	0	183	176	359
	1	293	562	855
Total		476	738	1214

Table 6.2: Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	29,604	1	<0,001		
Continuity Correction	28,908	1	<0,001		
Likelihood Ratio	29,223	1	<0,001		
Fisher's Exact Test				<0,001	<0,001
Linear-by-Linear Association	29,58	1	<0,001		
N of Valid Cases	1214				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 169,38.

b. Computed only for a 2x2 table

Table 6.3: Symetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	0,156	<0,001
	Cramer's V	0,156	<0,001
	Contingency Coefficient	0,156	<0,001
N of Valid Cases		1214	

The variable SM_Facebook could be interpreted in a way that the presence of a facebook account for the ICO is a determent for the failure of the ICO. A facebook account would therefore be bad publicity for the ICO. However, as mentioned above, this interpretation makes little economic sense.

To analyze the relationship between ICO_Fail and SM_facebook in more detail, see Table 7.1 - 7.3 below.

Table 7.1: ICO_Fail * SM_facebook Crosstabulation

Count

		SM_facebook		
		0	1	Total
ICO_Fail	0	41	125	166
	1	318	730	1048
Total		359	855	1214

Table 7.2: Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	2,192[a]	1	0,139		
Continuity Correction[b]	1,930	1	0,165		
Likelihood Ratio	2,258	1	0,133		
Fisher's Exact Test				0,144	0,081
Linear-by-Linear Association	2,191	1	0,139		
N of Valid Cases	1214				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 49,09.

b. Computed only for a 2x2 table

Table 7.3: Symetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	-0,042	0,139
	Cramer's V	0,042	0,139
	Contingency Coefficient	0,042	0,139
N of Valid Cases		1214	

We find that both the ICOs that fail and those that do not fail have a facebook account for the vast majority. Additionally, the chi-square tests and the symmetric measures show no significance. Therefore, it does not seem to be the case that the presence of a facebook account explains the failure of an ICO. Rather, it seems that facebook is so popular that it is used very frequently by both the ICOs that fail and those that do not fail.

Based on this finding, we perform a sample split. We do the binary logistic regression again, but only for the ICOs for which a facebook account is available.

Table 8.1: Regression results for SM-facebook = 1

Determent	Variable	B	S.E.	Sig.
Social Media Activity	**SM_twitter**	**2,169**	**1,235**	**0,079***
	SM_reddit	**-0,792**	**0,328**	**0,016****
	SM_medium	0,357	0,341	0,295
	SM_telegram	0,179	0,304	0,556
	SM_vk	1,352	1,027	0,188
	SM_bitcointalk	0,526	0,368	0,153
	SM_bitcoinwiki	-0,433	1,207	0,720
	SM_slack	-0,020	0,301	0,948
	SM_discord	-1,477	1,082	0,172
	SM_linkedin	0,146	1,204	0,903
	SM_instagram	18,548	17350,485	0,999
	SM_youtube	-0,107	1,214	0,930
	SM_blog	-20,740	40192,970	1,000
White Paper	WhitepaperDummy	-19,874	22936,430	0,999
Source Code	**SM_github**	**-0,948**	**0,316**	**0,003*****
ICO Team	Fin_Team	-0,010	0,022	0,640
Hard Cap/Soft Cap	Fin_hardcapDummy	-0,122	0,367	0,740
	Fin_softcapDummy	0,348	0,353	0,324
ICO Rating	**Rating**	**-0,573**	**0,315**	**0,069***
Country	**Fin_TaxHaven**	**-0,600**	**0,327**	**0,067***
	Country_HDI	0,793	2,479	0,749
Regulation	Fin_RegulatedDummy	-0,352	0,442	0,426
	Fin_BannedDummy	-0,138	0,956	0,885
	Fin_USRestrict	-0,194	0,475	0,683
Whitelist	**Fin_WhitelistKYCDummy**	**-1,595**	**0,339**	**<0,001*****
Control Variables	Fin_EthereumBlockDummy	0,343	0,516	0,506
	Fin_TokenDistributedDummy	-0,548	0,639	0,391
	Fin_FiatAcceptingDummy	0,235	0,477	0,623
	Fin_MinInvestDummy	-0,390	0,345	0,258
	Fin_PreICODummy	0,260	0,313	0,405
	Fin_BonusDummy	**0,809**	**0,321**	**0,012****
	Fin_NumCurrencies	-0,034	0,094	0,717
	Fin_VideoDummy	-0,371	0,451	0,411
(Intercept)	Constant	21,603	22936,430	0,999

Note: This table shows the output of the binary logistic regression after a sample split. Its goal is to analyze only those ICOs for which a facebook account exists. For this purpose, only those observations were left in the sub-dataset for which the variable SM_facebook takes the value 1. SM_facebook is therefore obsolete and thus no longer listed. The remaining individual variables are sorted according to the determents that are to be tested by them. Furthermore, the columns (from left to right) list the name of each variable, the beta, the standard error, and the significance based on a two-tailed t-test. Variables that have a significant impact on the failure of ICOs are marked in bold. *, ** and *** indicate a significance level at a 10%, 5% and 1% level, respectively.

Table 8.2: Model Summary

Step	Cox & Snell R Square	Nagelkerke R Square
1	0,194	0,321

Looking at Cox & Snell R Square and Nagelkerke R Sqare (Table 8.2), the model can be granted a moderate explanatory quality, much like the original model (Table 3.1). Regarding the independent variables, we see that of all the social networks, SM_reddit remains the most significant variable (significance level 0.05). Also, SM_reddit is negatively correlated with ICO_Fail. The theory for the niche social networks can thus be confirmed with regard to Reddit. The lack of activity of the ICO team on Reddit can be noted as a significant determent of the failure of the ICO. This can also be interpreted in an economically meaningful way. Reddit is a social network where people with a high interest in a certain topic inform themselves and exchange information. In the recent past, this could be seen, among other things, in the strong influence on the stock market price of the gamestopp share. This was achieved through the collusion of Gamestopp investors via Reddit. The present results suggest that a similar phenomenon is also present in ICOs.

White paper

The Descriptive Statistics in table 2 shows us that we have data on the presence of a whitepaper for 1,143 of the 1,288 ICOs. In addition, we see that a whitepaper has been published for a very large majority of all ICOs, at around 92%. The regression results in table 3.1 (p-value of 0,999) clearly shows that the mere presence of a white paper cannot serve as a significant determent of ICO success. However, this is a starting point for further studies. It is possible that after a closer look at the characteristics and quality of the white paper (compare Fisch (2018)), the white paper will prove to be a determent that is suitable for explaining success or failure from the investor's perspective.

Source code

As outlined above, the activity on Github is suggested as an indicator for high quality source codes.

Summary statistics in Table 2 shows us that we have data on activity on Github for 1,214 of the 1,288 ICOs. We see that this activity is given for about 37% of this data.

The output of the regression (table 3.1) proves to be of particular interest for the determent of the source code. The variable SM_github is highly significant at a level of 0,01 and negatively correlated with the dependent variable ICO_Fail. The lack of activity on this platform thus forms a very clear determent for the failure of ICOs. The original theory can thus be verified. Therefore, it can be said that if the source code for an ICO has been published on Github, it is less likely for the investor that his investment in the ICO will be a failure.

ICO team

The variable Fin_Team tells us the number of team members that were involved in the ICO process. This information is available for 890 of the 1,288 ICOs. The largest team has 49 members, the smallest only one. On average, an ICO team has 7.91 members. The median is 7 (compare table 2).

Regarding the output of the binary logistic regression (table 3.1), the variable cannot be considered a fully meaningful determent with a p-value of 0.224. At least, the (not significant) relationship with the dependent variable ICO_Fail is negative. This would theoretically mean that ICOs with larger teams tend to be more successful, what would be in line with the hypothesis.

Before the variable is discarded, it should be examined more closely. A look at table 9.1 shows a (not completely significant) skewness to the right of ICO_Team. Thus, there seems to be significantly more small teams than large ones.

Table 9.1: Skewness and Kurtosis

		Statistic	Std. Error
Fin_Team	Skewness	2,016	0,082
	Kurtosis	7,084	0,164

To eliminate this effect, the variable Fin_Team is transformed:

$$LnFin\_Team = LN(Fin\_Team).$$

With a beta of -0.440, the negative association with ICO_Fail is now more pronounced, but with a p-value of 0.321, the variable is even further from significance than before. However, closer examination reveals a significant correlation between Fin_Team and Rating (table 9.2).

Table 9.2: Correlations

		Fin_Team	Rating
Fin_Team	Pearson Correlation	1	0,401**
	Sig. (2-tailed)		<0,001
	N	890	809
Rating	Pearson Correlation	0,401**	1
	Sig. (2-tailed)	<0,001	
	N	809	1061

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

However, closer examination reveals a fairly strong correlation between Fin_Team and rating. It is suspected that Fin_Team does not prove to be significant for this reason. Therefore, the original sample is split. For this purpose, the dummy variable Rating_Trans is calculated. This takes the value 0 for ICOs with a low rating (0-2.49) and 1 for ICOs with a high rating (2.5-5). For the sub-sample set with the low rating, the binary logistic regression yields the following output:

Table 9.3: Regression results for Rating_Trans = 0

Determent	Variable	B	S.E.	Sig.
Social Media Activity	SM_twitter	-3,865	2,676	0,149
	SM_facebook	1,137	0,91	0,211
	SM_reddit	**-2,136**	**1,288**	**0,097***
	SM_medium	-0,866	1,033	0,402
	SM_telegram	**3,752**	**1,395**	**0,007*****
	SM_vk	**-6,503**	**3,365**	**0,053***
	SM_bitcointalk	-0,602	1,328	0,65
	SM_slack	**2,298**	**1,326**	**0,083***
	SM_discord	-13,188	4695,674	0,998
	SM_linkedin	0,085	1,682	0,96
	SM_instagram	16,442	12742,653	0,999
	SM_youtube	-2,616	2,594	0,313
White Paper	WhitepaperDummy	-18,466	19983,44	0,999
Source Code	SM_github	-0,15	0,956	0,875
ICO Team	**Fin_Team**	**-0,336**	**0,115**	**0,003*****
Hard Cap/Soft Cap	Fin_hardcapDummy	-0,405	1,03	0,694
	Fin_softcapDummy	0,527	1,152	0,647
ICO Rating	Rating	-5,003	3,065	0,103
Country	Fin_TaxHaven	-0,68	1,145	0,553
	Country_HDI	2,955	8,224	0,719
Regulation	Fin_RegulatedDummy	-2,634	1,803	0,104
	Fin_BannedDummy	**-5,774**	**3,207**	**0,072***
	Fin_USRestrict	**-4,28**	**1,954**	**0,028****
Whitelist	**Fin_WhitelistKYCDummy**	**-2,869**	**1,36**	**0,037****
Control Variables	Fin_EthereumBlockDummy	0,609	1,396	0,663
	Fin_TokenDistributedDummy	-29,736	6534,937	0,996
	Fin_FiatAcceptingDummy	-1,401	1,182	0,236
	Fin_MinInvestDummy	1,082	1,66	0,515
	Fin_PreICODummy	1,287	1,249	0,303
	Fin_BonusDummy	**-1,957**	**1,191**	**0,100***
	Fin_NumCurrencies	0,194	0,401	0,627
	Fin_VideoDummy	1,369	1,432	0,339
(Intercept)	Constant	65,077	21024,826	0,998

Note: This table shows the output of the binary logistic regression after a sample split. Its goal is to analyze only ICOs with a low rating. For this purpose, only those observations were left in the sub-dataset for which the newly created auxiliary variable Rating_Trans takes the value 0. The listed variables are sorted according to the determents that are to be tested by them. Furthermore, the columns (from left to right) list the name of each variable, the beta, the standard error, and the significance based on a two-tailed t-test. Variables that have a significant impact on the failure of ICOs are marked in bold. *, ** and *** indicate a significance level at a 10%, 5% and 1% level, respectively.

Table 9.4: Model Summary

Step	Cox & Snell R Square	Nagelkerke R Square
1	0,302	0,637

Looking at Cox & Snell R Square and Nagelkerke R Sqare (Table 9.4), the model can be granted an even higher explanatory power than original model (Table 3.1). In addition, we now find a highly significant (0.01) negative correlation between Fin_Team and the dependent variable ICO_Fail. Therefore, it can be said that in the case of a low rating, the number of team members is a good determent of the success or failure of ICOs. Small teams seam more likely to fail than larger teams.

Hard cap/soft cap

Summary Statistics (table 2) show that data on the Fin_hardcapDummy and Fin_softcapDummy variables are available for 1,254 of the 1,288 ICOs. The hard cap indicates the maximum number of tokens that can be sold in an ICO. The soft cap indicates the minimum number of tokens that must be sold during so that the planned venture can be carried out. Fin_hardcapDummy and Fin_softcapDummy form dummy variables that indicate whether a hardcap or a softcap has been defined for the ICO. The descriptive statistics show u that for 48% of the 1,254 ICOs a hardcap, and for 42% a softcap was defined.

The output of the binary logistic regression (table 3.1) shows, that no significant statistical correlation can be found between the independent variables Fin_hardcapDummy (p-value of 0,738) and Fin_softcapDummy (p-value of 0,281) and the dependent variable ICO_Fail. However, Table 10.1 - 10.3 also show that there is a strong correlation between these two variables.

Table 10.1: Fin_hardcapDummy * Fin_softcapDummy Crosstabulation

Count

		Fin_softcapDummy		
		0	1	Total
Fin_hardcapDummy	0	513	142	655
	1	216	383	599
Total		729	525	1254

Table 10.2: Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	229,588[a]	1	<0,001		
Continuity Correction[b]	277,854	1	<0,001		
Likelihood Ratio	236,976	1	<0,001		
Fisher's Exact Test				<0,001	<0,001
Linear-by-Linear Association	229,404	1	<0,001		
N of Valid Cases	1254				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 250,87.

b. Computed only for a 2x2 table

Table 10.3: Symetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	0,428	<0,001
	Cramer's V	0,428	<0,001
	Contingency Coefficient	0,393	<0,001
N of Valid Cases		1254	

For this reason, a sample split is performed with help of the variable Fin_hardcapDummy. The binary logistic regression is performed once for all ICOs with hard cap (sub set 1) and another time for all ICOs without hard cap (sub set 2). In both cases, however, this decreases the significance of Fin_softcapDummy (P-value of 0.643 for sub set 1 and P-value of 0.608 for sub set 2).

If the sample split is performed with the help of Fin_softcapDummy, this does not improve the result either. For the sub sample without softcap (sub set 3) the p-value for Fin_hardcapDummy is 0.889

and for the sub sample a p-value of 0.581. The complete deletion of the variable Fin_hardcapDummy also worsens the p-value for Fin_softcapDummy to 0.300 when binary logistic regression is performed.

Fin_hardcapDummy and Fin_softcapDummy must therefore be rejected as determents of the success or failure of ICOs.

Rating

Information on the aggregate rating of ICOs on various websites is available for 1,061 of the 1,288 ICOs (compare table 2). The rating for the worst ICO is 0.45, while the rating for the best ICO is 5. Table 11.1 also shows that the rating variable is approximately normally distributed. The output of the binary logistic regression shows us that there is a highly significant negative relationship between the independent variable Rating and the dependent variable ICO_Fail (significance level a = 0.01). The ICO ratings which can be found on the various websites can therefore be considered as a good indicator to avoid investments in failing ICOs.

Table 11.1 Skewness and Kurtosis

		Statistic	Std. Error
Fin_Team	Skewness	0,183	0,031
	Kurtosis	0,075	0,150

ZSkewness = 2,44 < 2,58; ZKurtosis = 0,207 < 2,58

Country

Two variables were proposed to determine the influence of the host country on the failure of ICOs. Fin_TaxHaven is a dummy variable that indicates whether the host country is a tax haven. This information is available for 894 of the 1,288 ICOs. Approximately 21% of these ICOs were hosted in tax havens (compare table 2). Country_HDI indicates the Human Development Index of the host country in the year the ICO was conducted. This information is available for 886 of the 1,288 ICOs.

Regarding the output of the binary logistic regression, the variable Fin_TaxHaven turnes out to be significant, but not the variable Country_HDI. Interestingly, a negative correlation can be found between Fin_TaxHaven and the dependent variable ICO_Fail. ICOs that are conducted in tax havens thus seem more attractive from an investor's perspective. This does not correspond to the original assumption. Thus, a sample split is carried out. Two sub samples are generated. One that contains only the ICOs hosted in a tax heaven (subset 1). The other that contains those hosted not in a tax heaven (subset 2). However, in both sub sets the variable Country_HDI turns out not to be significant (p-value of 0,777 in subset 1 and p-value of 0,307 in subset 2).

Table 11.2: Correlations

		Country_HDI	Fin_Team
Country_HDI	Pearson Correlation	1	0,102**
	Sig. (2-tailed)		0,005
	N	886	764
Fin_Team	Pearson Correlation	0,102**	1
	Sig. (2-tailed)	0,005	
	N	764	890

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

However, a certain correlation can be observed between Country_HDI and the variable Fin_Team. Accordingly, two additional subsets are created. Subset 3 includes all ICOs with small teams of 1 - 6 team members. Subset 4 includes all large teams from 7 to 49 members. However, even with these two subsets, no significant correlation between Country_HDI and the dependent variable ICO_Fail can be found in a binary logistic regression.

<u>Regulation</u>

The regulation of the ICO is represented by the three variables Fin_RegulatedDummy, Fin_BannedDummy and Fin_USRestrict. Fin_RegulatedDummy provides data for 891, Fin_BannedDummy for 892 and Fin_USRestrict for 1,254 of the total 1,288 ICOs. 10.21% of the ICOs can be found regulated, 2.02% are banned and approximately 4% are restricted in the United States (compare table 2). The output of the logistic regression shows no significance for any of these three variables.

<u>Whitelist KYC</u>

The variable Fin_Whitelist KYCDummy serves as a Dummy for whitelist KYC compliance for 1,254 of the 1,288 ICOs. In total, a whitelist exists for about 19% of these ICOs, on which participants identify themselves in order to gain (preferential) access to the token sale (compare table 2). The logistic regression output revealed a very significant negative association between the independent variable WhitelistKYCDummy and the dependent variable ICO_Fail (compare table 3.1). Consequently, the original theory can be confirmed. The lack of a KYC whitelist at an ICO forms a determent for its failure.

<u>Token</u>

The three control variables Fin_EtheriumBlockDummy, Fin_TokenDistributedDummy and Fin_FiatAcceptingDummy give more detailed information about the token that was issued in the ICO. These variables provide data for 1,254 of the 1,288 ICOs. Summary statistics (table 2) show that about 64% of the tokens of these ICOs are based on the Etherium Blckchain, for about 71% information about the number of issued tokens is available, but only 8% of all tokens can be purchased using a fiat currency. However, no significant statistical correlation with the success or failure of ICOs can be found for any of these variables (compare table 3.1).

<u>ICO circumstances</u>

The control variables Fin_MinInvestDummy, Fin_PreICODummy, Fin_BonusDummy and Fin_NumCurrencies, describe the circumstances and conditions under which the ICOs took place. The variables Fin_MinInvestDummy, Fin_PreICODummy, Fin_BonusDummy provide data for 1,254 of the 1,288 ICOs. Information on NumCurrencies is available for 936 ICOs. The descriptive statistics in Table 2.0 show that for approx. 13% of the ICOs a minimum investment is necessary to participate, for approx. 24% a pre-ICO was carried out and for approx. 32% a bonus was obtained during the ICO. The average number of currencies approved for the ICO is 1.84. Within the framework of the logistic regression, no significant statistical correlation could be found between these independent variables and the dependent variable ICO_Fail. However, a certain correlation between Fin_EthereumBlockDummy and Fin_BonusDummy could be found (compare table 12.1 – 12.3).

Table 12.1: Fin_EthereumBlockDummy * Fin_BonusDummy Crosstabulation

Count

		Fin_BonusDummy		Total
		0	1	
Fin_EthereumBlockDummy	0	383	63	446
	1	466	342	808
Total		849	405	1254

Table 12.2: Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	104,524[a]	1	<0,001		
Continuity Correction[b]	103,238	1	<0,001		
Likelihood Ratio	113,471	1	<0,001		
Fisher's Exact Test				<0,001	<0,001
Linear-by-Linear Association	104,440	1	<0,001		
N of Valid Cases	1254				

a. 0 cells (0,0%) have expected count less than 5. The minimum expected count is 144,04.

b. Computed only for a 2x2 table

Table 12.3: Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	0,289	<0,001
	Cramer's V	0,289	<0,001
	Contingency Coefficient	0,277	<0,001
N of Valid Cases		1254	

Building on this insight, we divide the data set into two sub-samples using variable Fin_EthereumBlockDummy. Sub-sample 1 looks at the ICOs whose tokens are not built on the Ethereum blockchain. Sub sample 2 looks at the ICOs whose tokens are. It can be seen that for the ICOs whose tokens are based on the Ethereum Blockchain, a positive significant correlation can be established between the fail of the ICO and the variable Fin_BonusDummy (compare table 12.4).

Table 12.4: Regression results for Fin_EthereumBlockDummy = 1

Determent	Variable	B	S.E.	Sig.
Social Media Activity	SM_twitter	-1,775	1,312	0,176
	SM_facebook	**1,154**	**0,381**	**0,002*** **
	SM_reddit	**-0,56**	**0,297**	**0,059***
	SM_medium	0,158	0,314	0,614
	SM_telegram	0,154	0,297	0,605
	SM_vk	1,391	1,152	0,227
	SM_bitcointalk	**0,721**	**0,328**	**0,028****
	SM_bitcoinwiki	0,274	1,428	0,848
	SM_slack	0,077	0,288	0,79
	SM_discord	-1,126	1,222	0,357
	SM_linkedin	-0,96	1,22	0,431
	SM_instagram	17,022	21149,276	0,999
	SM_youtube	2,271	2,032	0,243
White Paper	WhitepaperDummy	-18,56	16091,549	0.999
Source Code	**SM_github**	**-0,859**	**0,297**	**0,004*** **
ICO Team	Fin_Team	-0,008	0,021	0,718
Hard Cap/Soft Cap	Fin_hardcapDummy	0,004	0,355	0,991
	Fin_softcapDummy	0,311	0,333	0,351
ICO Rating	**Rating**	**-0,991**	**0,307**	**0,001*** **
Country	Fin_TaxHaven	-0,48	0,309	0,12
	Country_HDI	-1,031	2,439	0,672
Regulation	Fin_RegulatedDummy	-0,498	0,398	0,21
	Fin_BannedDummy	0,089	0,936	0,924
	Fin_USRestrict	-0,542	0,429	0,207
Whitelist	**Fin_WhitelistKYCDumı**	**-1,441**	**0,303**	**<0,001*** **
Control Variables	Fin_TokenDistributedD	-0,728	0,616	0,238
	Fin_FiatAcceptingDum	-0,279	0,457	0,541
	Fin_MinInvestDummy	-0,249	0,321	0,438
	Fin_PreICODummy	0,016	0,293	0,956
	Fin_BonusDummy	**0,672**	**0,303**	**0,027****
	Fin_NumCurrencies	0,085	0,115	0,458
	Fin_VideoDummy	-0,193	0,405	0,634
(Intercept)	Constant	25,785	16091,549	0,999

Note: This table shows the output of the binary logistic regression after a sample split. Its goal is to analyze only ICOs that issue tokens that are based on the Ethereum blockchain. For this purpose, only those observations were left in the sub-dataset for which the newly created auxiliary variable Fin_EthereumBlockDummy takes the value 1. The listed variables are sorted according to the determents that are to be tested by them. Furthermore, the columns (from left to right) list the name of each variable, the beta, the standard error, and the significance based on a two-tailed t-test. Variables that have a significant impact on the failure of ICOs are marked in bold. *, ** and *** indicate a significance level at a 10%, 5% and 1% level, respectively.

Table 12.5: Model Summary

Step	Cox & Snell R Square	Nagelkerke R Square
1	0,214	0,346

Video

The control variable Fin_VideoDummy indicates whether the company has published a video. The variabble provides this information for 1,254 of 1,288 ICOs. Approx. 56% of these ICOs publish a video. The binary logistic regression shows no significant statistical correlation between Fin_VideoDummy and the dependent variable ICO_Fail. The existence of a video can therefore not be considered as a determent for the success or failure of ICOs.

7 Conclusion

Finally, the following findings can be summarized:

The theory could be confirmed that the leak of activity on certain niche social networks serves as a determent of failure for ICOs. Approx. 70% of all ICOs have a Facebook account, however Facebook could not be found as a good indicator. As expected, the activity on the niche Reddit was found as a significant determent. This is explained by Reddit being a social network strongly used by experts and enthusiasts of a certain topic. Thus, ICO investors should particularly consider informing themselves via Reddit before investing into ICOs. The niche platforms bitcoinwiki and bincointalk however were not found to be such determents.

The mere presence of a white paper could not be confirmed as a determent. A more detailed qualitative examination of the white paper is probably needed to serve as a quality signal.

The activity source code platform Github was verified as a significant determent. Investors with good knowledge in computer science should consider checking the quality of the source code on Github. However, investors with no such skills can still regard the presence of a Github account for the ICO as a positive signal. This is explained by the assumption that it only makes sense to publish high quality source codes. Regulators may want to require the publication of the source code in the future.

However, the ICO ratings of different websites could be found as a good determent for the failure of ICOs. Also, for low ratings, the number of team members could be found as an additional indicator for success.

The presence of hard caps and soft caps instead could not be confirmed as determents. Apparently, these are not sufficient as a signal for the quality of the ICO-ventures.

The ICO host country being a tax haven interestingly decreases the likelihood of failure. However, this can possibly be attributed to the fact that the tax havens in the sample studied are primarily very highly developed countries such as Singapore and Switzerland.

For the regulation of the ICO no correlation with the failure of ICOs could be found. This is possibly due to the still very small number of regulated ICOs. Another explanation would be the skepticism of ICO investors towards state institutions. This may mean that regulation is not seen by investors as a signal of quality, but rather as an intervention in the independence of ICOs.

Finally, the existence of a KYC whitelist, in which token buyers can identify themselves to gain preferential access to token sales, was also found to be significantly negative related with the failure of ICOs. This seems very logical, as the whitelist forces token investors to disclose their identity. This increases transparency and reduces the uncertainty of ICO investments. ICO investors should therefore consider reducing their exposure to ICOs with KYC whitelists. Regulators may want to require them in the future.

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9 Appendix

Variable Definitions

Variable	Definition
Dependent variable	
ICO_Fail	Indicates whether an ICO can be considered as a failure
Independent variables	
SM_twitter	Dummy for twitter account (SM = social media)
SM_facebook	Dummy for facebook account (SM = social media)
SM_reddit	Dummy for reddit account (SM = social media)
SM_medium	Dummy for medium account (SM = social media)
SM_telegram	Dummy for telegram account (SM = social media)
SM_vk	Dummy for vk account (SM = social media)
SM_bitcointalk	Dummy for bitcointalk account (SM = social media)
SM_bitcoinwiki	Dummy for bitcoinwiki account (SM = social media)
SM_slack	Dummy for slack account (SM = social media)
SM_discord	Dummy for discort account (SM = social media)
SM_linkedin	Dummy for linkedin account (SM = social media)
SM_instagram	Dummy for instagram account (SM = social media)
SM_youtube	Dummy for youtube account (SM = social media)
SM_blog	Dummy for a blog (SM = social media)
WhitepaperDummy	Indicates whether a white paper was published for the ICO.
SM_github	Dummy for github account (SM = social media)
Fin_Team	Number of team members during the ICO (after quality check)
Fin_hardcapDummy	Indicates whether a hard cap was specified during the ICO (after quality check)
Fin_softcapDummy	Whether a soft cap was specified during the ICO (after quality check)
Rating	Overall rating quality of the ICO
Fin_TaxHaven	Indicates whether the ICO was issued in a country that is considered as a tax haven (after quality check)
Country_HDI	Human development index of the country and year the ICO was issued.
Fin_RegulatedDummy	Indicates whether the ICO was regulated (after quality check)
Fin_BannedDummy	Indicates whether the ICO was banned (after quality check)
Fin_USRestrict	Indicates whether the ICO is restricted from selling coins in the US (after quality check)
Fin_WhitelistKYCDummy	Indicates whether the ICO is whitelist KYC compliant (after quality check)
Fin_EthereumBlockDummy	Indicates whether the token is using the Ethereum blockchain (after quality check)
Fin_TokenDistributedDumm	Indicates whether there are information about the number of tokens (after quality check)
Fin_FiatAcceptingDummy	Indicates whether the token can be purchased using a fiat currency (after quality check)
Fin_MinInvestDummy	Indicates whether there is a minimum investment amount to partake in the ICO (after quality check)
Fin_PreICODummy	Indicates whether a pre-ICO was held before the ICO (after quality check)
Fin_BonusDummy	Indicates whether a bonus could be obtained during the ICO (after quality check)
Fin_NumCurrencies	Number of currencies that the ICO accepts to purchase (after quality check)
Fin_VideoDummy	Indicates whether the company has published a video (after quality check)

Note: This table gives an overview of the definitions of the variables used to test the suggested determents. At the top we find the dependent variable ICO_Fail used for the binary logistic regression. Below that, the individual independent variables are listed. Additional auxiliary variables created to create sub datasets are not listed. The left column lists the name of the variable, the right column contains a short definition. The abbreviation "Fin" at the beginning of some variables stands for "Final" and shows that this variable has been subjected to a quality check. "SM" indicates that the variable gives information about a social media.