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An empirical analysis of the Initial Coin Offering using Social Network Analysis

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Abstract

The Initial Coin Offerings (ICOs) are digital token offerings, based on the innovative Blockchain technology, and serve as a mean to collect funding through the Internet to be allocated to a project, a startup or a consolidated company, eliminating the intermediation of any external platform, paying agent or professional investor. ICO proponents are usually groups composed of entrepreneurs, professionals, technicians and managers, assisted by an advisory committee.

Using different centrality and connectedness measures from Social Network Analysis, in this thesis we analyze how the quality of the relationships characterizing team members and advisors' impact on the ICO fundraising success. In particular, we want to assess if the social capital owned by ICO proponents could explain the success of the token offering, and in which way it could be used to improve such fundraising process.

The research shows interesting results. In fact, regression analyses suggest the positive impact of the social network connections on the final result of the funding campaign. Our findings are robust to the test of different indexes connectedness, such as the belonging to the largest component of the network, as well as various measures of centrality.

Abstract

Le Initial Coin Offerings (ICO) sono offerte di token digitali, implementate sull'innovativa tecnologia Blockchain, e fungono da strumento per raccogliere finanziamenti attraverso Internet per un progetto, una startup o una compagnia affermata, eliminando l'intermediazione di qualsiasi piattaforma, agente di pagamento o investitore professionale. I soggetti dietro ad un'ICO sono di solito gruppi composti da imprenditori, professionisti, tecnici e dirigenti, assistiti da uno o più consulenti specializzati.

Utilizzando diverse misure di centralità e connettività prese dalla Social Network Analysis, in questa tesi analizziamo come la qualità delle relazioni che caratterizzano i membri del team di progetto e dei consulenti incida sul successo della raccolta fondi. In particolare, vogliamo valutare se il capitale sociale delle persone che implementano un'ICO, possa spiegare il successo delle emissioni di token e in che modo potrebbe essere utilizzato per migliorare tali processi di raccolta fondi.

La ricerca mostra risultati interessanti. Infatti, i dati delle regressioni statistiche dimostrano l'impatto positivo delle connessioni sociali sul risultato finale dell'ICO. I nostri risultati risultano essere robusti rispetto ai test effettuati attraverso diversi indici, come l'appartenenza al più grande componente della rete e varie misure di centralità.

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Executive Summary

A singularity of the mankind is the creation and exploitation of instruments to overcome the challenges of Nature; it happened from the caveman to the modern man. In particular, during the First Industrial Revolution, the men overcame their natural limits through the invention of the steam engine, hence reducing the distances between people. Then, the invention of the electricity pushed even forward the boundaries of human progress, then becoming the basement of another crucial instrument for our development: the Internet. In human history, it is doubtless the instrument with the biggest potential for connecting people around the world through the creation of a digital environment in which people can interact freely with each other. Anyone can have a video call with a person on the other side of the globe simply with a click. Obviously, this gives many advantages also to companies and governments; the creation of Internet revolutionized relationships, both personal and economic, alongside with business models of each single firm in the world. Nevertheless, Internet presents some risks. Economic frauds can be implemented by individuals from the other side of the web, and inherently causing a lack of trust in some of its application. The uncertainty and the moral hazard of Internet users are a serious problem for the development of the crypto-world.

Since 2008, a new human's instrument is evolving and, day by day, is gaining so much importance thanks to its potential disrupting power to attract the interest of many actors from different sectors: industrial, legal, financial, economic, and so on. This technology is the Blockchain. In brief, the Blockchain is a distributed immutable ledger in which transactions between individuals can be recorded in different ledger's units, called blocks. The blocks create a dataset based on consensus, cryptographically secured from tampering and revision. The main singularity of this technology is the impossibility to change past transactions, allowing the disintermediation in those fields in which a trusted part is needed. The immutability is made possible by its decentralized nature, as the Blockchain is distributed in all the computers (nodes) linked to it, and a copy of the ledger is inside each node. This means that in order to modify a data it is necessary to modify all the nodes. Specifically, the 51% of the nodes. Is necessary, as one of the main pillars of the Blockchain is that it is based on the consensus of the participants.

However, as the technology is still in the early stage of its development and some features need further improvement, the system experienced few attempts of attack over time. Nonetheless, advocates of this revolution firmly support the idea that it may cover the lack of trust coming from Internet.

Moreover, transactions through the Blockchain cannot be done using Fiat Money; they imply the use of a cryptocurrency. The most known cryptocurrency is the Bitcoin, developed by Satoshi Nakamoto, a pseudonym for the unknown person (or people) that in 2008 conceived the first Blockchain (the Bitcoin one). The Bitcoin launch was the proof that real transactions can be implemented through the use of a virtual currency, without the financial intermediation of banks or governments. In this sense, the current financial institutions increasingly have to pay attention to the future (the very near future) developments of Blockchain and cryptocurrencies, given their great disruptive potential. Actually, many financial subjects are moving toward these technologies; Bank of America applied for 82 patents for the Blockchain (many of which have already been granted), IBM created a related business unit ("IBM Blockchain"), JP Morgan created its own cryptocurrency ("JPM Coin"), and the number of these cases is steadily growing.

In this turbulent and evolving environment, an application of Blockchain and cryptocurrencies has already entered powerfully in the traditional funding methods: The Initial Coin Offering (ICO). ICO is essentially the crypto-version of the crowdfunding. It is defined as *"an open call for funding promoted by organizations, companies, and entrepreneurs to raise money through cryptocurrencies, in exchange for a token that can be sold on the Internet or used in the future to obtain products or services and, at times, profits."* The token is basically a cryptocurrency whose value after the sale is established simply by its demand, but it gives some rights as well: the access to the platform of the venture launching the ICO is the most common one, while the second one is the right to collect a share of the profits coming from the venture's business. This alternative financing method has allowed (mostly) startups and established companies to raise more than $22 billions in just the 2017 and 2018. This huge number has been achieved thanks to the benefits given by the Blockchain compared to the traditional financing methods. Indeed, disintermediation and decentralization - giving the opportunity to reach investors situated in every corner of the globe only using an Internet connection - are exploited to reduce the costs of a fundraising campaign. The ICO regulation is constantly evolving but its change is boundend to country-specific legal conditions and degree of maturity towards the Bolockchain environment. Moreover, the decentralised nature allows to avoid those countries with stricter rules. Generally, the requirements for an ICO can be easily satisfied. For a startup, the only requirements are an Internet connection and a white paper, an explanatory document in which are reported the main information about the venture and the ICO. The ICO phenomenon has rapidly evolved over time also thanks to several projects contributing to the development of cryptocurrencies and Blockchain. For example, running an ICO was made simpler by the Ethereum Blockchain, the second largest cap cryptocurrency behind Bitcoin, with its standard. Thus, differently from the first ICOs, the knowledge about tokens and Blockchain can be easily acquired and upgraded.

We have used the word "acquired" specifically. As happened for other financing methods, the figure of the advisor was introduced also for ICOs. This figure has become very relevant, so that today all the teams running an ICO have an advisory board. This role is a proper job figure. In fact, often advisors oversee more than one ICO. Advisors are experts in the ICO proceedings who provide the team with many services such as regulatory oversight, token development, ICO website design, investor relations management and ICO advertising. In few words, they use their ICO proceedings knowledge and network of relationships to increase the probability of success of the campaign.

This study is focused on this matter. It aims to understand how the network composed by the team members of the venture launching the ICO and by the advisors is useful to spread the knowledge about ICOs, and if the kind of such relationships can enhance the probability of success of the fundraising. In a certain sense, this work tries to study in deep the effect of human relationships in an environment where the main linkage consists in the communication with a computer interface. In doing so, we exploited some instruments coming from the Social Network Analysis (SNA), that is the study of networks and human relationships. Specifically, we used the concept of centrality and its various measures. Centrality refers to the position that an individual, or node, has within network. As founded by many scholars, the centrality and its measures are correlated with the diffusion of the knowledge and best practices in professional networks, as the one of the ICOs. Moreover, we search for the relation between the past successful funding campaign run by advisors and team members, and the probability of success of the ICO. This relation should be a signal of the skills owned by the ICO participants, as previously found by Butticè et al. (2017) for the crowdfunding. It is linked with the *fil rouge* of the study. Indeed, as the skills of the participants are the human capital of the venture, the focus is still on the human side of the ICO.

Thus, our work is built on two different literatures. The first one relates to the determinants of success in the ICO that, in turn, is a specific direction of development following the signaling theory, initially formulated by Akerlof (1970) in his paper "*The Market for "Lemons": Quality Uncertainty and the Market Mechanism*", which earned him the Nobel prize. The literature on the ICO's determinants of success is young, but several studies are already present. Most of the works focused on the ICO features, the characteristic of the team, the links in the social networks, and the information disclosed about the project (Adhami et al. 2018; Amsden & Schweizer, 2018; Fisch, 2019), but no study used the instruments of SNA in relation to the ICO success.

The other literature is obviously related to the SNA. We studied this matter starting from the graph theory, the study of main elements constituting a network (the node and the edges). Then, we approached the SNA on an historical perspective, understanding how it was developed over the time and how its concepts and measures were evolved by the scholars. In particular, we focused on some centrality measures and their calculations in unweighted networks and in the weighted ones. The weight is a value given to the edges that can represent something, as the level of knowledge accumulated or the number of relationships between two nodes. Specifically, we studied the degree centrality (only for unweighted networks), the strength centrality (only for weighted networks), the eigenvector centrality, the betweenness centrality and the efficiency. Afterwards, we analyzed some studies about the application of the SNA, mainly in economic and financial contexts. From these studies, we have taken some important concepts for our work. For instance, the relation with the degree, eigenvector and betweenness centralities, and efficiency with the spread of innovation and knowledge in the networks (Bajo et al., 2016; Cheng et al., 2019; Kim, 2019; Latora & Marchiori, 2003), but also the idea that larger networks generate more knowledge and resources for the ventures within (Nicholson et al., 2004).

Reviewing these literatures was paramount for developing our research hypothesis. The first hypothesis links the centrality measures referred to the ICO and the ICO success, under the assumption that a more central ICO has more opportunities to learn best practices and to spread information about the ICO as advertisement. The second set of hypotheses is based on the idea that larger network can create more knowledge and provide more resources to the ICO. Indeed, the ICO network is composed by some sub-networks (components), and hence we conjectured that the belonging to the largest component is related with the ICO success. Finally, the last set of hypotheses aims at testing the link between the occurrence of previous successful campaign by the ICO member and their future success.

We tested our research hypotheses using a sample of 933 Initial Coin Offerings, occurred between October 2015 and February 2018, and another one of 10297 constituted by team members and advisors. First of all, we assumed that the time horizon was enough thin (first relation created in March 2017) to ignore the temporal dimension; we called it as simultaneity assumption. So, we built a network that we called *static* network. Then, we performed some T-test analysis to understand the differences in the means between the population of successful ICOs and the failed ones. The results showed a statistically significant differences for the belonging to the largest component and for the occurrence of previous successes. It was not found for the centrality measures. The regression models confirmed these results, and hence we decided to change our initial approach. Indeed, we refused the simultaneity assumption and we built a network that took into account the time factor. In doing so, we added the weights to the edges. Specifically, the weights were used to represent the amount of cumulative knowledge assuming that the knowledge is proportional with the passing of time. Adapting the centrality measures' calculation with the usage of the weight, we computed again the centrality measures. In this case, the T-tests found a statistical difference in the means also for the centrality measures. The regression models performed verified these results and also our research hypothesis.

To give more strength to our results, we performed some robustness checks, examining deeply our variables of interest. Regarding the past successes, we found that also the simple previous experience by the ICO proponents is positively related with the ICO success. This further analyzes was done because the T-tests showed a higher mean of the presence of past failures in the case successful projects than in the case of failed ones. It was different by what we expected; in fact, we expected a sort of black sheep effect, therefore a negative relation with the past failures and the future successes. The second robustness check was done on the centrality measures. We studied their quadratic behavior demonstrating that when the centrality measures assume too high values, they have a negative effect on the ICO success; only the efficiency measure we tested did not show such behavior. Even if the cases in which the values were overcome are few, these behaviors may be due to the difficulties in processing a high amount of information, to the spillover of secret information about the projects and the advisors' moral hazard, as well as to the high retribution asked by advisors with many links or having a brokerage position. Finally, the last robustness check consisted in the addition of the direction to the edges of the network in order to allow the exchange of information from the older ICOs to the younger ones. However, it showed no difference from the previous model. It means that the weights and the way in which we have conceived the centrality measures are a good indicator also for the time factor. Moreover, this result gave again more strength to our research hypotheses.

The reminder is organized as follows: in section 1 we provide both an overview of the Initial Coin Offering phenomenon (paragraph 1.1), a literature review on the ICO determinants of success (paragraph 1.2), and a literature review on the Social Network Analysis (paragraph 1.3); section 2 define the scope of this work showing the research hypothesis we want to verify and the methodologies used; section 3 describes the analysis performed, specifically, the data collection process (paragraph 3.1), the data analysis explaining also the construction of the static network (chapter 3.2), the first univariate analysis using the static network (paragraph 3.3), the models of the multivariate analysis using the static network (paragraph 3.4), the new analysis performed with the dynamic network from the network construction to the results' explanation (paragraph 3.5); the performing of the robustness checks related firstly to the success, unsuccess and experience, measures, secondly to the quadratic effect of the centrality measures, and thirdly to the addition of the direction to the edges of the network (paragraph 3.6); the conclusions and hints for further researches (chapter 4).

1. Literature Review

1.1 Initial Coin Offering (ICO)

The global financial system allows us to manipulate trillions of dollars and involves billions of people every day. Considering additional costs due to tariffs and delays, problems related to redundant and burdensome practices, and the possibility to pave the way for fraud and crime, it can be seen how this system is not perfect. These inefficiencies derive from an antiquated system composed of both industrial technology and paper processes; it is centralized, therefore not inclined to change and vulnerable to attacks and failures of the various systems and is also exclusivist and denies access to financial instruments to billions of people. A solution to this stalemate has emerged in the blockchain (Tapscott & Tapscott, 2017) and, as many startups have started doing, through the Initial Coin Offering it is possible to overcome the strict regulations to access to the funding that are currently in force for traditional forms of financing (Investopedia).

1.1.1 Blockchain: an innovative technology and its application

This sub-paragraph will describe the main characteristics of the Blockchain, the ICO underlying technology, and some applications in the real world.

There is no shared definition of Blockchain (Halaburda, 2018), but it can be defined as a distributed, immutable database based on consensus that maintains a continuously growing list of transaction data records, cryptographically secured from tampering and revision (BlockchainHub). In essence, it is a data structure in which each element takes the name of block (hence the name, the set of blocks forms a chain). Each block consists of:

- Contents of the block (e.g. in the Bitcoin protocol contains the block size, the number of transactions and the transactions themselves);
- Header (info about the block such as: the version, identifier of the previous block, hash merkle root, timestamp, nonce) (Zheng et al., 2017).

According to Tapscott & Tapscott (2017), the Blockchain technology has some peculiar characteristics, such as:

1. Distributed database: each part of the Blockchain has access to the entire database and its history; no part controls data and / or information but each party can directly verify the registrations of the transaction partners, without the need for intermediation.
2. Peer-to-peer transmission: communication takes place between peers / users and not through a central node; each node stores and forwards the info to the other nodes.
3. Transparency with pseudonym: each transaction and its value are visible to anyone who can access the system. Each node / user has an alphanumeric identification address of 30 characters but can also choose to remain anonymous; transactions take place between Blockchain addresses.
4. Irreversibility of registrations: when the transaction is entered in the database and the accounts are updated, the registration cannot be changed as it is connected to the records of previous transactions. Algorithms and computational approaches ensure that registration is permanent, chronologically ordered and available to users on the network.
5. Computational logic: Blockchain transactions can be programmed; users can set certain algorithms and rules that activate transactions automatically (i.e., smart contracts).

In most cases it does not require a permission to access, making public information accessible to all users. This is the case of the public (or permission-less) Blockchain, that allows users to write data without authorization. There are also private Blockchains (permissioned) that are formed by known and reliable participants.

The innovative technology of the Blockchain was originally developed as the underlying technology of cryptocurrencies (e.g., Bitcoin): it allows to store all the information related to the transactions carried out, which are collected in blocks that, chronologically ordered, form a potentially infinite chain.

As Nakamoto (2008) explains, these blocks are approved by the network nodes through a mechanism with majority approval of the computers (nodes) of the network, and when a new block is approved becomes the last link in the chain. Two contrasting transactions cannot belong to the same block and a transaction belonging to a subsequent block cannot conflict with the previous one. If several blocks containing simultaneous transactions are approved at the same time, the chain will have as many bifurcations as the approved blocks (all valid). Since the network recognizes as valid only the longest bifurcation of the chain, it rejects the others and invalidates its transactions (Nakamoto, 2008).

For block approval, the Blockchain implements a consensus mechanism that changes according to the system adopted (for example, Bitcoin requires proof-of-work, PoW, which is the most common mechanism). The PoW is an economic measure that allows to protect the Blockchain from attacks of type Denial of Service (DoS) (Wüst et al., 2016). It is based on the competition between peers of the network for the processing of blocks that must be added to the chain in order to receive prizes (block reward). The PoW is strongly linked to the mining activity. In fact, to ensure that the transaction added to a block (together with the others made at the same time) is confirmed, and therefore become part of the Blockchain, a new block must be added: the miner is the one who competes with the other miners to get the right to add a new block of transactions. The competition consists of a decryption work (resolution of a cryptographic puzzle generated by the Blockchain system - the proof-of-work problem) that requires a high computational power; if it is resolved, the miner can select transactions and insert them into the newly generated block. Some users can bind commissions to their transactions, so that the miners can include them with priority; this mechanism lengthens the approval time and can result in uncompetitive transactions waiting for confirmation for a long time, highlighting the possible inadequacy of the PoW in sustaining large volumes of transactions. At the same time, the PoW ensures the modification of the Blockchain is onerous, deters hackers from attacking it and makes it impossible to falsify (e.g., the network recognizes only the longest chain valid, so to tamper with a block you need to modify all those following, including those in the process of approval). The key feature of this scheme is asymmetry: work must be moderately difficult but flexible on the request side (if too simple, it can be vulnerable to DoS attacks and spam) and also easy to control by the service provider. According to Tapscott & Tapscott (2017),

the miners' earnings may not be sufficient for the future implementation of large-scale technology: the reward per block is reduced each time, and at the same time the algorithms that the miners must solve become more difficult. According to the authors, the miners will prefer operations that offer higher optional compensation and when the reward is close to zero the fees will become higher and the average person will no longer be able to afford a transaction within the network. This would cause a decrease in mining activities that would result in a decrease in security on the network.
Proof-of-stake (PoS) is a different way to validate transactions and get distributed consensus. This concept states that a person can mine or validate block transactions based on his health or stake (i.e., the number of coins he holds); for example, more Bitcoins are owned by a miner, more mining power possesses he has. In this way, instead of using energy to respond to PoW problems, a PoS miner must be limited to an extraction that reflects the amount of crypto coin he has. Then, in the PoS there is no reward for miners due to the creation of blocks (but they earn the transaction costs - or fees - and take the name of "forgers") (Saleh, 2018).

In addition to the aforementioned Bitcoin, another decentralized platform is the Ethereum, which has found great use in the phenomenon of Initial Coin Offerings. One of the main objectives of Ethereum is the implementation of the so-called smart contracts (Bhargavan et al., 2016). The smart contract is a program that runs on the Blockchain through the consensus protocol. Its operation is based on the codification in programming language of any set of rules, the same rules of a traditional contract. For example, a smart contract can allow the transfer of cryptocurrency to the occurrence of a given event specified in its set of rules (Olickel, Saxena, Chu, Luu, & Hobor, 2016).

The advantage of the Blockchain compared to the traditional system linked to a central authority, lies in cutting costs and in the possibility of each user to view an incorruptible and indestructible database. Control is moved to the automation of known algorithms and to the work of a network that benefits from following the rules rather than violating them. Blockchain technology is increasingly used in other areas by virtue of its characteristics. Thanks to its decentralized management, it is the ideal tool to transmit any data in a secure manner, eliminating significantly the entire intermediate chain and giving security and confidentiality to the exchange of data without having to use intermediary companies (Linkov et al., 2018). The figure 1 illustrates the areas of application of the Blockchain in the Italian sphere.

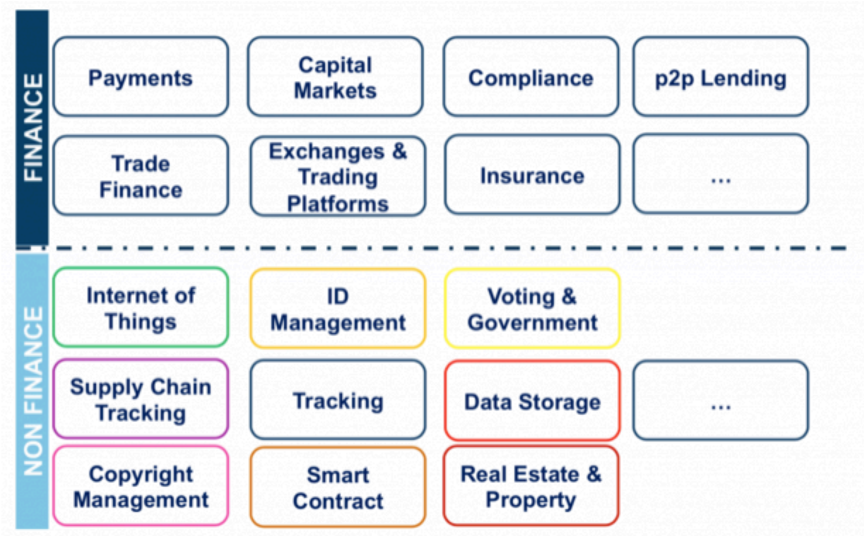

Figure 1. Blockchain applications. Source: Osservatorio of Politecnico di Milano

- Blockchain in finance and banking: the lack of intermediaries in the management of transactions would allow banks to reduce commission costs, giving significant savings, and would allow for faster and more reliable transactions (Yermack, 2004). For example, NASDAQ, NYSE, LSE and stock exchanges around the world are testing the ability of the Blockchain to make trading more efficient (Natarajan et al., 2017).
- Blockchain in insurance: several studies show how in this sector the use of this technology can bring advantages. Security and decentralization are a strong element that can prevent insurance fraud and at the same time ensure better governance, reporting and data quality. In addition, insurers may have improved risk management and can maximize opportunities for their funds and corporate capital through more effective, useful and secure strategies, obtaining updated and accurate news about market changes (Lamberti, Gatteschi, Demartini, Pranteda, & Santamaria, 2017).
- Blockchain in agri-food: for companies in the sector, Blockchain can give the possibility to improve the traceability and transparency of its products in order to

offer the consumer a totally reliable service (Xavier, Boldú, Fonts, Kamilaris, & Prenafeta-Boldΰ, 2018).

- Blockchain in the industry 4.0: the undoubted advantages refer to the possibility of preserving information, giving the certainty of their truthfulness. The fields in which it can be applied concern the Internet of Things (IoT), machine automation, logistics, supply chain, relations between companies (Zhang & Wen, 2015).
- Blockchain in healthcare: with the Blockchain it is possible to manage, through a shared system, patient clinical data in a safe and fast way; this favors the improvement of the service provided to patients and allows doctors to examine the patient's clinical history in order to support it with the best care in a short time (Krawiec et al., 2016).
- Blockchain in the public administration: the fields in which it is most evident its potential utility, are those of public registers (for example, land register and real estate registers) and that of the administrative procedure management, reducing time and costs and improving transparency (Berryhill et al., 2018).
- Blockchain in retail and digital payments: the Blockchain would allow to extend the current methods of payment in the shop through the cryptocurrencies, allowing faster and, above all, cheaper payments. However, it should be stressed that a number of problems still need to be addressed, such as the time it takes to manage a transaction as it should be complemented by a set of clearer regulations (Foroglou & Tsilidou, 2015).
- Blockchain in the protection of personal data: the Blockchain allows to store the digital identity of users, ensuring privacy (Maxwell & Salmon, 2017).

1.1.2 Cryptocurrency: Bitcoin, Ether and altcoins

Since the ICOs were born as a financing method for new or, in rare cases, established projects, we think it is right and proper to dedicate a sub-paragraph to the mean of the financing: the cryptocurrencies.

The first cryptocurrency using Blockchain was the Bitcoin that since its birth it was the largest cap cryptocurrency, and so the most famous. Then, over than 2000 alternative coins (or altcoins; alternative coins to the Bitcoin) and tokens were created but, generally, their value was defined by the Bitcoin one. Thanks to the work of Nakamoto (2008), the Bitcoin became a mean of payment for goods and services but the birth of Bitcoins was due to the need of incentivize miners for solving the cryptography puzzle for the creation of new blocks. (Lee et al., 2018). So, Bitcoin started in the crypto-world and was initially used by miners and enthusiasts. The payment can be done by software, app or various online platforms. The process of exchange is defined by the Blockchain, and hence it has all the features described in the previous paragraph: decentralization, peer-to-peer transactions, no need of intermediation, public ledger, and network verification. The figure 2 shows the Bitcoin price and the market capitalization. It is impressive the value reached at the end of 2017; over the 20.000$. Obviously, it created a lot of hype and interest from financial sector, but many analysts were cautious and suggested the presence of a bubble. Seeing the graph and the arguments of many commentators (N. Smith, 2018), the bubble was true, and the value collapsed even if, today, it seems quite stable.

Figure 2. Bitcoin price and market capitalization. Source: CoinMarketCap

We must do a clarification. Bitcoin and Blockchain diffusions are strictly correlated but it is not the same thing. The Blockchain is the underlying structure of Bitcoin (and other cryptocurrencies) and needs Bitcoin to implement transactions between nodes. Bitcoin could exist without Blockchain, but it would not guarantee the assurance of the exchange and would not avoid frauds during the payment. It was understood by Buterin, that in his white paper (Buterin, 2013) described the potential of the Nakamoto's work, and laid the groundwork for the Ethereum Blockchain. Ethereum expanded many functionalities from Bitcoin. Ethereum allows developers to build and deploy decentralized applications (Dapp) and introduced an improvement of smart contract, a set of rules that ensure the automatic realization of a contractual clause after the occurrence of a specific event; for example, the refund of money to investors when the ICO's minimum target capital is not reached. The improvement is called ERC20 token standard contract and allows the generation of other cryptocurrencies (or tokens). ERC20 token standard contract is the main reasons of the big diffusion of this Blockchain because these two features are crucial for the implementation of an ICO. In the figure 3 there is the price and the market capitalization of Ether, the Ethereum's cryptocurrency. The value of altcoins followed the Bitcoin's one and Ether is not an exception; at the end of 2017, it reached its maximum value and then it fell down, exactly like Bitcoin.

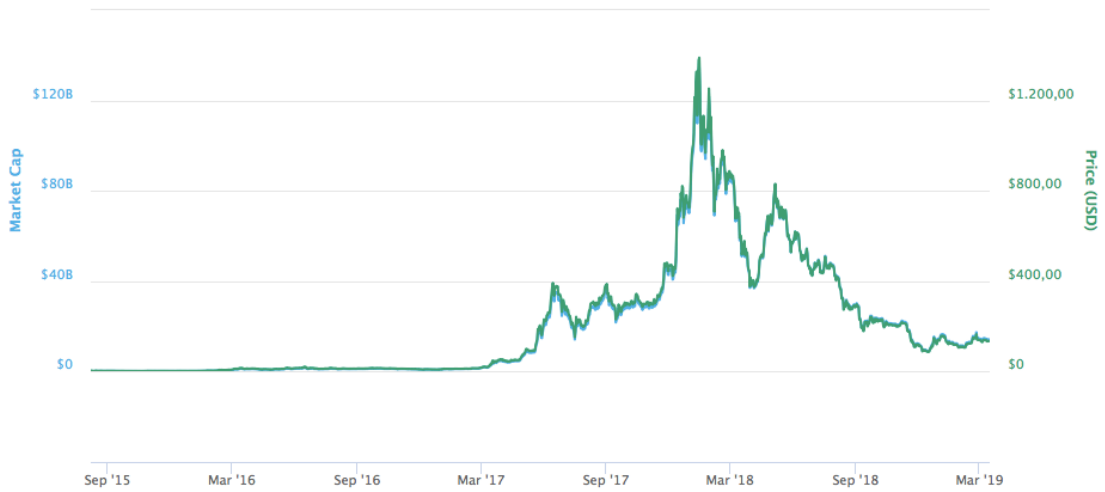

Figure 3. Ether price and market capitalization. Source: CoinMarketCap

As said before, many other altcoins were created. The total capitalization of the cryptocurrency market is equal to $134,7 billion. The table 1 represents the top 10 cryptocurrencies for market capitalization. Here, we can understand why the Bitcoin value influences the altcoins' ones; its market capitalization is almost five time larger than the

Ethereum's one, that is over 4 time larger than the Litecoin's one; also, the price suggests the strong attention of investors to the Bitcoin compared to altcoins. In the sixth position, we can see the Bitcoin Cash. It is a coin born from the hard fork of the Bitcoin Blockchain. A hard fork occurs when a present Blockchain is divided and a new Blockchain is created. It is happened for Bitcoin (Bitcoin vs Bitcoin Cash), for Ethereum (Ethereum vs Ethereum Classic) and, again, for Bitcoin Cash (Bitcoin ABC vs Bitcoin SV). Differently from the general market sentiment, the Bitcoin Cash hard fork generated a lot of turbulence influencing also the Bitcoin price (F. Izzi, 2018). Another interesting trend is the one of the stablecoins; coins tied up to an external value to the crypto-world, mostly the dollar. Referring to this tendency, in the top 10 there is a stablecoin, Tether, linked to the dollar.

Cryptocurrency	***Market Capitalization***	***Price***	***Circulating Supply***
Bitcoin (BTC)	*$ 68.841.740.729*	*$ 3.914,25*	*17.587.475*
Ethereum (ETH)	*$ 14.066.834.711*	*$ 133,68*	*105.231.090*
Ripple (XRP)	*$ 12.987.455.576*	*$ 0,31*	*41.432.141.931*
Litecoin (LTC)	*$ 3.441.184.829*	*$ 56,53*	*60.874.536*
Eosio (EOS)	*$ 3.279.916.982*	*$ 3,62*	*906.245.118*
Bitcoin Cash (BCH)	*$ 2.326.730.633*	*$ 131,66*	*17.671.638*
Stellar (XLM)	*$ 2.116.668.823*	*$ 0,11*	*19.215.591.246*
Binance Coin (BNB)	*$ 2.100.321.313*	*$ 14,88*	*141.175.490*
Tether (USDT)	*$ 2.021.107.797*	*$ 1,01*	*1.996.357.066*
TRON (TRX)	*$ 1.523.908.150*	*$ 0,02*	*66.682.072.191*

Table 1. Top 10 cryptocurrencies statistics

1.1.3 Initial Coin Offering: characteristics

In this sub-paragraph we want to provide a definition of ICO, clarifying and explaining the features of an ICO (also citing previous studies), to allow the reader to better understand some specific elements of the phenomenon. Before doing it, it is proper to observe that this financing method is not regulated and has not defined standards. Each ICO may differ from the others in many aspects, but it is possible to find some frequent elements.

First of all, we provide a definition. As stated by Adhami et al. (2018, p. 1), "Initial Coin Offerings (ICOs) can be defined as open calls for funding promoted by organizations, companies, and entrepreneurs to raise money through cryptocurrencies, in exchange for a "token" that can be sold on the Internet or used in the future to obtain products or services and, at times, profits."

Token

The reader will ask for the explanation of the word "token". The token is the cryptocurrency issued by the venture which performs the ICO, and it guarantees some types of rights. It is up to the company deciding the functions of its token, but it is possible to identify five main clusters of rights:

- Currency: the right to use the token as a currency, to buy goods and services and to store value;
- Access & Payment: the right to access to a certain platform on which spend the token;
- Governance: the right to vote for the strategic decisions of the venture issuing tokens;
- Profit: the right to receive at the end of the year a share of the profit gained and dividends;
- Contribution: the right to contribute to the project development through some kinds of improvements.

Moreover, from these rights, the tokens can be classified in (A. Lielacher, 2017):

- Currency token: token acts as online currencies that can be used to buy and sell products and services and can be held as a store of value. It is the translation of the currency right.
- Security token: token represents a share in a company. It is the merger of the governance and the profit rights.
- Utility token: token provide access to a company's platform, product, or service. It is given by the Access & Payment right.
- Asset token: token represents a physical asset or product. It is a characteristic of the stablecoin that we mentioned in the previous paragraph.

- Reward/reputation token: token is given as rewards to users on a platform.

The most used typologies for ICO are the currency token, the security token and the utility token.

Underlying Blockchain

Before deciding the token features, the company has to decide the underlying Blockchain used. Most of the fundraising campaigns used the Ethereum Blockchain for its useful ERC20 token standard contracts that simplifies the ICO implementation (Fenu et al., 2018).

Code

Decided the underlying Blockchain, the team behind the ICO has to implement the computer code for the smart contract that will drive the campaign. The code is often published, mostly on GitHub, in order to allow investors to analyze it and verify its correctness. It is also true that the crowd difficulty will be able to understand the code and appreciate it, but, in the past, it was demonstrated that the code publication is a clear signal of the project's goodness for investors (Fisch, 2019).

Token supply

An important decision about the ICO proceedings is the choose of the overall token supply. The team is free to decide if setting a limit to the token supply. There is usually a cap on the token supply. Some ICOs have been uncapped but, in this way, buyers cannot know the represented share of the token bought on the overall supply. Nevertheless, it happened for capped campaigns that the sales oversubscription created an incentive at the start of the campaign, leading to Blockchain congestion and high transaction fees (Howell et al., 2018).

Soft cap and hard cap

The supply decision drives other features. The presence and the quantity of a minimum target capital, called soft cap, and of a maximum target capital, called hard cap. The soft cap, especially, is a very important feature that can determine the success or the failure of the campaign. Indeed, if the campaign does not raise its soft cap the money will be backed to the investors. It is evident the relevance of this specific parameter.

Token distribution

Then, the team has to design the distribution of the tokens. Obviously, most tokens are distributed to the crowd but there are also different subjects that can receive them. Tokens can be reserved for team members and advisors, for ensuring liquidity, for community but also for airdrop and bounties, explained below.

Airdrop and bounty program

Sometimes, to improve the token diffusion and liquidity, the venture can decide to launch an Airdrop campaign that is the provision of tokens for free or in exchange for very simple tasks (like sharing of ICO contents on personal social networks' pages). It differs slightly from another ICO features; the bounty program. It consists in the exchange of tokens for more complex tasks; the translation of the white paper in another language, the fixing of bugs, or the testing of the code.

Price

The price definition is a crucial decision but there is no a defined trend. However, many studies (Benedetti & Kostovetsky, 2018; Catalini & Gans, 2018; Cerezo Sánchez, 2017; Momtaz, 2018) focused on the price decision and the underpricing effect when the token is listed on a trading platform.

Bonus

The team can decide to offer some bonuses to attract ICO participants. Basically, the most used bonuses are called:

- Early bird: it is a discount on the token price for the first contributors of the campaign. Therefore, the ICO period is divided in tranches and the bonus may be given on the basis of the time or of the token sold (example for time, in the first 10 days the tokens are sold at 1$, then at 1,5$; example for number of tokens, the first 100 tokens may be sold at 1$, the others at 1,5$);
- Major contribution: it is a quantity discount.

Duration

The team has to communicate also the starting date and the ending date of the campaign. Obviously, the ending date depends also from the achievement of the hard cap that determines the ICO's end. The variance of the ICOs duration is very high. Some ICOs end after one day through the achievement of the hard cap and some other months. A particular case is the one of EOS, ended in the June of 2018, that lasts one year and collected $4,2 billion.

Pre-sale

Finally, the team has to decide if making a pre-ICO (or presale) or not. It may be done to attract private investors (sometimes the found raised in the presale are sufficient and the public offering is cancelled, as happened at Current, CRNC) or to raise the money required to cover the ICO expenditures.

ICO steps

Generally, the funding campaigns follow a standard roadmap to sell their tokens (Kaal & Dell'Erba, 2017).

1. Announcement on crypto-forum and social networks (the most used are Bitcoin Talk, Reddit, Medium);
2. Presentation of an executive summary to selected investors, to have some suggestions about the project implementation and ICO proceeding;
3. Drafting of the white paper and publication on the official website; the whitepaper is the clarification paper that provide information about the venture and token sale;
4. Drafting of the yellow paper and publication on the official website; yellow paper provides technical specifics about the making of the project;
5. Pre-ICO launch, an offer to selected investors;
6. ICO marketing on social networks;
7. ICO launch
8. Listing of the token on a trading platform (the most used is CoinMarketCap);

White paper

As anticipated at step 3, the white paper is the clarification document provided to investors. Its structure changes from an ICO to another, but it generally includes information about the market, the business model, the company history (if it is not a startup), the company's values, the strategy, the information about the team members and advisory boards, the information about the ICO characteristics. At the end of the document sometimes it is present a risk disclaimer that indicates the risk of the investment. As said before, it is up to the venture choosing the information to include in the white paper. Fisch (2019) discovered a positive relation between the quality of the white paper and the success of the ICO; in line with the signaling theory for IPOs (Leland & Pyle, 1977).

Use of funds

Many ICOs decide to communicate in their white paper how they will use the funds collected. Being a free choice of the team (like practically everything in ICO), many times the team does not disclose it. We have found five main clusters for the use of funds:

- Software development: it is an important item because many projects are based on the Blockchain and its applications; for this reason, it is a fundamental expenditure;

- Business development: this item is more traditional, in fact as all ventures also the crypto-ones have to implement their operations;
- Marketing costs: it is referred basically to the costs for the marketing of the funding campaign. Indeed, it is an expenditure that is increasing a lot in the market so that many companies have increased interest in this field;
- Legal costs: it is due to the risk of regulations and to the many legal holes;
- Reserves: another traditional item that needs to cover unexpected losses and events.

Roadmap

The roadmap represents all the phases of development of the company in the time horizon. It is often designed as a timeline chart in which are evidenced some milestones; a simply way to show to investors the development strategy of the venture.

1.1.4 Initial Coin Offering: market overview

This sub-paragraph wants to explain the history of the market and its current size, with a little note on the regulations and risks incurred.

Boreiko & Sahdev (2018) divided the ICO history in five main stages:

1. Prototype stage: the majority of ICOs (actually few) focused on the infrastructure and platform development to improve and spread the Bitcoin environment.
2. Initial start-up stage: unlike the previous phase, the most of the ICOs required to investors a formal registration (Know Your Customer, KYC) and provided a sort of risk disclaimer. The first bonuses were introduced.
3. Last start-up stage: the regulators were very interested in the phenomenon and ICOs started to think on the right procedures. Many campaigns declared the governing jurisdiction for the token sale.
4. Early growth phase: the ICOs started to follow the roadmap described by Kaal & Dell'Erba (2017), written in the previous paragraph. It is the momentum of maximum hype of the Bitcoin.

5. Waiting for the regulators decisions around the world, the ICOs overcome the VC funding in the fintech industry and enter in their mature phase.

Now, we continue with a full and coherent description of the ICO's history.
Starting from the beginning, the first ICO was launched in the 2013 by J.R. Willet with his Mastercoin, now Omni (L. Shin, 2017). The next years were quite calm and stable and few other funding campaigns were done, including Ethereum ICO in 2014. As mentioned in the previous chapter, Ethereum creation was an important step for the ICO development thanks to the Dapps, and ERC20 token standard contract creations. In particular cloning an ERC20 contract makes easy to create a new token, issue a certain number of tokens, and trade them with Ethers (Fenu et al., 2018). In 2016, all the ICOs raised an overall amount of $103 million and started its battle against the traditional venture capital (Kalle & Chwierut, 2017). However, the ICO history continued in a cryptically way. On one hand, the 2017 was the year of the confirmation with a total amount raised of $5,6 billion (Williams-Grut, 2018). On the other hand, a big part of the ICOs were discovered to be scams. It is due to the low entry barriers that drive to the moral hazard. It is due to the fact that to enter in this market is sufficient the making of a document describing the project, the white paper, and an Internet connection; nothing difficult to have. This simplicity in entering the market, merged with the high potential of the financing method, pushes some ventures to create a token only to participate in ICO fundraising, not because they need it. In numbers, it translates that almost 20% of the overall number of ICOs is scams (Shifflet & Jones, 2018). In addition to the scams, some ICOs have resulted in substantial phishing, Ponzi schemes, and other dishonest activities. Regulators spread in the world were interested by the huge market size and the risks described. The first was the U.S. Securities and Exchange Commission (SEC) that in July 2017 has issued a bulletin about the risks implied in the ICO investment activity, affirming that it had the authority to apply federal securities law (Chohan, 2017). The next year, through another bulletin, the SEC affirmed that the token may be treated as securities after performed the Howey test (Bramanathan, 2017). Many other regulators around the world took some measures against the ICO and in some nations, like China and South Korea, they were banned. However, there were also positive behavior for the ICO regulations, as done in Hong Kong and New Zealand.

The figure 4 represents the cumulative amount raised by all the ICOs launched over time. As we can see, the 2018 confirmed the positive trend of the past years with about $16,5 billion raised on the 31st of October.

Figure 4. Cumulative ICO amount raised. Source: CoinDesk

1.1.5 ICO vs traditional funding methods

The following sub-paragraphs will describe the traditional financing methods for startup (Crowdfunding and Venture Capitalist) and established companies (IPO) in order to understand the similarities and the differences between them and the ICO.

1.1.5.1 Crowdfunding

The crowdfunding is, without doubts, among the financing method, the most similar to the ICO. As defined by Belleflamme et al. (2014), "Crowdfunding involves an open call, mostly through the Internet, for the provision of financial resources either in form of donation or in exchange for the future product or some form of reward to support initiatives for specific purposes". From the definition it is possible to see some common points with the ICO.

First of all, it is an “open call”; it means it is addressed to the crowd and everyone can participate, exactly as the token sales. This element represents the common philosophy under the two financing methods; i.e. the democratization of the sources of financing (Assadi, 2018). People can actively inquire about some projects of their interests and invest their money into them. Differently from any other forms of financing (exception for ICO, clearly), it is possible to promote the projects on social networks and blogs in order to reach the maximum number of people. Indeed, both crowdfunding and ICO, at least in their early stages, are addressed to fans, enthusiasts and, in general, people that are near to the sector of the project. Of course, the Internet technology is fundamental to reach as many people as possible. In the beginning, the crowdfunding was developed as a way to finance artists from different fields (Agrawal, Catalini, & Goldfarb, 2014). Indeed, the first crowdfunding Internet platforms were linked to the music sector, and then other arts (like film) followed. The steps are totally similar to the ICO ones. In the beginning, only crypto-enthusiasts and Bitcoin fans were interested in the investments, but the hidden potential arose in both cases. Obviously, with the increasing of the phenomenon size other subjects were interested and exactly as described for the ICO, also the crowdfunding was regulated.

Coming back to the definition, we want to evidence another common point between the two financing methods. The crowdsourcing definition says, “for the provision of financial resources either in form of donation or in exchange for the future product or some form of reward”. Indeed, the crowdfunding is divided in four main typologies (Hossain & Oparaocha, 2017):

- Equity-based: funders invest their money expecting a return from their capital. Entrepreneurs give real shares of the company, so diluting their control on the company and reducing their own profit from any distribution of dividends.
- Donation-based: funders donate without return expectations. It is mainly done for utilitarian purposes and charitable initiatives.
- Lending-based: it is a peer-to-peer lending and funders may invest their money expecting to be refunded in a certain time with or without interests. In particular, no interests are promised in those projects that want to provide some kind of social benefit.

- Reward-based: funders invest their money with a non-monetary return expectation. The team behind the project promises to potential customers their product or service by paying a lower price than the usual one. It is generally done for the music industry (album), publishing industry (books), gaming industry (videogames), and film industry (Blue-Ray).

The resemblance with ICOs is clear for equity-based, but less evident for reward-based crowdfunding. Indeed, the selling of security tokens is the crypto-translation of the equity-based crowdfunding, both ensure control and profit distribution of the company participating the fundraising campaign. In a certain sense, the selling of utility token is similar to the reward-based crowdfunding. As a matter of fact, the utility token allows to have an exclusive channel for buying the company's products and services. It allows the funders to buy them through the venture cryptocurrency, and it is reasonable to assume that it would be less expensive than paying with fiat currency. Despite the homonymity, the concept of reward-token is very different from the reward-based crowdfunding; the reward token is inherent to the user's reputation on a certain platform. In crowdfunding there are no similar concepts to the currency token and the asset token. Anyhow, the security tokens and the utility tokens are the most diffused typologies in the ICO phenomenon. Then, in no ICO event there were the concepts of donation or lending. Referring to the donation, ICOs were born as an activity to finance a project as well as in crowdfunding, but there is always a return expectation, monetary in the case of security token and non-monetary in the case of utility token. Finally, even if some ICO projects are born to be crypto-lending platform (as Nexo, SALT Lending), no ICO campaigns proposed the investment in exchange of an interest rate.

The two methods of financing are mainly addressed to startups, in few cases an established company decides to launch an ICO or a crowdfunding campaign. They are usually used when funding from founders, friends and family and business angels are insufficient and face a funding gap problem (Collins & Pierrakis, 2012). The financial crisis aggravated this problem (Block & Sandner, 2009; Duygan-Bump et al., 2015; Fink et al., 2012; Mach et al., 2014) and it enables the crowdfunding, firstly, and ICO, then, to arise.

Regarding the characteristics of the campaign, crowdfunding and ICOs have again a lot of common elements. As said before, both can promote their fundraising on social network pages, and indeed some studies (Benedetti & Kostovetsky, 2018) about ICO's team social activity are based on several previous study on the crowdfunding's one (Lu et al., 2014; Moisseyev, 2013; Mollick, 2014). Both ICO's and crowdfunding's teams can decide to fix or not a minimum funding target. In case of crowdfunding, they can set up the crowdfunding in two ways, "keep it all", no minimum target, or "all or nothing". The latter option is the equivalent of the ICO soft cap: if it is not reached the money will be return to the investors.

On the other hand, the main difference between crowdfunding and ICO is the need of intermediation. The crowdfunding campaigns need an online platform that is able to manage the exchange of money inducing some extra-cost for entrepreneurs but, at the same time, reassuring investors from the risk of frauds while ICOs use the Blockchain and cryptocurrency to guarantee the exchange of money but they are not able to cover investors from the risk of scam.

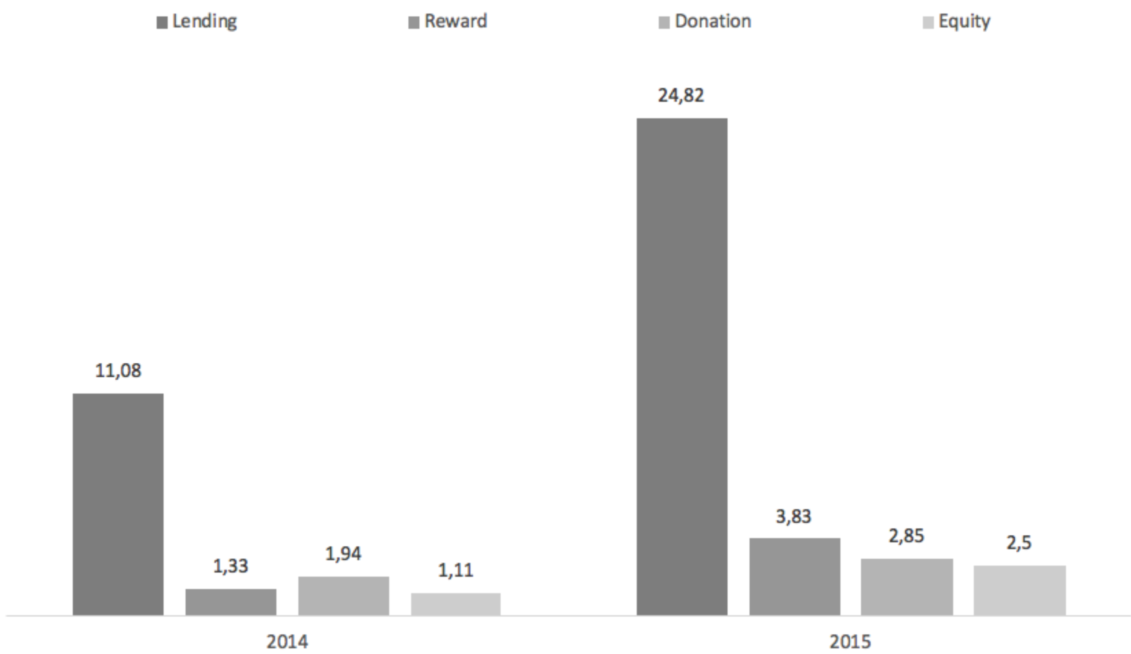

Figure 5. Amount raised in $ billions for crowdfunding type. Sources: Massolution (2014) and United Nations Procurement Division, UNPD (2015)

1.1.5.2 Initial Public Offering (IPO)

An Initial Public Offering (IPO) consists in the mechanism of listing on an Exchange with the aim of offering shares of the own private corporation to the public for the first time. From this definition it is possible to find many differences with the ICO phenomenon. First of all, the listing on an Exchange implies the satisfaction of many requirements. To get an idea, we provide a list of some of the NASDAQ Global Select Market financial and liquidity requirements (Nasdaq, 2019):

- Pre-Tax Earnings: Aggregate in prior three fiscal years > $11 million and each of the prior three fiscal years > $0 and each of the two most recent fiscal years > $2.2 million (Standard 1);
- Cash Flows: Aggregate in prior three fiscal years > $27.5 million and each of the prior three fiscal years > $0 (Standard 2);
- Market Capitalization: Average > $550 million over prior 12 months (Standard 2), Average > $850 million over prior 12 months (Standard 3), $160 million (Standard 4);
- Market Value of Publicly Held Shares or Market Value of Publicly Held Shares and Stockholders' Equity: $45 million.

Considering that there are several other criteria, it is clear that this strict regulation is quite far from the ICO market. Obviously, the satisfaction of requirements brings ownership dispersion, extra-costs and a lot of commitment (Booth & Chua, 1996). This is one of the reasons of the decision of some established companies (actually not many) to choose an ICO campaign rather than an IPO one.

The biggest difference is the gap of safeguard against frauds and scams. Even if some fraud cases were occurred also in the IPO market (Wang et al., 2010), their numbers are very far from the ICO ones (Shifflet & Jones, 2018). IPOs ensure safety and protection to the investors while ICOs, also given the uncertain regulation, cannot do it.
Differently from the crowdfunding, IPOs and ICOs do not share the same underlying philosophy. As a matter of fact, the IPO is not addressed to all people but is mainly exclusive to institutional investors such as mutual funds and investment banks. Actually,

this problem can be overcome through the use of a private Blockchain. Moreover, it would be possible to sell a part of the tokens to the crowd using a hybrid Blockchain, a mix between public and private Blockchains.

However, it is possible to find common features with ICO, specifically referring to the security token sales. Indeed, we can proxy a security token sale as a crypto version of the IPO. Both sell the rights to the investor in receiving profit sharing and, not always, in the participation in the governance activity of the company. We specified "not always" because companies entering in the IPO market may decide to sell different classes of shares with unequal voting rights (B. Sharfman, 2017). Likewise, teams behind ICOs are free to decide if include the voting right in their token.

As mentioned above, the SEC announced that security token has to be treated as normal security because they result positive to the Hoewy test (Bramanathan, 2017). So, future changes of regulations may correlate more these two funding methods and many Exchanges are moving to this direction to integrate the advantages given by the Blockchain to IPO market (Natarajan et al., 2017). In fact, the Blockchain is able to reduce hugely costs and times of IPO and Exchanges around the world want to avoid the disruptive effect of the new technology.

The common points increase when the ICO venture takes the decision to list its token on a trading platform. As for the price of shares listed on an Exchange, the token price can fluctuate driven by the market sentiment, and the metrics used are practically the same.

1.1.5.3 Venture Capitalist

Venture Capitalist (VC) and ICO were born to be means through which a startup can achieve funding, especially in seed and early stages. For this reason, we want to explain how VC works in order to make a comparison between the two markets.

The VC phenomenon was born as an alternative to the banks to provide financing to firms who were not able to have a collateral for a loan. It was born in the 1946 when its founding father, George Doriot, recognized the need for risk capital and created its own firm to cover this funding gap (Metrick & Yasuda, 2011). The first venture capital limited partnership was created in 1958 to circumvent the regulations for closed-end funds and, even if primarily they attract a limited number of investors, in the 1960s and 1970s became more common (Gompers & Lerner, 2001). VCs developed in the years until it gets to the structure that we know today. Nowadays, VCs use the Venture Fund as investment vehicle. Venture Funds are structured as a limited partnership ruled by partnership agreement covenants of definite life. The capital is committed by the Limited Partners that are predominantly institutional investors and is managed by the Management Company that is the business of the fund. The General Partner is the VC partner of the Management Company. General Partner is the real decision-maker and the responsible of the fund performance. Finally, the financings are given to the Portfolio Companies (the startups) in exchanges for shares of preferred equity. Practically, Venture Funds gain from a liquidity event that may occur in one of the following ways:

- IPO: as describe in the previous paragraph, it is the public offering of company shares;
- Trade sale: the startup is sold with a private offer, to a bidding company or to another fund;
- Buy back: the entrepreneur buys back the shares;

If a liquidity event does not occur, the venture is left to its own destiny and the investment is written-off.

VCs distribute equity capital to startups in order to help them to reach their high growth potential; it happens, generally, in high-tech industries (Bronzini et al., 2017). Obviously, investing in startups is risky since products and services are not finished (prototypes), inexperience of funders can make them wrong and market can reject their proposal, in fact several projects fail (Cantamessa, et al., 2018; Kalyanasundaram, 2018). For this reason, VCs try to invest only in projects with very important economic returns.

VC implements a screening and evaluation phase crucial for identifying those companies with high growth potential, looking for signals correlated with venture potential and quality (Busenitz et al., 2005). Moreover, VC investment is done not only with money. It was demonstrated that VC plays an active role in the future performance of the venture (Kelly

& Hankook, 2013; Savaneviciene et al., 2015). It was due to the provision of strategy suggestion (Hellmann & Puri, 2000), human resources practices (Hellmann & Puri, 2002) and innovation strategies (Da Rin & Penas, 2007).

Naturally, VCs observed closely the evolution of the ICO, so that they invested $991 million in 2017 in Blockchain startups (Morris & Cordeiro, 2018). Indeed, it is not a secret that a part of the amount raised of some ICOs came from VCs. Therefore, the first crypto-VC arose, like FinShi Capital.

Seeing figure 6, it is clear that VC and the crypto-environment, as symbol of high-tech innovation, are strictly related, so that a study of Mangrove Capital (Jackson, 2017) put in evidence the correlation between the two funding methods. The paper shows the main benefit that ICO can give to the VCs, the author calls it the tokenization. Indeed, tokens are able to make an asset liquid because they can represent a part of it and can be traded easily. In this way, a VC can change its exit strategy because he may not wait for a liquid event. Moreover, the VC can also decide to acquire tokens from a company as easily as for ICOs. It could change the way in which VCs actually act, approaching them to a more active trading strategy.

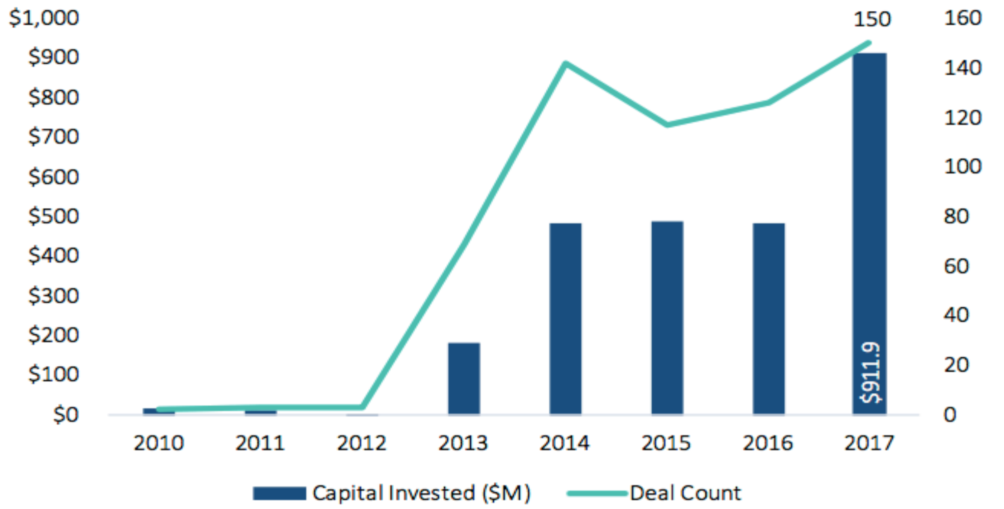

Figure 6. Global VC activity in Blockchain companies. Source: Pitchbook

Another ICO's element that can improve the VCs is the capacity to overcome the geographical barriers of VC. Studies demonstrated that VCs are focused on the area in which they are (Chen et al., 2010; Mason & Harrison, 2002). On the contrary, ICOs are able to attract capital from different regions of the globe, given their natural decentralized basis. Some papers support this thesis explaining the crowdfunding capability to collect money around the world (we have already discussed the similarities between crowdfunding and ICO in the paragraph 1.1.4).

1.2 Determinants of Success in ICO

The aim of this paragraph is to provide an idea of what asymmetric information and signals mean in the economic literature and then, wants to focus on previous studies on ICO signals able to show to investors the quality of the venture, determining the success of the fundraising campaign.

1.2.1 Asymmetric information and Signaling theory

The asymmetric information is the information gap about the object of the exchange (product, service, share, and, in our case, token) between the seller and the buyer, almost all the economic transactions have asymmetric information.

Initially, the notion was developed by Akerlof (1970) in his paper that allows him to receive the Nobel Prize in 2001. Briefly, he wrote about the car market assuming there were high-quality cars and low-quality ones ("lemons"), but the only subjects able to distinguish them were the car sellers. Both the types of cars were sold at the average price between the price of a high-quality car and of a low-quality one. The buyers could not know in advance which car they were buying. Akerlof stated that this information asymmetry incentivized the sellers to sell good of less than the average market quality. It implies a reduction of the average quality goods of the automobile market.

The Akerlof paper was continued by Spence (1973) that used the job market to build his model on the effect of signals in the reduction of asymmetry information. In particular, the author used the education of the individual as useful signal for the employer. In the model, an individual can manipulate a signal, but it has a cost, called signaling cost.

From the classic theory developed by Akerlof (1970) and Spence (1973), several works were done about signaling theory and information asymmetry. Specifically, a stream referred to the function of signals in the raising of funds evolved through several studies.

Regarding the funding process, Mattsson (2002) applied the signaling theory of Spence to high tech startups that look for equity funding examining the VC decision making. At the end of his paper, the author affirmed that the use of signaling theory is effective in approaching the information asymmetry presence in the fundraising of high-tech venture.

Signaling theory was used to understand the importance of signals in IPO (Ragozzino & Reuer, 2011; Williams et al., 2010; Zhu, 2011), VC (Busenitz et al., 2005; Plummer et al., 2016; Umit et al., 2013) and crowdfunding (Ahlers et al., 2015; Courtney et al., 2017; Piva & Rossi-Lamastra, 2018). Particularly, scholars focused their researches to understand which factors can be considered determinants of success for the funding process.

A determinant of success may be the composition of the team, the skills developed and the education level achieved by the members, the social networking, the sector of the company, the business model, the resources implied and many others.

Coming back to the ICO phenomenon, the next sub-paragraph will show many studies developed in the recent years about the determinants of success for the token sale.

1.2.2 Analysis of several studies

Starting from the ICO's boom at the end of 2017, many studies were done on the topic, in order to assess the presence of some factors that frequently appears on successful token issues. In the next pages we will resume the main results of these empirical studies. The review of the literature on the topic is useful in order to identify the basis of our research.

The first study we are going to analyze was conducted by Yadav (2017) in order to explore the signals for investing in an ICO. This research was just exploratory, not statistical findings were studied. Indeed, the author did interviews to understand which elements are considered by investors to give money, by entrepreneurs to disclose the right information to lead a successful ICO. The research was based on six semi-structured interviews addressed to three typologies of subjects: entrepreneurs, investors and community. Once the individual analysis of each interview was complete, the final results about the "potential" signals for investment in an ICO were generated via triangulations of research insights from literature research, online ICO analysis, and the semi-structured interviews. Along with this, the insights were designed keeping in mind the use for investors or for entrepreneurs organizing an Initial Coin Offering. As result of the study, the signals that are relevant to assess quality in the ICO ecosystem are token liquidity, distribution of token holdings, digital community sentiments, white papers' quality of information, local government sentiment towards Blockchain technology and the duration of existence of company before the ICO. Conversely, the presence of bounty program and paid promotion is seen as a very negative signal for investors. An important issue for our work is the digital community sentiments. In fact, Yadav affirmed that "the whole Blockchain ecosystem runs on community engagement". In the Chapter 2, we develop our hypothesis that link the community engagement with network analysis.

Flood and Robb (2017) explain the born and raising of the Blockchain and the ICO phenomenon. The purpose of the authors was to answer to the question "what makes a good ICO?". According to the research, the three main elements that make a good ICO are the use of Blockchain to run the business, the confidence in the solution and in team from the public, and the ability of the team to follow the national and international regulations. Obviously, the first element does not mean that Blockchain must be used every time, but it means that it should be used when it brings benefits to the project. Blockchain is often being applied indiscriminately to scenarios where it simply is not necessary, and so a company should only consider its use and an ICO if they have a problem aligned with FITS (Fraud, Intermediary,

Throughput, Stable Data). Therefore, Blockchain could be a solution where there has been a past likelihood of fraud, when there is a need for trust in an intermediary or middleman, when the throughput or transaction speed is a factor, or when there is a need for stability in the data being used.
Moreover, the authors explain how the team should act in order to receive the trust of investors. The use of a roadmap that shows how the funds from the token sale will be used is the first step to do. Then, the drawing up of the white paper is the principal way to communicate all the details of the project. One of the main elements pointed out by the author is the presence of the list about the members that compose the team. The team needs to be listed so that someone looking at participating in the ICO can see their skills and talents. It further demonstrates their accountability to the business and token holders and allows for the public to be able to self-investigate team's origins which can allow for more trust, or possibly uncover further risks.
Finally, the subscription on an ICO listing agents is a way to increase the transparency and the confidence in investors. This third element to a good ICO is less about having a successful ICO that raises money, and more about being in a position to hold onto the funds raised. It can be troubling that while ICOs are a novel way of raising money for businesses, because of the early stage development of Blockchain technology, it can be difficult for most people to understand both what Blockchain and ICOs represent. This situates ICOs in the "sophisticated investor" class which is reflected in US regulations. Concluding, we can understand the relevance related to the ability to follow the national and international regulations, ensuring to a larger part of investor the safety of investment. This latter could be done only protecting low-skilled investors through more thorough and effective regulation of the phenomenon.

The paper of Amsden & Schweizer (2018) established a measure of success (token or coin tradability) for ICOs and developed a theoretical framework for how venture uncertainty, venture quality, and investor opportunity set relate to it. It is found that venture uncertainty (for instance the lack of a presence on GitHub and Telegram, short whitepapers, high percentage of tokens distributed) is negatively related to ICO success, while high venture quality (better connected CEOs and larger team size) is positively related. Furthermore, a higher price of Ether, decreasing the relative attractiveness of ICOs (investor opportunity

set), is negatively correlated with ICO success. It shows also that providing a hard cap in the pre-ICO, which helps investors measure success in the presale, is positively related to funding success.
These findings are relevant to entrepreneurs who consider ICOs as the fundraising method of choice and investors alike, providing insights on how to assess an effective ICO campaign. Moreover, the study reveals other different and useful results. ICOs that are not on GitHub and Telegram signal less transparency and fewer communication channels. Short whitepapers indicate a less sophisticated business plan and make it less likely that the ICO-related token will become tradable. Also, the higher the percentage of tokens offered in the ICO, which is very comparable to the equity offered in equity crowdfunding or stock-related IPOs, the less incentivized entrepreneurs will be to take the necessary steps to having tradable tokens.
Having tradable tokens also correlates with team size. Overall, it is found that a successful ICO requires multiple important ingredients from beginning to end: the venture should transparently provide information to potential investors, it should communicate a sophisticated and sound business plan, the entrepreneurs should stay incentivized and have a team in place that is capable of executing the business plan while managing the logistics of having tradable tokens. Without all of these characteristics, an ICO is likely to fail, and investors are likely to lose their investments (assuming no soft cap is in place). The entrepreneurs' business will also most likely be unrealized, resulting in a loss of time and resources for them.

Instead, the research of Burns & Moro (2018) analyzes the main factors contributing to the success of an ICO based on signaling theory, human capital theory and investor sentiment. The results of their regression analysis allow us to know that the ICO characteristics and market sentiment surrounding the ICO date provide insight into the potential returns of the ICO, although the team quality plays a smaller part as a signal of the token's growth prospects for investors. This study has found that ICO characteristics, in fact, affect the success of an ICO; a higher initial token price in the ICO negatively affects the four-month Return On Investment (ROI) for investors as well as the first-day returns, and the use of the Ethereum platform negatively affects the first-day returns. Regarding the effect of management team quality on ICO success, the influence of the quality of the management team on ROI and first-day returns is slight compared to that of ICO characteristics and market sentiment. However, there are surprising results based on the team dynamics which include the size of the team being negatively correlated to the ROI yet positively correlated to the total amount raised in the ICO, suggesting the quality of human capital may serve as a signal for investors in the ICO and subsequently improve the amount that the ICO team is able to raise. Furthermore, the ICO team is unable to have a strong impact on the ongoing improvement in the token, and therefore a larger and more established ICO team may not be of much importance for investors. The market sentiment is the consensus of the market regarding the token and ICO. This has shown to be highly influential regarding the success of the ICO. The number of Twitter followers for each ICO team's page positively affects the ROI and the total amount raised in the ICO. Another interesting result is that a high number of news articles released prior to the ICO negatively affects the ROI whereas it positively affects the amount raised in the ICO.

The work of Catalini & Gans (2018) adds a different view on the topic. In particular, it shows that entrepreneurs have an incentive to use subsequent product pricing choices to ensure that crypto tokens issued to fund start-up costs retain their value even when they do not confer the typical rights associated with equity. Countering this, it is necessary to consider commitment issues that arise when agents other than the entrepreneur hold tokens for any period of time in the hope that the tokens will increase in value. While entrepreneurs will still price to retain token value, they may be tempted to issue more tokens post-ICO, expropriating early token holders. Discretionary pricing is an important instrument in this context because it allows for price discovery, whereas discretionary monetary policy is a major concern. Such constraints might bind if the entrepreneur needs to take advantage of the expectations of future demand to increase the value raised through an ICO and cover the development costs of a new digital platform.

Howell et al. (2018) provide another research on the factors that predict success. The work focuses in particular on the effect of liquidity and underlying utility function of the tokens. In particular it shows that liquidity is higher when token issuers take steps to reduce information asymmetry and bond their promises to create viable business platforms. The promoters have to take credible steps to commit to the construction of a credible Blockchain business in order to enhance the probability of success of the fundraising event.

It is also found that tokens are more successful when they have an underlying utility function, a result with relevant implications for the current regulatory debate over whether tokens are investment securities.

The analysis of Adhami et al. (2018) covers the characteristics of the nascent market for ICOs. Although the quality of information provided by proponents is typically poor and offering details on governance and the use of proceeds are opaque, the study shows that ICO success rate is remarkably high (81%). Project heterogeneity is quite significant and only a minority of the campaigns could be considered a security offering.

The econometric analysis reveals that the probability of success of an ICO is unaffected by the availability of the white paper but is strongly and positively affected by the presence of a set of codes for the Blockchain project. White papers have different lengths and information quality, and the only presence of one such document as an attachment to the ICO announcement is not particularly valued by potential contributors, especially because these documents have no certification or audited features. However, the informative power of coding strings is very strong for ICO projects, and the availability of sets of codes (even partial ones) is a tangible proof-of-concept that is appreciated by the investors, which also reveal themselves to be quite tech experts. Regarding the ICO terms and the marketing of tokens, bonus schemes were found to be only marginally significant for the probability of success of the campaign. In contrast, presale initiatives (preceding the ICO) appear to be strongly significant and positively related to ICO success, revealing that testing the market with a targeted, smaller token sale is a valuable strategy to entice ICO funders. Furthermore, the conditions of the cryptocurrency markets underlying the ICOs that do not create ex-novo Blockchains of their own, as measured by average return and volatility, are not considered by investors and, thus, do not affect the probability of success of the ICO. The market for ICOs shares several features of the crowdfunding realm, including low contributor protection, a limited set of available information, no supervision by public authorities, and no relevant track record for proponents. ICO contributors are likely driven by intrinsic motivations, similar to crowdfunding.

The literature on crowdfunding analyzes both single campaign characteristics and platform characteristics, whereas studies on the likelihood of ICO success can only rely on project and project promoter-related factors because no platforms exist that manage ICO campaigns.

Indeed, each entrepreneurial team can easily reach and manage tech-expert token sale participants through the Blockchain, and no evidence exists that suggests that a specific platform for ICOs could increase or rationalize fundraising volumes.

Finally, the paper of Fisch (2019) is another fundamental investigation on the topic, and it is also the more recent that we present in this part. It analyzes the signals showed by an ICO from a statistical point of view. In the study, 423 ICOs are used to understand the crucial determinants of their success (or not). The author links the previous signaling theory literature with the ICOs. In particular, he identifies three main characteristics of the ICO: context, technical environment, investment risk, absence of disclosure requirements along with anonymity. The first one is referred to the complexity of the Blockchain technology and underscores the importance for the investor to understand the application proposed by the venture. The second one emphasizes the high-risk degree and the high risk propension of ICO investors. The last one is more philosophical than the others and it is linked to the desire of anonymous transactions.
The author considers that a major transparency in the ICO environment could bring benefits for its development. Furthermore, Fisch argues about the big information asymmetry in the investor-investee relationship in ICOs to explain the importance of the signals. About this point, he focuses on the technological capabilities as signal of high-quality firms and identifies patents, technical white paper and high-quality source code as good indicators. Patents do not seem to constitute an effective signal in the ICO context. This finding is surprising and in contrast to prior research in entrepreneurial finance. An explanation might be that patents are of limited usability for DLT (Distributed Ledger Technology) and Blockchain ventures because code (and software) is not generally patentable in various jurisdictions. In these jurisdictions, only supporting technologies or very specialized elements of code would be patentable. Closely connected, most Blockchain firms reveal their code freely on GitHub. Because patents require a technological invention that is previously undisclosed, they cannot be obtained if the code is already revealed. Another explanation might be that most ventures are in such early stages that they may not yet have a technology advanced enough to be patented. Also, the results indicate that ICO ventures may not consider patents to be an important part of their strategy when raising funds because patents are used so rarely by these ventures. A final explanation refers to the receiver's ability to interpret and then act upon the signal. Because patents may not be as suitable in the ICO

context, investors may not be overly familiar with the concept of patents. In contrast, venture capitalists and business angels pay a lot of attention to patents and are familiar with them.

A technical white paper (or yellow paper) may be an effective signal in ICOs in contrast to patents. Interestingly, both constitute a detailed description of a venture's technological efforts. However, while they are similar in terms of general content, a technical white paper is less restrictive with respect to legal necessities (paying fees, involving a patent lawyer, referencing prior knowledge). Most importantly, however, patents require that an invention is previously undisclosed, while a venture can publish a technical white paper to demonstrate its technological capabilities even if it has already revealed its code. To some extent, technical white papers may constitute a substitute for patents in the specific context of ICOs.

Finally, a high-quality code is associated with an increased amount of funding. The source code is a relatively objective characteristic that most investor's guides suggest investors assess when making an informed decision about investing in ICOs. While most investors may not understand the detailed technicalities of source code, GitHub presents multiple aggregate metrics that seem to help investors refer to the venture's underlying technological capabilities.

This study further indicates that traditional indicators of venture quality may not be as useful in the ICO context as they are in other domains of entrepreneurial finance. Instead, the results indicate that investors seem to consider a different set of indicators that are highly specific to the ICO context, such as the usage of the Ethereum-standard or token supply.

The results suggest also that ventures with high technological capabilities should make sure to communicate these capabilities because investors assess them to infer the venture's quality and invest accordingly. However, ventures face a tradeoff when revealing potentially proprietary information publicly. While signaling higher technological capabilities enables ventures to attract investors, it also allows competitors to imitate their technology more easily.

Furthermore, in spite of the results suggest that revealing technological information of high quality is conducive for raising higher amounts of funding, it is unclear whether negative effects (for instance imitation) might counteract this positive effect in the long run. Ventures should carefully consider this tradeoff when revealing information during their ICO campaign. Further implications for ventures can be derived from the other variables, which suggest multiple factors that contribute to raising larger amounts of funding. For instance, the results suggest that ventures should utilize the Ethereum-standard and release a greater number of tokens to increase the amount raised.

1.3 Social Network Analysis (SNA)

In this paragraph we will introduce the Social Network Analysis (SNA) whose centrality measures will be exploited in our work. First of all, we think it may be useful to provide a brief description of the SNA history in order to defining the subject. After we will introduce the matter explaining the most important concepts and the classic centrality measures, crucial elements for our study. Finally, we will describe a list of studies that approached the SNA from various perspetctives, mainly focused on economics and financial sectors.

1.3.1 History of SNA

The world in which we live was absolutely changed by the creation of Internet and its huge diffusion. Today, people are able to send messages, call to another person from the opposite part of the globe just with one click. In this world, where the connection is easy and (almost) for everyone, the networks take on an important role and only through their study it is possible to understand definitely the mechanisms that drive people. Therefore, it is clear why many firms analyzed networks of their costumers, in particular web-based social networks. Companies can extrapolate many useful information that can be used for new product development, understanding customer needs, but also for other active actions as leveraging customers decisions through the identification of the so-called influencers (de Valck et al., 2009). In this environment, it is evident the potential utility that Social Network Analysis (SNA) could have.

In our opinion, it’s worth to introduce the topic of SNA with a brief summary of the academic historical events that characterize the research on the topic, from the very first seminal papers to the explosion of application possibilities on the phenomenon in the late 1990s (Freeman, 2005).

Actually, the SNA born far from Internet, exactly in the 1930s from the studies of Jacob L. Moreno, a psychiatrist, and Helen Jennings, a psychologist. They created the ancestor of the SNA, the sociometry through their studies on inmates of a prison and among people living in a reform school for girls. Initially, their studies generated a high interest among American psychologists and sociologists, indeed the latter were focused on the human relationships rather than the characteristics of individuals. However, the interest decreased fast; in the 1940s most of the experts had come back to the traditional elements studied, leaving the interactions between people aside. In the same period, another research group, led by an anthropologist, W. Lloyd Warner, also adopted the Social Network Approach. They conducted social network research in two communities, Yankee City and Deep South, but their results didn’t attract as much interest as did Moreno and Jennings. An alternative version of the research appears in 1936, when a German psychologist, Kurt Lewin, started to conduct with his research group in the University of Iowa. Together, they develop a structural perspective and conducted social network research in the field of social psychology. However, all research till this point didn’t produce a standard across all the social sciences and accepted in all countries.
Instead, after the 1930s and until the 1970s, numerous centers of social network research appeared, each involved a different form and a different application of the social network approach. The research moved on without a clear line until 1970s, when White and his students at Harvard built a generalized structure of the research topic. Following the contributions of White and his students, Social Network Analysis fit the new standard paradigm and became widely recognized as a field of research. A breakthrough occurred in the late 1990s, when the world of physic was attracted by the SNA. First, Duncan Watts and Steven H. Strogatz addressed a standard topic in SNA, the “small world”. And a year later Albert-Làslò Barabàsi and Rèka Albert examined the distribution of degree centrality. After, this research field found many applications and its tools was used also to study the new networks composed by computers (Freeman, 2005).

After this little excursus on the SNA's history, it is necessary to clarify some aspects and to provide some definitions. More recent researches will be discussed at the end of this chapter.

1.3.2 Definitions

First of all, the SNA is strictly related with the Graph theory (Harary and Barnes, 1983), therefore, it is important to explain all the elements of these matters.
A social network is a social system composed by subjects (or organizations – for example startups doing an ICO) called nodes, that are tied by one or more particular types of interdependency, such as friendship, common interest, financial exchange, knowledge or prestige (Wasserman and Faust, 1994). SNA considers social relationships constituted by nodes and ties (also called edges) where the individual actors within the networks are represented by the nodes, and the relationships between the actors by ties. The network can also be used to measure social capital – the value that an individual (or a company) gets from the social network. In the SNA's view, the important issue is the relationships between individuals and their ties rather than their characteristics. Even if this approach seems to reduce the self-determination capacity of individuals, it turned out to be useful in many contexts (Wasserman and Faust, 1994).

According to Graph theory (Ruohonen, 2013), a graph is formed by a set of vertices, V, and a set of edges, E, connecting the vertices. In particular, E is a multiset that means its elements can occur more than once. To understand the methodologies used in this work, it is essential to understand the relation between graphs and matrices. Indeed, a graph can be represented by a matrix. The adjacency matrix of the graph $G = (V, E)$ is an $n \times n$ matrix $D = (d_{ij})$, where n is the number of vertices in G and d_{ij} is the number of edges between the $node_i$ and $node_j$.

Defined how a graph can be designed, some concepts of SNA will be explained (L. C. Freeman, 1979; Nieminen, 1974; Wasserman & Faust, 1994):

- Centrality: this measure gives a rough indication of the social power of a node based on how well it "connect" the network.
- Centralization: the difference between the number of links for each node divided by maximum possible sum of differences. A centralized network will have many of its links dispersed around one or a few nodes, while a decentralized network is one in which there is little variation between the number of links each node possesses.
- Degree: the sum of ties to other actors in the network referred to a single actor.
- Bridge: an edge is said to be a bridge if deleting it would cause its endpoints to lie in different components of a graph.
- Structural hole: static holes that can be strategically filled by connecting one or more links to connect together other points. Related to ideas of social capital: if you link to two people who are not connected you can control their communication.
- Betweenness: the extent to which a node lies between other nodes in the network. This measure considers the connectivity of the node's neighbors, giving a higher value for nodes which bridge clusters. The measure reflects the number of people wherewith a person is connecting indirectly through their direct links.
- Closeness: the degree an individual is near all other individuals in a network (directly or indirectly). It reflects the ability to access information through the ramifications of network members. Thus, closeness is the inverse of the sum of the shortest distances between each individual and every other person in the network. The shortest path may also be known as the geodesic distance.
- Cohesion: the degree to which actors are connected directly to each other by cohesive bonds. Groups are identified as 'cliques' if every individual is directly tied to every other individual, 'social circles' if there is less stringency of direct contact, which is imprecise, or as structurally cohesive blocks if precision is wanted.
- Density: the degree a respondent's ties know one another/ proportion of ties among an individual's nominees. Network or global-level density is the proportion of ties in a network relative to the total number possible (sparse versus dense networks).
- Path length: the distances between pairs of nodes in the network. Average path-length is the average of these distances between all pairs of nodes.
- Prestige: in a directed graph prestige is the term used to describe a node's centrality.

- Radiality: degree an individual’s network reaches out into the network and provides novel information and influence.
- Structural cohesion: the minimum number of members who, if removed from a group, would disconnect the group.
- Structural equivalence: refers to the extent to which nodes have a common set of linkages to other nodes in the system. The nodes don’t need to have any ties to each other to be structurally equivalent.

1.3.3 Centrality Measures

This paragraph will focus on one of the main elements of this work: the centrality. Many researches (Bajo et al., 2016; Cheng et al., 2019; Horton et al,, 2018; Nicholson et al., 2004) have studied the effects of centrality in different contexts.
Before showing the results of different recent studies taken by the previous literature, a description of seven measures of centrality will be provided.

Degree Centrality

The first is the degree centrality, C_D, the simplest one. It uses the sum of the direct relationships of a single individual, j, as a measure of the quality of his interconnectedness (Nieminen, 1974). Using the adjacency matrix, as described in the previous paragraph, the formula used to calculate this measure is:

$$C_D(x) = \sum_{i=1}^{n} d_{ix}$$

The degree centrality has its advantage in its simplicity and easiness to understand but it does not take into consideration the indirect contacts (relationships over the first reached node).

Closeness centrality

Closeness centrality, C_C, founds itself on the concept that vertices with a shorter distance to other ones can propagate information with higher quality through the network (Beauchamp, 1965). It is the inverse of the sum of the distance, $d(x, i)$, between the node x and all the nodes in the network. In formula (Freeman, 1979):

$$C_C(x) = \frac{1}{\sum_{i=1}^{n} d(x, i)}$$

In comparison to the degree centrality, the closeness centrality considers the effect of the indirect nodes, but it does not give value to the specific position of the specific node.

Betweenness centrality

Betweenness centrality is a way of detecting the amount of influence a node has over the flow of information in a graph. It is often used to find nodes that serve as a bridge from one part of a graph to another. Betweenness centrality is based on the fact that an individual is important if it is present in as many of the briefest paths as possible between pairs of other members (Newman, 2005). The idea is that the exchange of information between two individuals is dependent to the people that link them. Defined g_{ij} as the number of shortest paths. Its formula is (Freeman, 1979):

$$C_B(x) = \sum_{i=1, i \neq j}^{n} \sum_{j=1, j<1, j \neq x}^{n} \frac{g_{ij}(x)}{g_{ij}}$$

Eigenvector Centrality

Eigenvector Centrality is based on the idea that a relationship to a more interconnected node contributes to the own centrality to a greater extent than a relationship to a less well interconnected node (Landherr et al., 2010). The assumption is that each node's centrality is the sum of the centrality values of the nodes that it is connected to. The nodes are drawn with a radius proportional to their centrality. The adjacency matrix and centrality matrix for the solution are shown. The centrality matrix is an eigenvector of the adjacency matrix such that all of its elements are positive. Defining v_j= $(v_1, \dots, v_n)$ referring to an eigenvector for the maximum eigenvalue $\sigma_{max}(A)$, the formula for the eigenvector centrality is (Bonacich & Lloyd, 2001):

$$C_E(x) = \frac{1}{\sigma_{max}(A)} \sum_{j=1}^{n} a_{jx} * v_j$$

Efficiency

The efficiency of a network is a measure of how efficiently it exchanges information. The concept of efficiency can be applied to both local and global scales in a network. On a global scale, efficiency quantifies the exchange of information across the whole network where information is concurrently exchanged. The local efficiency quantifies a network's resistance to failure on a small scale. That is the local efficiency of a node characterizes how well information is exchanged by its neighbors when it is removed. Broadly speaking, the efficiency of a network can be used to quantify small world behavior in networks, that is a mathematical graph useful for the peculiarity of its properties (Latora & Marchiori, 2003). Efficiency can also be used to determine cost-effective structures in weighted and unweighted networks. The formula of efficiency for a node j is very similar to the closeness centrality. The difference is that if two nodes are not connected, their distance is $d(x,i) = +\infty$. Defined $e_{xi} = \frac{1}{d(x,i)}$ and considering that if $d(x,i) = +\infty$, it implies $e_{ij} = 0$, the formula of efficiency is:

$$C_{EFF}(x) = \sum_{x \neq i}^{n} e_{xi}$$

Katz's Centrality Measure

According to Katz not only the number of direct connections but also the further interconnectedness of actors plays an important role for the overall interconnectedness in a social network (Katz 1953). Therefore, Katz includes all paths of arbitrary length from the considered node to the other nodes of the network in the calculation of his Centrality Measure. This measure could be seen as a variant of the Eigenvector Centrality. Defined the power of the adjacency matrix A as the presence of links across intermediaries and the coefficient α as the value of attenuation comprised between 0 and 1 and smaller than the reciprocal of the absolute value of the largest eigenvalue of A, the formula is:

$$C_{KATZ}(x) = \sum_{j=1}^{\infty} \sum_{i=1}^{n} \alpha^j \, (A^j)_{xi}$$

PageRank

PageRank is the first and most famous algorithm used by Google Search to rank web pages in their search engine results (Page 1999). The algorithm uses the classic methodologies of Social Network Analysis. In fact, this measure could be seen, as we have previous seen with the Katz's Centrality Measure, a variant of the Eigenvector Centrality. PageRank works by counting the number and quality of links to a page to determine a rough estimate of how important the website is. The underlying assumption is that more important websites are likely to receive more links from other websites.

1.3.4 SNA: recent studies and applications

In this last part of the chapter, as we previously anticipate, the focus will be on the more recent studies and applications of the Social Network Analysis. This is done in order to prove the various possible applications of SNA, which demonstrate the usefulness in very different fields of this kind of analysis. The choice to give priority to the most recent work, instead, is selected to show the modernity and the attention among researchers on this methodology. The following research will be presented in chronological order.

The first work that we analyze is the paper of Nicholson et al. (2004). This research propose advances the resource dependence and social networks literature by investigating a board's structural social capital created as a consequence of interlocking directorates. Using approaches and measures developed by Social Network Analysis, it compares the interpersonal directorship networks of the top 250 companies in the United States and Australia. The authors find that the smaller, sparser Australian network is only marginally less compact and connected than the larger US network at the firm level of analysis. However, at the director level of analysis the US network is much larger and more connected than its Australian counterpart. Furthermore, they suggest that scholars studying the resource dependence role of boards should consider using measures of interpersonal links as well as traditional measures of inter-firm links. The comparison of US and Australian corporate opportunity networks raises three interesting points.

First, large networks (such as in the US) provide more connectedness for participants than smaller counterparts (such as in Australia). If these differential opportunities are utilized by participants to the same extent, would expect a number of potentially important implications. For instance, the larger the network, the greater access to resources for a firm. Similarly, innovation and information should diffuse more rapidly through a larger network and we would expect that any information asymmetry or innovation advantages would not last as long in a larger network.

Second, despite directors in both systems holding, on average, similar number of positions, the US director has a much greater potential network in which to build and exploit social capital.

Third, there is the question about the relationship between networking and opportunity structure. The authors propose that a significant part of the social capital of a board comes through the person-to-person contacts that board members make with members of other boards. These contacts create an interpersonal network among board members. Moreover, they state that the interpersonal network arises as a consequence of interlocks between firms. Once these links are dense enough to create a large, central national network, directors are brought into a single, connected communication network of significant breadth and scale. This is a resource for building the social capital of individual directors and enhancing the social capital of boards and, in turn, may have implications for board, firm and system performance.

In another typology of research, Social Network Analysis is used to measure the connectedness of directors within the entire director network (Horton et al., 2012). The results show that executives' and outside directors' compensation is associated with the characteristics of their social connections. Executive directors, such as CEOs, CFOs, and outside directors, such as chairmen, who have high levels of closeness and better brokerage positions earn higher compensation. It also shows evidence that these aggregate connections which generate the firm's connectedness are positively associated with future performance. This finding is inconsistent with managerial power and rent-extraction by executives, and consistent with executives receiving compensation for the resources they bring to a firm. Overall, on average, connections are beneficial to the individual as well as to their firm.
A number of hints apply to this study. First, as in any network study, the social network is incomplete. Although director interlocks have been found to reflect social ties, authors do not capture all possible ways through which a director can obtain an information advantage (such as golf club memberships, religious activities, political affiliations etc.). Nevertheless, these social or grey ties add noise to the network estimates potentially biasing downwards the network effect. Second, while the authors have tried to control for human capital and its potential endogeneity with social capital measures, it shouldn't be excluded that higher ability directors have a higher probability of acquiring better network positions. However, it shows some comfort from the results of their analysis, that there appears to be diminishing returns from a director's human capital (educational attainment etc.) in relation to future firm performance, as opposed to her social capital results. Third, as with any study of this kind, there is a possibility of a correlated missing variable driving the results.

Using SNA, several researchers analyze how various IPO characteristics are affected by the location of a lead IPO underwriter in its network of investment banks generated by participation in previous IPO underwriting syndicates. Bajo et al. (2016) developed the basic hypothesis that investment banking networks allow lead IPO underwriters to induce institutions to pay attention to the firms they take public and to perform two possible information-related roles during the IPO process: an information spread part, in which the lead underwriter may use its investment banking relationships to transmit flashy information about these IPO companies to different institutional investors, and an information mining role, in which its investment banking network assists the main IPO underwriter to pull out information useful in pricing the companies' IPOs from various institutional investors. The empirical results of the study can be summarized as follows. First, IPOs underwritten by several central lead underwriters are linked with biggest absolute values of IPO offer price audit. Second, IPOs underwritten by several central lead underwriters are combined with higher IPO and secondary market valuations and higher IPO initial returns. Third, IPO firms underwritten by several central lead underwriters create stronger participation from some financial market players. Such firms are followed by a bigger number of financial analysts and have more institutional investor holdings. Finally, the shares of firms doing IPO by several central lead underwriters have better secondary market liquidity and greater post-IPO long-run returns.

The following work was done by (da Silva et al., 2019). The objective of this recent application of SNA tried to study the social interaction among participants in Online Discussion Forums (ODF). Data were collected from ODF logs of the majors in Business Administration and Accounting in a Brazilian private university. This study identified who the most central participants in the community are, the topological properties of the networks, the interaction patterns, and analyzed the evolution of the interactions in the 3 years before the publication. This study found that these interaction networks are sparse, with low density, which shows that only a few of all the possible connections among participants exist and students could be more engaged in participating, interacting, and collaborating with others. An irregular interaction pattern is observed as far as major's semesters are concerned. In the Accounting major, participants interact more in the first semester and interaction diminishes in the last semesters. In the Business Administration major, there is also more interaction in the first semester, but also a very intense collaboration when students reach the end of their major. The giant component phenomenon was observed in all networks constructed. The size of the largest component obtained varied from 80.53% to 97.49%. In the considered span of time, the number of active participants has been around 45% to 50%. The results have also shown that the main incentive to participate in an ODF seems to exist when students are graded by the professor. Students also seem to feel less confident to engage themselves in the ODFs in the university environment and seem willing

to create a second environment via WhatsApp groups, where they might feel more secure to give their opinions and express themselves.
In a Distance Education (DE) environment, collaboration among students is a key factor for promoting and developing learning and engagement. The authors believe that students participating in ODFs form a Community of Practice. To develop student learning and gain real value from group work, the process of belonging to a team becomes significant. Thus, it is important to identify key participants in such communities because learners will also become more involved with and engaged in activities if they are stimulated by others' behavior.
The results of this study show that, by using SNA, major coordinators and professors could identify and characterize interactions as well as develop new actions to keep students engaged by identifying courses in which students have not been participating in discussions adequately. Also, SNA allowed the identification of those students who are greatly connected to others and can be used to stimulate student participation or convey information and expected behavior from the coordinators.
Cheng et al. (2019), instead, explore the link between a firm's connectedness within the interlock network and informed trading. Corporate directors may leak nonpublic, material information to a subset of investors in their social networks. Such leakage would likely lead these investors to engage in informed trading at the cost of other market participants, thus undermining the integrity of capital markets.
Interlock centrality is positively associated with short-sale activity in the period before a negative earnings surprise is announced and that this positive association is driven by Eigenvector Centrality (that captures both the quantity and quality of a board's ties) and Betweenness Centrality (extent to which a board serves as an information broker) rather than by the quantity of such ties in interlock networks.
The authors then explore whether the interlock centrality-related short selling can be attributed to director information leakage. The paper shows that the association between interlock centrality and informed short selling is more pronounced for firms whose directors have a greater number of interactions with the directors of outside firms in the network. This provides supportive evidence that director information leakage is the plausible underlying channel by which centrality-related informed trading occurs. Moreover, the research states that the positive association between interlock centrality and informed trading is less

pronounced for firms with higher transparency. This result suggests that firms can mitigate centrality-associated informed trading by improving corporate transparency. Finally, we rule out an alternative interpretation that the documented positive association is attributed to short sellers' superior ability to process public information.

In another very interesting paper, Kim (2019) investigates through SNA the effects of a whole network on firm innovation performance among firms engaged in the Korean semiconductor industry using three variables, namely main component, eigenvector centrality, and closeness centrality. The effects are then analyzed using two-step generalized method of moments estimates.

Establishing strategic alliances has been seen as a central strategy for firms because it can help in sharing risks, conserving resources, and giving enhanced opportunities for gaining new competencies. In recent decades, the Korean semiconductor industry has been making remarkable progress in the world market, where firms have excellent competitiveness; to maintain this success, innovation must be centered. In the process of innovation, the influx of external technology plays an important role in increasing the innovation capacity of a firm. In other words, a firm's technological alliance networks can be thought of as an inimitable and non-substitutable asset by facilitating access to unique resources and capabilities.

It is well-known that external networks play an important role in firm innovation; yet there is a lack of understanding from past studies of which positioning is beneficial, especially in terms of individual firms in a whole network, because if a network is incorrectly built, it could be wasteful in terms of time and cost. Therefore, constructing a whole network in a homogeneous industry, observing the development of external networks that have been formed over time, and creating and analyzing the panel data can provide unique insights for making alliance strategies to strengthen the company's capabilities. In addition, past data can be used to form networks of the future, and it can be used for judging with whom to form a strategic alliance in the future through comparison with competitors.

Another study uses SNA change effort that effectively facilitated faculty's adoption of Evidence-Based Instructional Practices (EBIP), which is to organize faculty into teaching-focused Communities of Practice (CoPs) (Ma et al., 2019). We examined the social interactions of faculty within CoPs and investigated whether faculty in CoPs that were actively adopting EBIP (adopting CoPs) had more frequent conversations and collaborations around teaching with their colleagues than faculty in CoPs that did not adopt EBIP (non-adopting CoPs). A sociometric survey was administered to document 89 faculty members' social interactions within 22 CoPs.

The Social Network Analysis reveals some core findings. First, the social network structures of the adopting CoPs reveal greater cohesion with larger core and active memberships than non-adopting CoPs. Second, the social network structures suggest that there is more abundant and more efficient information sharing among the adopting CoPs than the non-adopting CoPs.

The adopting CoPs have higher density, more connectedness, and less breadth than the non-adopting CoPs. Network density and connectedness in the adopting CoPs is at or near 100%, which means that all members of the CoP are included in teaching conversations, whereas the non-adopting CoPs did not involve all purported members (connectedness below 100%). In addition, people working in highly connected networks also receive greater social pressure in terms of sharing knowledge because they need to maintain good communication with colleagues in order to build good relationships. Therefore, a high density of adopting CoPs reveals that there is likely much more communication in the adopting CoPs than the non-adopting CoPs. This higher level of communication suggests higher levels of knowledge sharing and higher potential for learning. High density, more connectedness, and less breadth also indicate that the social networks of adopting CoPs have a more balanced power structure.

While the idea of organizing STEM (Science, Technology, Engineering, Mathematics) faculty into CoPs to stimulate the adoption of EBIP has had theoretical support from the literature, this study provides the first evidence for what network structures in a faculty CoP can lead to sustained improvement in instruction. The results confirm the expectation that social network analysis may be useful in understanding faculty teaching communities and that CoPs may provide a useful lens for interpreting social network data. The model of collaborative joint ownership of reforms can be brokered when a few key members may drive the reforms and actively engage all members of a community in distributed decision making regarding those reforms.

Another study by a Chinese research group explored the spatial structure and effects of the association network of CO_2 emissions in the Chengdu-Chongqing urban agglomeration through SNA (Song et al., 2018). By using data from the agglomeration from 2005–2016, an association matrix of CO_2 emissions was calculated through a modified gravity model. In addition, the association network of the urban agglomeration was constructed. The structure of the association network of CO_2 emissions was investigated by relating it to the global network, individual network, and spatial agglomeration. The study was concluded by examining the structural effects of the association network of CO_2 emissions. The major findings are reported below:

1. The global network structure revealed that the network density and association strength of the spatial association network of CO_2 emissions in the agglomeration are increasing on a yearly basis, indicating closer CO_2 emission connections among cities in the urban agglomeration. From a static perspective, there are still significant differences in inter-city CO_2 emissions, providing evidence of the imbalance in the spatial structure of CO_2 emissions within the urban agglomeration.
2. The individual network structure indicates that the out-degrees of Chengdu and Chongqing are considerably higher than those of other cities and their in-degrees. This shows that there is a strong spatial spillover effect in Chengdu and Chongqing. This is demonstrated by the fact that, starting from 2011, the Betweenness Centrality values of Chengdu and Chongqing were in decline, (in other words the “bridge” role of the two core cities weakened) while the Closeness Centrality values of the different smaller city start growing over the average. This states that the radiation effect of Chengdu and Chongqing and proves that secondary cities are moving toward the network center.
3. The spatial agglomeration assessment revealed that the Chengdu-Chongqing urban agglomeration is divided into four subgroups based on geographic location.
4. The effect analysis showed that the association network structure of CO_2 emissions has a significant influence on the regional CO_2 emission intensity and the differences in CO_2 emission intensity among cities. The increase in network density not only lowers the regional CO_2 emission intensity greatly but can also narrow the differences in inter-city CO_2 emission intensity. Meanwhile, increasing node

centrality, especially regarding the Degree Centrality and Closeness Centrality, is beneficial for lowering CO_2 emission intensity.

The above research indicates that the success of regional (urban agglomeration) CO_2 emission reduction concerns not only individual cities, but the establishment of long-term, coordinated emission reduction mechanisms within the whole region.

The last work we want to present research, the more recent of our selection, is focused on inter-firm cross-shareholding relationships to investigate the effects of cross-shareholding relationships and network positions on the financing constraints of private Chinese firms (Peng et al., 2019).

Debt financing is one of the most important means of external financing for private enterprises in China. In recent years, the research on enterprise's debt financing costs has been paid more and more attention by the scholars at home and abroad, as evidenced by the construction of social network relationships to alleviate the information asymmetry on both sides of the loan. In this paper, the relationship between the cross-shareholding network and corporate debt financing costs is investigated by using the Social Network Analysis method, which focused on listed companies involved in cross-shareholding on China's Shanghai and Shenzhen Securities Market.

Based on the data of Chinese private listed firms, the results of this research indicate that private Chinese listed firms involved in inter-firm cross-shareholding relationships seem to be free from financing constraints. This means that these firms probably have easier access to external funds via their inter-firm cross-shareholdings. Meanwhile, when the region in which private firms are located in has a higher level of financing marketization, the relieving of financing constraints of private firms by their entering into cross-shareholding relationships will decrease. The results demonstrate that cross-shareholding relationships can substitute, to some extent, the formal institutions on the opposite side. Furthermore, given the complexity of inter-firm cross-shareholding networks, we find that a private firm's degree of financing constraints is significantly decreased by its centrality and structural holes in the cross-shareholding network, which provide opportunities for shared resources, information transfer and exchange. This demonstrates the importance of obtaining access to resources and information through networks, and further confirms to a certain extent that the firms' behavior is embedded in their social networks.

Based on the perspective of social network information transmission, this paper empirically examines the influence of the cross-shareholding network of Chinese private listed companies on their debt financing constraints and provides more empirical evidence of the network effect of cross-shareholding between Chinese enterprises. In practice, this paper finds that the cross-shareholding network can significantly alleviate the asymmetry of information and reduce the cost of debt financing for private enterprises and enterprises with a high degree of financing constraints. For the above-mentioned types of companies, it be possible to build a cross-shareholding network to give full play to its role in information transmission.

2 Scope definition and research problem description

2.1 Introduction

The aim of this thesis is to study the importance of social networks in the ICO field, using centrality measures and understanding if they can play a determinant role in the success (or not) of an ICO, and the effect of previous successes by the ICOs' proponents in future crypto-funding campaigns.

Unlike established firms, ICO projects (or ICO ventures, in the rare cases when an already registered venture entered this market) are stamped by strong information asymmetry and opacity. In a way, information asymmetry is higher than in crowdfunding campaigns, because in the latter case platforms screen the different campaigns to avoid low-quality projects in order to defend their image (Colombo et al., 2015). This screening and selection phase is missing in the case of ICOs. Thus, the market for lemons problem introduced by

Akerlof (1970) arises: the best projects may easily find financial support from banks, business angels and venture capitalists (Hoenig & Henkel, 2015), while the worst projects could try to raise money through an ICO. Social capital is an asset that can reduce agency problems. Social capital refers to the elements of social structure that form a resource for action (Coleman, 1988). It summarizes how individual mobilize resources through relationships (Adler & Kwon, 2002). Unlike other forms of capital, it is jointly owned by the parties in the relationship and cannot be appropriated by an individual (Lazega & Burt, 1995).

Our work is builds on the literature regarding the SNA, with a focus on the centrality measures and their effects in real cases, and the ICOs, understanding the main characteristics and,
particularly, the drivers for their success.

In these years SNA increase its diffusion and many scholars and researchers used its tools to explain some social phenomenon. At the same time the 2017 and 2018 were the years of ICOs. This new funding method has arisen from the Blockchain with the aim to democratize the sources of financing.
The work links the ideals of decentralization and connection, coming from the Blockchain and ICO fields, with the study of social networks. This linkage is as natural as innovative because in the current literature there are no studies that exploit the SNA's tools to analyze ICOs. We want to fill this lack in the current literature, expanding the knowledge related to the role of social relationships in the crypto-funding universe. Our research provides some interesting results both for teams that want to design their own funding campaign through a token sale both for investors that want to understand signals for a successful ICO.

2.2 Objectives

A nascent literature in the business and finance field is analyzing the ICO phenomenon (Adhami et al., 2018; Fisch, 2019; Venegas, 2017; Zheng et al., 2017). We contribute to this pioneering research analyzing how the quality of network relationships among ICO proponents and advisors affects the fundraising success.

Using SNA (Freeman, 1979; Nieminen, 1974; Wasserman & Faust, 1994), we consider the participation of single individuals to several different ICO projects, at various levels, and the relationships among them to understand how the network can influence the results of an ICO. Social capital may explain how individuals mobilize their resources through the relationships with others to facilitate business success in a competitive environment (Sözbilir, 2018). The network of contacts that ICO proponents are connected to (through participation in different ICO projects and advisory board) can play an important role in the information extraction and legitimization processes during the token offering.

Exactly as in many economic and financial fields, the relationships between individuals can bring effective advantages in the development of the project and of the funding campaign, spreading relevant information and best practices.

Moreover, the crypto-world is actually misleading and tricky, and indeed many ICOs have been discovered as scams (Shifflet & Jones, 2018). In fact, there are some cases in which the components of the team are totally invented people; no physical person under the name disclosed. In this deceptive environment, the only element that could be a signal of concreteness is the human relationship. Through the building of networks and the reputation of the proponents of an ICO, investors can be sure about the truthfulness of the project.

The topic is important for a number of reasons. Firstly, by adopting the Blockchain technology, ICO teams may reduce the costs of capital raising, avoiding intermediaries (crowdfunding platforms) and payment agents (banks, credit card circuits), but also increase their business opportunities operating on the web as it has never been done before the Blockchain era. Another element of interest is the opportunity to reduce marketing costs for the campaign through the social contacts within the crypto-community, exploiting the word of mouth and the reputation of people behind the ICO. Therefore, it is worth investigating the impact of social networking on the fundraising success.

Secondly, ICOs favor open-source project development and decentralized entrepreneurial activity, generating a built-in customer base and positive network effects (Chen, 2018). Therefore, analyzing the quality of social capital of ICO teams contributes to better understand the impact on innovative projects' performance, especially in an open-source and decentralized context (Giudici & Rossi Lamastra, 2018).

Third, the quality of the ICO team is one of the few signals that investors can observe. Due to the lack of any audited offering prospectus and of any screening from third parties, information asymmetry and opaqueness are particularly severe, and the risk of moral hazard is high. Nowadays, the Akerlof (1970) "market for lemons" is difficultly applicable in this environment. Indeed, it was proven that a number of ICOs have been pure scams and the team disappeared after raising money (Zetzsche et al., 2017). Understanding the relationships between the characteristics of the team and the probability of success plays a decisive role in guiding proponents through the structuring of future token sales and in displaying the main signals that potential contributors seek. Regarding the reputation of individuals launching a funding campaign, it was proven for crowdfunding projects that the prestige, measured from the past experiences of proponents, is a clear signal to enhance the opportunities to reach the monetary target set (Butticè et al., 2017).

People and their network of relationships could be a real proof for the project trust and the spread of best practices could be crucial for the development of the phenomenon.

In the next paragraph, we build our research hypotheses and then we create a framework for the following analysis, based on the several studies, that merges the social network analysis with the research of the determinants of success for an ICO.

2.3 Research questions and hypothesis definition

Building on a union of various frameworks, we try to connect the ICO's success with the social network of the funding team and of its advisory board, developed through the participation in previous token sale events.

To reach this aim, we started from the work of Fisch (2019) to understand from the current literature which are the drivers for the ICO success. Specifically, the author found statistically significant variables related to the ICO campaign as the duration in days, the token supply, the kind of token sold, the Ethereum-based development, the publication of computer code and the Bitcoin value.

From a social network analysis perspective, we have pick up part of frameworks from many works (Cheng et al., 2019; Georgieva et al., 2016; Kim, 2019; Nicholson et al., 2004) that studied the effect of measures of centrality in many fields, including the success in different kinds of funding campaign as IPO and crowdfunding.

Finally, we decided to develop the framework used by (Butticè et al., 2017) where the authors studied the effect that previous successes and previous failures by the team members had on the crowdfunding campaigns.

Success

As measure of success, we decided to use a binomial variable (1=success; 0=failure). We considered as successful the projects able to reach the minimum target capital, that in the crypto field is called soft cap. A characteristic of the latter variable, actually common with the most of the ICO features, is the non-mandatory disclosure of it. For those projects that have not communicated the soft cap, we checked on the website their effective success or the return of money to the investors. Indeed, it is a common practice that when an ICO does not achieve its goal the money is backed to the investors. It is guaranteed by the rules of the smart contracts, highly diffused on the Ethereum Blockchain, and rarely is not implemented. Therefore, the unsuccessful projects were identified as those unable to reach the soft cap, with no amount raised, and with the money-back process put in place.

We built a network composed by ICOs, in which we studied if the network relationships and the past experience in the ICO field of the members are relevant in the right execution, and then in the success, of the token offerings. To do so, we used some centrality measures, the belonging to the main component of the whole network and the participation in previous ICO by the members of team and its advisory committee.

Largest connected component in the whole network

In the network of companies built, there are obviously sub-networks because not all the ventures are linked between themselves. Each sub-network is separated from the others and the size of the sub-network is relevant for the spillover of information (Kim, 2019). The sub-network with the biggest size is called the largest connected component. Of course, it is composed by projects that included individuals with many social links in their team and advisory board. Those individuals developed their relationships through the participation in more ICOs, and hence they have the opportunity to exploit their experiences and to diffuse best practices. For this reason, we suppose that the affiliation of a team in the largest connected component has an effect on the result of the funding campaign. The goodness of this concept could be not only a signal for investors that could check the importance of the team and advisors, but also an effective way for new proponents to enter the crypto-world, ensuring themselves the opportunity to avoid past problems experienced by their precursors. And hence, we tested our hypothesis:

H1: The belonging to the largest connected component has a positive effect on the success of the ICO

Centrality measures

To determine the quality of relationships and information flows in a network, we borrow from social network theory (Freeman, 1979). According to this framework, the central location of an agent in a network and the nature and extent of its connections to other agents in that network affect the flow of information to and from the agent (Bajo et al. 2016). Social network analysis has been adopted in the finance literature to investigate cross-shareholding relationships among different companies (Niki et al., 2011), board interlocking (Cheng et al., 2019; Nicholson et al., 2004), underwriter in IPOs (Bajo et al., 2016), networks in venture capital syndication (Hochberg et al., 2007). To our knowledge, this is the first work considering the setting of Initial Coin Offering. We argue that ICO proponents' relational ties and network positions can contribute to reduce information asymmetry and induce a greater number of potential pledgers to pay attention to the offering, increasing the probability of fundraising success and providing legitimization to the project. Value-relevant information are more efficiently transmitted across networks (Cheng et al., 2019) and individuals' connectedness improves action coordination and efficacy (Horton et al. 2012). According to Bajo et al. (2016) we refer to the quality of relation ties and network positions as network centrality. Specifically, we used four centrality measures to explain four different concepts.

The pure number of relationships (whose measure is the degree centrality) of an individual indicates the number of people touched. Obviously, the higher the number the more popular the individual is in the network and, in the specific case of an entrepreneurial network, the probability to learn best practices and to avoid errors increase. We believe that this concept could be adapted also for the ICOs; if the team members and advisors have many links with other people of the crypto-environment, they are facilitated in exploiting past experiences and understanding easily the game's rules, and hence in the ICO process-making. It is also important to consider that the more the connections a team has, the more the word of mouth and the more the chances to exploit it and to reduce the marketing costs. In a certain sense, this practice could have a direct effect for the soft cap definition because many ICOs set their fundraising target also on the basis of the marketing costs of the campaign. So, we developed the following hypothesis:

H2.a: The ICO's degree centrality is a measure of word of mouth capacity and of the amount of information received, and hence its relationship with the probability of fundraising success is positive

Likewise, to the degree centrality, the eigenvector centrality measures the number of links that a node has within the network, but it goes a step further. It introduces another important aspect related to the information flow that is the position occupied within the network. Obviously, a node placed at the limits of the network has less probability to reach information than one placed in the center. In fact, eigenvector centrality tells how well-connected a node is, considering not only how many links it has, but also how many links its connections have, and so on through the network. In few words, it tells that even if an individual has only one single relation with another one in the network, but the latter is very well-connected and has a good opportunity to spread and catch useful information, the first individual, in turn, can receive important best practices. The same comment done for the degree centrality about marketing is worth for this measure. In ICO terms, it means to have the highest chances of success. For this reason, we propose that:

H2.b: The eigenvector centrality has a positive effect on the word of mouth and the chance to learn best practices, and hence on the ICO success

Another way to measure the centrality of a node is the closeness centrality that uses the average distance of a node from the others. Clearly, the less the average distance to reach a node the less the effort to exchange information with it. After this assumption, the closeness centrality is a measure of efficiency and effectiveness for the information flow. Actually, the closeness centrality is inefficient in a disconnected network as the one studied in this work. For this reason, we used the efficiency that, similarly to the closeness, measures the efficiency of the information exchange in a network (Latora & Marchiori, 2003). Clearly, the word of mouth effect may be improved by high efficiency of the information flow. People behind an ICO with a high level of efficiency can exploit better their relationships to drive their project to success. It follows the hypothesis:

H2.c: The efficiency influences the possibility to receive information about best practice and to diffuse information about the company reducing marketing costs, and hence it is related to the token sale success

The last element covered about the centrality is referred to the particular position that some people have in a network. We are talking about the bridge. A node acts as a bridge when it is positioned in the shortest path between two other nodes. An individual, recognized as bridge, has likely an important role in the information flow because he has the power to block it or let it continue. In the SNA theory, a bridge is a node that cover a structural hole, a gap between individuals that have complementary source of information. However, it is also true that if there is another path not too long, the exchange of information may be just a little less efficient. Anyway, a high betweenness centrality indicates an important role in the flow of information because it means the individuals are a crossroad for the spread of information, and hence they may have higher probability of knowing best practices that it is translated in a higher probability of conducting a good ICO. In this case, the betweenness centrality is not related directly to the word of mouth, but it may be important for the information spread of other ICOs. So, the implication of marketing cost reduction is not as evident as for the other indicators. We test the hypothesis:

H2.d: The higher the betweenness centrality the higher the opportunity to learn best practices, and hence the probability of the ICO success

<u>*Previous team members' successes*</u>

We built the previous hypothesis observing the phenomenon on an overall ICO-perspective. On a single-individual-perspective we believe that projects' participant past successes in past ICOs are a signal for the success of the new ICO. Indeed in the crowdfunding context, the success in a previous campaign of a single person have a positive effect on the success of future campaigns (Butticè et al., 2017). For this reason, we posit that the individual past success of a participant is a signal for a good ICO. We test these hypotheses:

H3.a: The occurrence of past successes of individuals taking part of a new ICO is positively related to its success

H3.b: The number of past successes of individuals taking part of a new ICO is positively related to its success

Moreover, we decided to study if also the previous failures are a discriminant in the investors' decisions. In other words, we want to understand if the crypto-environment has memory of the people who failed a token sale; a sort of black sheep effect. As done for the successes, we built an unsuccess index for each ICO. So, we test the following hypothesis:

H3.c: The occurrence of past failures of individuals taking part of a new ICO is negatively related to its success

H3.d: The number of past failures of individuals taking part of a new ICO is negatively related to its success

2.4 Methodologies

The graph below (figure 7) represents the main phases of our work.

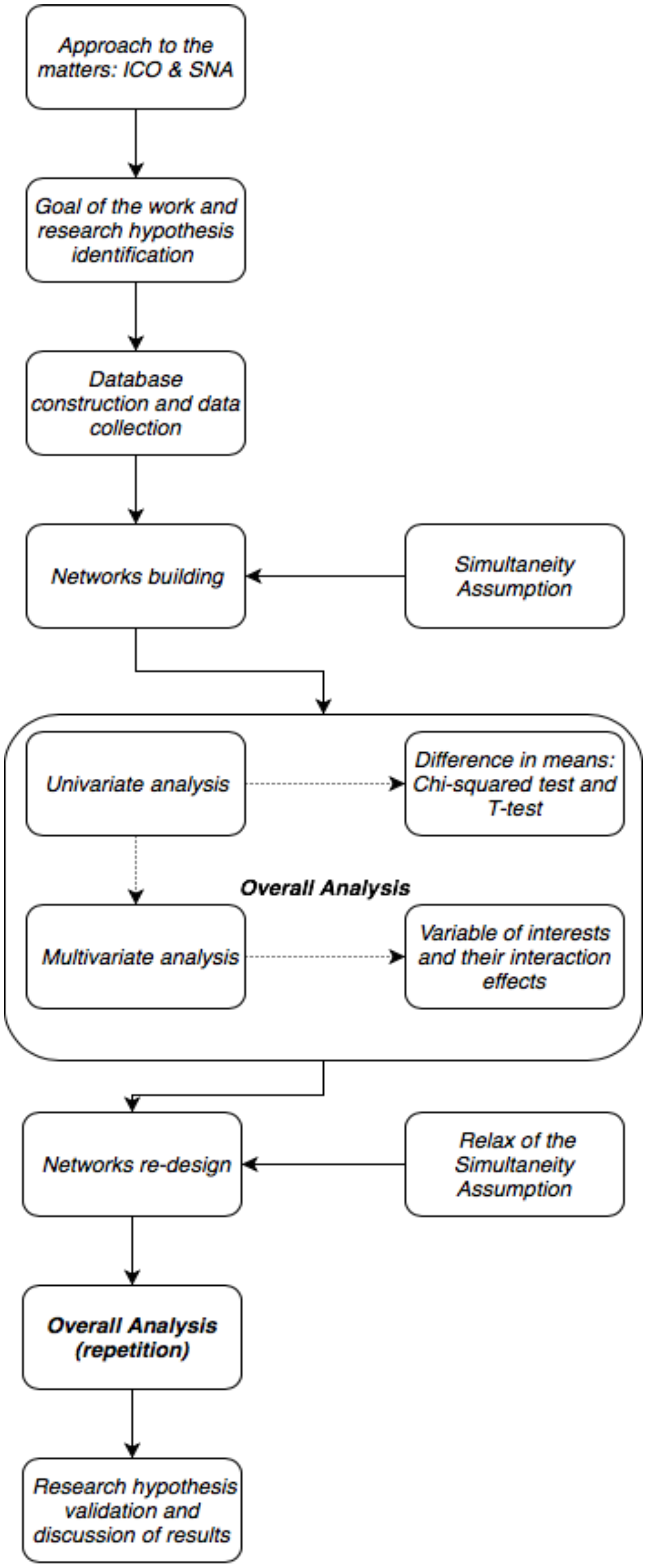

Figure 7. Main phases of our work

We approached the matter because of the increasing relevance that the cryptocurrency and Blockchain have been having on the financial sector starting from the boom of 2017 since today. Indeed, the Initial Coin Offering phenomenon became so important that many regulators (the first was the SEC) were interested in it. By the way, the 19^{th} on March in 2019, the CONSOB, the Italian financial market Regulator, published a discussion paper to move toward the introduction of regulation for the Initial Coin Offerings in Italy.

However, another topic that was arising particularly in the academic field was the Social Network Analysis, whose many studies were done but nothing about the ICOs.
For this reason, we decided to combine these two research matters in order to understand the relation between one of the main elements of SNA, the centrality, and the success of an ICO. In particular, we applied four centrality measures and the concept of the largest connected component to understand the role of network relationships within the network composed by the ICOs proponents.

We started collecting information about the current and past ICOs and we approach for the first time to the crypto-world. Specifically, we continued the compilation of a database composed by the token sales and their features while we built a completely new one in which we gathered information about the members of the ICO in order to construct the social network used to do the centrality measures.
We extracted the information required manually from the web. Overall, we collected information for 933 ICOs and for 10297 people.

Meanwhile, we started to increase our knowledge about the themes of Social Network Analysis and the determinants of success in fundraising campaigns, given the few, but growing numbers of study about the ICOs. Particularly, we mastered the knowledge about some financing method that we have already studied in our courses; the VCs, the IPOs, and the crowdfunding. Starting from a basis of graph theory developed during the university career, we have approached for the first time the Social Network Analysis, starting from masterpieces of the SNA as the works of Freeman (1979) and Wasserman & Faust (1994), since arriving to more recent studies as those of Bonacich & Lloyd (2001), Horton et al. (2012) and Newman (2005).

Being innovative research, we merged many methodologies used in other works. Starting from the works of Bajo et al. (2016), Cheng et al. (2019), Georgieva et al. (2016) Latora & Marchiori (2003), and Nicholson et al. (2004), we introduce a number of constructs related to the centrality of ICO proponents and advisors in a network (degree, eigenvector, betweenness, efficiency and belonging to largest connected component). These statistics are intended to measure both the number and the quality of network connections. About the history of successes obtained by ICO's proponents, we used the framework of Butticè et al. (2017), creating a new variable suitable to describe the individuals' ability to succeed. Referring to the campaign characteristics, we mainly followed the work of Fisch (2019) and Adhami et al. (2018) who studied the effect of the ICOs features on the success of the fundraising campaign.

Collected all the data, we exploited the software *R* and package *igraph* to build the individual network, composed by ICO proponents, and then the ICO network, composed by the ICO that we have treated as node able to communicate through the individuals (if an individual participated in two different ICOs, the ICOs are connected). Both the networks were constructed under the assumption of static network (static because we used a single time period). This assumption is due to the fact that the first link of the network occurred in March 2017, and hence our time horizon was enough thin (smaller than one year); it led us to the statement of simultaneity for the creation of the links, in order to simplify our model. Once built the networks, we calculated the centrality measures.
As we will see in the next chapter, the results of the models created to predict the ICO outcome, led us to change the perspective and reject the assumption of simultaneity. In doing so, we gave a value to the age of the relationships and built a new dynamic network (dynamic because it takes into consideration the time factor). From the dynamic network, we extrapolated new centrality measures, useful to the development of new regression models.

Moreover, we considered the past successes of the individuals for each ICO and we built some indexes representing the number of past successes and failures experienced by ICO proponents. In this case, we obviously took into consideration the time factor since the beginning.

Before doing the regression models, we decided to do some analysis of the variables' means in order to understand if there were differences between the mean of the successful ICOs and failed ICOs; if a difference was found, we could infer that the variables studied may be candidates for becoming determinants of ICO success. In particular, we performed some T-test for our variable of interests; centrality measures, occurrence of past successes, success and unsuccess indexes and belonging to the largest connected component.
The results of this analysis were not so positive for the centrality measures built with the static network, but we continued to analyze them to understand deeply if there were relations with the campaign success.

Then, we performed some logit regressions including all the control variables and, using one at a time, the variable of our interest. Immediately, we found some significant results about the belonging to the largest connected component and the occurrence of previous success by the proponents and no relevant outcomes for centrality measures, as suggested by T-tests.

At that moment we decided to ignore the assumption of simultaneity and change our ideas. Basically, we assigned a weight to the edges of the network. The weights represent the number of days from the first connection created in the network to the last day of the ICO referred to; assuming a proportional relation between the time and the knowledge developed, the weights are also a measure of the cumulate knowledge in ICO proceedings. In this way, we penalized the older ICOs. In a certain sense, it was coherent with reality. The first ICOs could not count on the knowledge about the phenomenon, neither on large community able to support it. Their costs in the building the relationships were higher than the ones of the younger projects.
Found a robust basic assumption, we continued our work. First of all, we calculated the centrality measures, taking into consideration the fundamental difference given by the use of the weights, and always given a practical explanation to our decisions.

Built the dynamic network and calculated the new centrality measures, we repeated the same steps of analysis done before. We searched for differences in means for the centrality measures, and immediately we understood that we were on the right way.

The T-tests confirmed our impressions and finally, we built our ultimate regression models that validated our research hypothesis.

Afterward, we performed some robustness checks to be sure of the strength of our results. Specifically, we searched for quadratic effects about the centrality measures, we added some variables in order to better understand the results achieved. First of all, we considered as variable the effects of the number of successes but also the effects of past failed ICOs conducted by the proponents. Another interesting variable used was the presence of past experiences ever by the proponents. An additional robustness check consisted of the introduction of directed edges from the older nodes to the younger ones, in order to allow the information exchange only from past projects to new ones, and not vice versa.
These robustness checks validated our results and added some details to them.

3 Empirical Analysis

3.1 Data collection process

We have collected information for a sample of 933 ICOs that started their funding campaign from August 2015 to February 2018 around the world, in which we have put data referred to the ICO. This period was wild and turbulent because this phenomenon increased incredibly and the Bitcoin, the largest cap cryptocurrency, reached the value of 20.000 dollars (17/12/2017). This boom doubtless influenced the ICO market, but it showed also its potential because, never as in that period, it has attracted so much attention.

Figure 8 represents the number of ICOs failed and completed with success from our data sample. It shows clearly the huge increase of 2017 but also the important trend of 2018 that in first 2 months had reached 40% the whole 2018 in terms of number of campaigns. Furthermore, the ratio between successes and total ICOs has incremented from 2017 (from 70% to almost 82%) but, obviously, we will wait for the completed data to express an opinion.

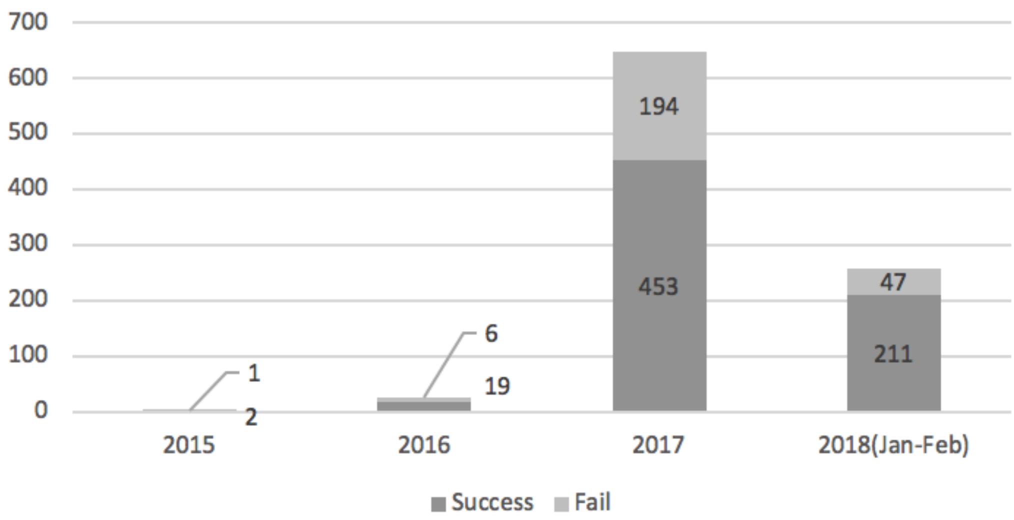

Figure 8. ICO success/fail

For the selected sample we have built two databases, one referred to the ICO features that characterize the most common elements of all the ICOs, and one referred to the composition

of the teams, collecting the names and the role (team member or advisor) for a total amount of 10297 participants.
In particular, for the first database we have collected:

<u>*ICO design-related information*</u>

- Availability of the White Paper: it is the document disclosed for future investors in order to provide information about the business model, the token offering and the team behind the venture. Being a non-mandatory document, it is not standardized, and its content can vary a lot between a company and another one. Additionally, often it is included a disclaimer of risks specific to the investment activity.
- Availability of the company code: the companies can decide to make public the computer code used to define the smart contracts and their applications. This source is often disclosed on GitHub.
- ICO duration: the duration in days of the token offering.
- Occurrence of the presale: it is used mainly for the ICO marketing. It is an instrument to attract investors, create a contributors' base and have an idea of the hype level of the project.
- Typology of bonus: bonuses are offered to incentivize the acquisition of the tokens. In particular, we have found mainly the presence of two typologies of bonus: early bird and major contributor. The early bird bonus is the practice of offering tokens at a lower price for the first contributors, while the major contributor bonus consists is like a quantity discount (the more the tokens bought the lower the unitary price).
- Token supply: it is the number of tokens generated for the ICO.
- Token distribution: the whole token supply is then distributed to different subjects. We have collected data for the most common ones:
    - Community: when tokens are offered to the crypto-world
    - Management: when tokens are retained by the team or internally by the firm to achieve some results (ex. Liquidity goals)

  - Reserved for bounties: in other word given in exchange for some tasks useful to the venture (ex. The translation of the white paper in a specific language)
  - Reserved to crowd sale: the real token offering to investors
- Use of funds: we have selected five main clusters which are:
  - software development
  - business development
  - marketing development
  - legal
  - reserves
- Token role: we have collected the usage opportunities guaranteed by the ownership that are divided in:
  - Currency: when the token is born to be an alternative to the fiat currencies
  - Access and payment service: when it can be used to access to the firm's platform and to buy the firm's product/service (the word "utility token" is commonly diffused for this usage)
  - Profit: when it gives the right to profit distribution
  - Governance: when it gives voting rights
  - Contribution: when it gives the right to contribute to the development of the business
- ICO price: the average price of the token in the ICO period.
- Soft cap and hard cap: minimum and maximum target for funding. In particular, the soft cap is very important to establish the success of the ICO because if it is not reached, a process of money return is often put in place as settled in the smart contract.

ICO's outcome

- Success or failure: as explained in the previous chapter, an ICO is considered failed if the soft cap is not reached or when the money-back process is done. If the soft cap is not declared by the team, the money-back process is not run and the amount of money raised is far from zero, the ICO will be considered successful.
- Fund raised: the equivalent in dollars of the funding amount raised, calculated considering the value of cryptocurrencies at time of the ICO's end.
- The first day of trading result: if the token was listed on a listing website, we have collected the open price, the close price, the highest and the lowest prices of the first day of trading.

General information

- Company's name
- Sector of the venture and product/service offered
- Team's origin country
- Sale jurisdiction: the country in which the ICO is done
- Token ticker
- Underlying blockchain

Crypto-environmental

- Bitcoin average price for the ICO period
- Ethereum average price for the ICO period
- Bitcoin price the day after the end of the ICO
- Ethereum price the day after the end of the ICO
- 7 days and 30 days return of the cryptocurrency price related to the underlying blockchain of the venture

- 7 days and 30 days volatility of the cryptocurrency price related to the underlying blockchain of the venture

For the second database, we have collected the names and surnames of the ICOs' participants, indicating the role (team member or advisor) occupied during every single campaign. So, it is constituted by the participants in the ICO's projects, for a totality of 10297 proponents, distributed for the 26,69% in advisors and the 73,31% in team members.

Collected these data, we have built, before, the network composed by the participants, and then the one composed by the ICOs, and calculated the centrality indicators.
As explained in paragraph 2.4, we have built the ICO's network, creating a link when a person participated in two different ICOs. We have supposed that the relationships were present all along the time horizon of reference (the simultaneity assumption). It was validated by the fact that the first link was created in March 2017, and hence our time horizon (11 months, less than one year) was quite thin to suppose that the analysis of the time sub-periods was not relevant in the creation of relationships. So, we have created the static network.
However, after the regression analysis, we have decided to relax the assumption of the static network, and so we have re-constructed the network in a dynamic way. In short, we have given to the edges of the network a weight whose value was as low as the age of the edge. The weight is like the level of knowledge that could be absorbed by the ventures and it increases with the time. In this way, older edges will be more penalized than younger ones because it is easier to catch better-quality information in more developed networks. A more detailed explanation will be given in the sub-paragraph 3.5.1, after the discussion of the results of the first multivariate analysis.
Hereafter, we will call the first one as "static network" and the second one as "dynamic network".

Figure 9 shows the largest connected component of the whole static network; it is the sub-network with the highest number of nodes in the whole network. It means that there are other nodes separated from it that are not present in the figure. The sizes of the circle indicate the number of participants and, considering the positions of the larger nodes, it is possible to understand that larger teams have more relationships than the smaller ones. In fact, it is quite intuitive that the number of people is positively related with the total number of relationships; just suppose that the average number of relationships outside the team for a single person is equal among the participants.

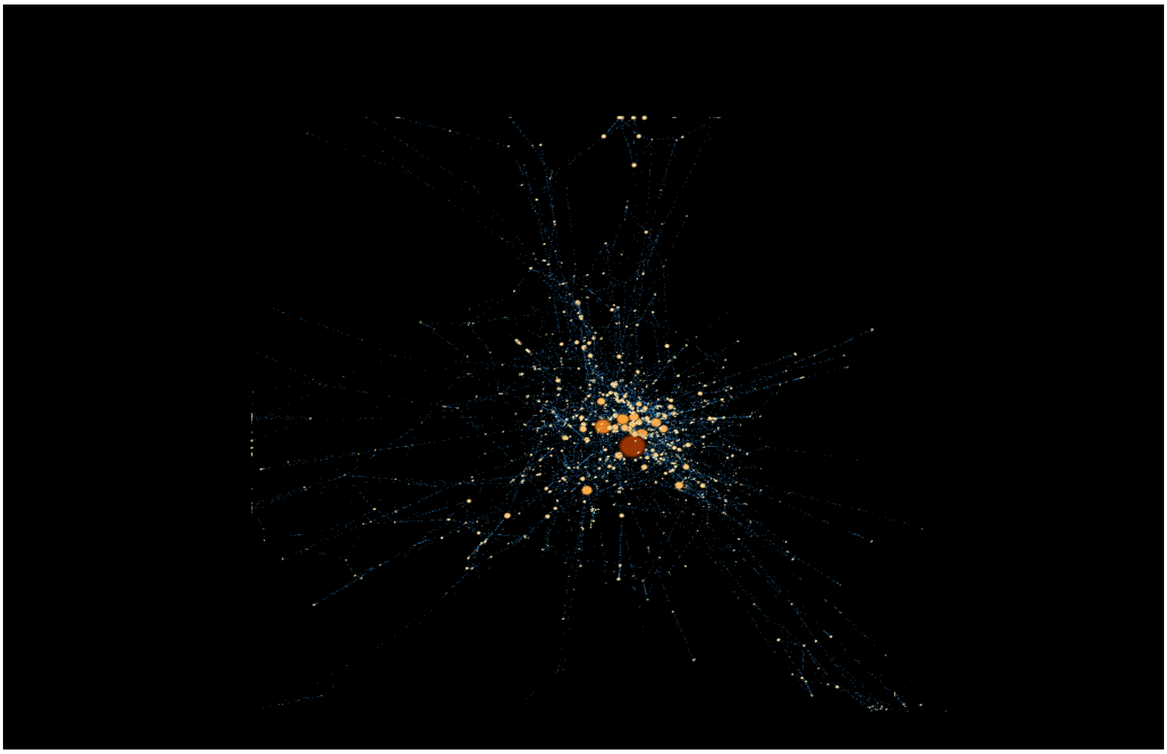

Figure 9. Largest connected component of the whole STATIC network

<u>*Sources of data*</u>

We have collected these data from different sources and entirely manually, without using data scraping tools and programs. The sources were:

- Institutional websites of the companies
- White papers
- ICOBench: a well-known website specialized in the collection of the main characteristics of the ICOs and particularly in the disclosure of team members and advisors. We have used this website as the main source for both the databases.

- ICOrating, ICOdrops: websites specialized in the ICO features' collection. We have used these two websites when the information on ICOs was not present in ICOBench.
- ICOholder, TrackICO: websites specialized in the collection of the people behind the ICOs. We have used them when the information on team and advisors were not present in ICOBench.
- Twitter account of the companies: we have checked mainly the period of the ICOs to check the official updates of the ventures.
- Medium account of the companies: Medium is a social network focused on the crypto-environment and used by ventures to disclose information about their business and the ICO results.
- LinkedIn, Facebook: used to verify the identity of members when the information on the main sources was unclear.
- Coinmarketcap: this portal is specialized on the secondary market. It provides information on most of the cryptocurrencies listed as daily values and volumes, the market cap, the total circulating supply, the percentage change for many time horizons, and several market analytics.

In this collecting work, we had the opportunity to understand the information asymmetry present in the ICO universe because the information is often very difficult to find and, sometimes, the data are discordant between whitepapers and websites, or between different websites. Nevertheless, we have seen that projects with a clear whitepaper and a good advisory board were often successful in the fundraising process. For this reason, we have tried to study in deep the importance of the role of advisors and their ability to spread the information related to the project. As described in paragraph 2.3, we have linked this ability with the concept of centrality.

3.2 Data analysis

In this paragraph we explain how we decided to use the data collected, providing an explanation of the variables used to implement the analysis.

Static centrality measures

First of all, we have constructed two undirect and unweighted networks; one for the individuals that developed and promoted the token sales and the other one for the ICO. The people network is composed of 10297 members divided in team members, involved in the project development, and advisors, involved in the ICO promotion. The ICO static network uses the funding campaigns as a node, and the relation is created by the participation of an individual in two different ICOs. In this way, the two ICOs are connected.
Built the networks, we have calculated the measures of centrality. Using *R* software and the package *igraph*, we have defined the adjacency matrix and, for each individual. The adjacency matrix is the matrix which elements represent the links between nodes: if the node i and node j are linked the element in row i and column j will be 1, otherwise 0. So, we have calculated:

- Degree centrality, as defined by Nieminen (1974): it uses the sum of the direct relationships of a single individual, x, as a measure of the quality of his interconnectedness. Defined a_{ix} as the adjacency matrix element of row i and column $x : C_D(x) = \sum_{i=1}^{n} a_{ix}$
- Betweenness centrality, as defined by Newman (2005): is based on the fact that an individual is important if it is present in as many of the briefest paths as possible between pairs of other members. Defined g_{ij} as the number of shortest paths: $C_B(x) = \sum_{i=1,i\neq j}^{n} \sum_{j=1,j<1,j\neq x}^{n} \frac{g_{ij}(x)}{g_{ij}}$
- Eigenvector centrality, as defined by Bonacich & Lloyd (2001): the assumption is that each node's centrality is the sum of the centrality values of the nodes that it is connected to. The nodes are drawn with a radius proportional to their centrality. The adjacency matrix and centrality matrix for the solution are shown. The centrality

matrix is an eigenvector of the adjacency matrix such that all of its elements are positive. Defining v_j= $(v_1, \ldots, v_n)$ referring to an eigenvector for the maximum eigenvalue $\sigma_{\max}(A)$: $C_E(x) = \frac{1}{\sigma_{max}(A)} \sum_{j=1}^{n} a_{jx} * v_j$

- Efficiency, as defined by Latora & Marchiori (2003): it is the inverse of the sum of the distance, $d(x,i)$, between the node x and all the nodes in the network and if two nodes are not connected their distance will be $d(x,i) = +\infty$. Defined $e_{xi} = \frac{1}{d(x,i)}$ and considering that if $d(x,i) = +\infty$, it implies $e_{ij} = 0$, $C_{EFF}(x) = \sum_{i \neq x} e_{ix}$

The next step is the adaptation of these measures to the ICO projects. Many approaches were analyzed.

The first idea was to use the average of the measures for the members of a single ICO. The main problem of this approach was that it does not consider the effect of "internal links". Now, we make an example to better explain the concept of internal link.
Let's imagine three ICO projects: project A composed of 100 members, project B and C by 3 members. Supposing that 1 member of the ICO B participates in the ICO A and another B member participates in ICO C (and hence they create a link between the projects), we can say that the project B is the best-connected project in this network. For sake of simplicity, we calculate the degree centrality using the degree centrality (C_D) measure. The project A has a centrality equal to $\frac{99*99+(99+2)}{100} = 99{,}02$, the project B $\frac{2+(99+2)+(2+2)}{3} = 35.67$, and the project C $\frac{2+2+(2+2)}{3} = 2{,}67$.
Unlike what we expected, project A has the highest degree centrality. It is due to the internal links effect. The 99 links that each member has in project A have a strong effect on the overall centrality. For this reason, we have discarded the average approach.

As suggested by the study of Cheng et al. (2019), we have built a network composed by ICOs where a link occurs when an individual participates in two or more projects.

Then, we have improved the Nicholson et al. (2004) way of designing the network. They have built a network composed of two typologies of nodes: the participant nodes and the

project nodes. In this way, we can combine the individual network and the ICO network in order to collect more completed information.
Indeed, we have built the individual network and then we have developed the ICO one including the individuals into the ICO node.
We remember to the reader that building the static network we have not taken into consideration the time factor. So, we call as "static centrality measures" the variables referred to this static network.
Then, we have used four variables to build our model which are:

- *degree*, to indicate the ICO's degree centrality
- *betw*, to indicate the ICO's betweenness centrality
- *eig*, to indicate the ICO's eigenvector centrality
- *eff,* to indicate the ICO's efficiency

Referring to the hypothesis *H1* formulated, we have introduced a dummy variable to signal the presence in the largest connected component of the whole network called *largest_component*.

<u>*Dynamic centrality measures*</u>

As explained in the previous paragraph, after the first regression analysis we have decided to give a weight, representing the moment in which the link was created, to the edges of the networks in order to consider the time factor.
And in doing so, we have constructed a new adjacency matrix which elements are not only 1 and 0 but are the weights of the edges. The new dynamic measures of centrality are calculated in a different way from the static ones.
Moreover, we introduced the "sister" of the degree centrality that is called strength centrality. In order to be coherent with the flow of our work, we will provide a further explanation in paragraph 3.5.2, after a detailed clarification about the construction of the dynamic network.

<u>Successful measures</u>

Defined the centrality measure, we have also focused on the effect that previous successful ICOs has on the current one.

For this reason, we have implemented a variable able to indicate the success level of each individual of the network. We wanted to have an index that, not only considered the success rate of a person, but also the number of projects' participation.
So, for each individual we have calculated:

$$Success\ Index_{ind} = \frac{s^2}{p}$$

Where:

- s is the number of successful projects participated by individual i;
- p is the number of projects participated by the individual i;

We have calculated the index for each person more times, precisely one a month. In this way, we have considered the time factor and the personal history of the successes. The square is due to the fact that we wanted our index was able to distinguish the number of participations, and not only the success rate of such participations. For example, let's imagine the participant A took part to 10 projects with 10 successes and the participant B to only 3 projects and 3 successes, without the square their Success Indexes would be equal to 1. Conversely, including the square, the A's Success Index is equal to 9 while the B's one is 2. Then, for each whole ICO we have summed the individual success factors and we have obtained the overall one, that we have called *succ_index*. The formula is:

$$Success\ Index_{ICO} = \sum Success\ Index_{ind}$$

Using the same method, we set up a variable that took into consideration the unsuccess index. Then, the formula used is:

$$Unsuccess\ Index_{ind} = \frac{u^2}{p}$$

Where:

- u is the number of failed projects participated by the individual i;
- p is the number of projects in which the individual i;

Then, we have calculated the unsuccess index for ICO, called *unsucc_index:*

$$Unsuccess\ Index_{ICO} = \sum Unsuccess\ Index_{ind}$$

Other two variables were introduced to indicate the presence of people with participation in previous successful campaigns and also in previous unsuccessful campaigns. To do so, we have used two dummy variables, called respectively *prev_succ* and *prev_unsucc.*

Experience measure

As we will explain in the paragraph 3.1.1, during the analysis of the difference in means between successful ICO and failed one, we observed the positive effect of the successful measures and, unexpectedly, of the unsuccessful ones. It led us to hypothesize a relation between past experience in previous crypto-funding campaigns and success of future ICOs. For this reason, we added a dummy variable, *prev_exp*, that indicates the presence in the team and the advisory board of individuals with past experience in the conduction of at least one ICO.

ICO variables

From the data collected, we have selected some typologies to implement our model. In some cases, we have introduced some dummy variables. The variables used are the following:

- *eth_block*: a dummy variable that indicates if the Ethereum Blockchain is the underlying Blockchain of the firm doing ICO.
- *code*: a dummy variable that indicates the availability of the computer code.

- *duration*: the number of days of the ICO period.
- *supply*: the token overall supply.
- *tokdistr*: the token distributed in the crowd sale.
- *curr*: referred to the currency usage of the token.
- *utility*: referred to the ability to access and pay on the company platform given by the token's ownership.
- *govern*: referred to the voting right given by the token's ownership.
- *profit*: referred to the profit right given by the token's ownership.
- *contrib*: referred to the contribution right given by the token's ownership.
- *price*: the average token price during the ICO period.
- *soft*: a dummy variable indicating the presence of the soft cap.
- *hard*: a dummy variable indicating the presence of the hard cap.
- *softcap*: the amount in dollars of the soft cap.
- *hardcap*: the amount in dollars of the hard cap
- *endbtc*: Bitcoin value the day after the end of the ICO.
- *endeth*: Ethereum value the day after the end of the ICO.

Table 2, in the next page, is a practical summary of all the variables used, correlated with their explanation.

Variable name	*Explanation*
Centrality variables	
largest_component	*1 if the company belongs to the largest connected component of the whole network, 0 otherwise*
degree	*the degree centrality of the company calculated for the static network*
betw	*the betweenness centrality of the company calculated for the static network*
eig	*the eigenvector centrality of the company calculated for the static network*
eff	*the efficiency of the company calculated for the static network*
dyn_deg	*the strength centrality calculated for the static network*
dyn_betw	*the betweenness centrality of the company calculated for the dynamic network*
dyn_eig	*the eigenvector centrality of the company calculated for the dynamic network*
dyn_eff	*the efficiency of the company calculated for the dynamic network*
Success variables	
succ_index	*the sum of the individual success indexes of the ICO members*
prev_succ	*1 if ICO members completed previous funding campaigns successfully, 0 otherwise*
unsucc_index	*the sum of the individual unsuccess indexes of the ICO members*
prev_unsucc	*1 if ICO members failed in previous funding campaigns, 0 otherwise*

Experience variable	
prev_exp	*1 if in the team there is the presence of at least one individual that conducted a previous ICO, independently from the outcome of it, 0 otherwise*

ICO variables	
eth_block	*1 if the company is Ethereum-based, 0 otherwise*
code	*1 if the computer code is available on the web, 0 otherwise*
duration	*the number of days for the ICO proceedings*
supply	*the total number of tokens supplied for the ICO*
tokdistr	*the number of tokens for sale*
curr	*1 if the token is created for currency usage, 0 otherwise*
utility	*1 if the token is created for accessing to the company platform and for paying company's product/service, 0 otherwise*
govern	*1 if the token ensures voting right, 0 otherwise*
profit	*1 if the token ensures access to profit distribution, 0 otherwise*
contrib	*1 if the token allows to contribute to the development of the business, 0 otherwise*
price	*the average token price during the ICO period in dollars*
soft	*1 if a minimum target amount is set, 0 otherwise*
hard	*1 if a maximum target amount is set, 0 otherwise*
softcap	*the equivalent of the minimum target amount in dollars*
hardcap	*the equivalent of the maximum target amount in dollars*
endbtc	*the price of the Bitcoin at the day after the end of the ICO in dollars*
endeth	*the price of the Ether at the day after the end of the ICO in dollars*

Table 2. Variables introduced in the model

3.3 Univariate analysis with static network

3.3.1 Overview of the samples

Before showing the result of the univariate analysis, we retain useful to show some general statistics of the two samples collected (933 ICOs and 10297 participants) in order to better frame the phenomenon studied. Particularly, we want to put in evidence information about the geographic distribution, the team and advisor board composition, the final results of the funding campaigns, the main sectors of business, and some other ICO design related characteristics.

First of all, we want to show the overall results of the campaigns. Table 3 shows the number of ICOs completed successfully and failed. 73,42% of our sample achieve success.

	Number	*%*
Completed	*685*	*73,42%*
Failed	*248*	*26,58%*
Total	*933*	*100%*

Table 3. ICO Completed vs Failed

Concerning the geography, we want to point out the main countries in which the ventures' headquarters are placed. As shown in table 4, the two main countries are United States (19,83%) and Russia (11,36%). The recent history tells us that these two countries are very active in the Blockchain industry and our data confirm it. The third most common country of origin is United Kingdom (6,68%), followed by Singapore (6,65%), Switzerland (5,14%), and Canada (3,11%). A singularity of the crypto market is the opportunity to grow their own business in a decentralized way; it means that the members of the company work in different places, exploiting the web. Indeed, 5,04% of our sample developed the company in a decentralized manner. The column "*success*" of table 4 points out the percentage of success in each country. We can note that success varies a lot according to the country and it is not related to the quantity of ICO done in that country.

Country of origin	***Observations***	***%***	***Success***
US	*185*	*19,83%*	*75,14%*
Russia	*106*	*11,36%*	*64,15%*
UK	*63*	*6,68%*	*70,97%*
Singapore	*62*	*6,65%*	*87,10%*
Switzerland	*48*	*5,14%*	*85,42%*
Decentralized	*47*	*5,04%*	*87,23%*
Canada	*29*	*3,11%*	*58,62%*
Estonia	*20*	*2,14%*	*75,00%*
Australia	*19*	*2,04%*	*73,68%*
China	*18*	*1,93%*	*88,89%*
Netherlands	*18*	*1,93%*	*77,78%*
NA	*15*	*1,61%*	*66,67%*
Other	*303*	*32,58%*	*69,74%*
Total	***933***	***100%***	**-**

Table 4. Top 10 country for number of ICOs and relative percentage of success

The following statistics analyzed considers the composition of the teams that launched the ICO, separating people in two main roles: team member and advisors.
Team members are those people that develop the project in all its aspects; from the writing code activity to the operations, passing through the business model creation. Instead, advisors are those people that work for the right implementation of the funding campaign. They can help thanks to their network or their knowledge about the crypto-investments.
Table 5 shows enough the heterogeneity of the composition of the team behind ICOs.
Obviously, the size of the team and advisory board depends on the companies' needs. For example, a very complex project could require a high number of competencies that can be

difficultly acquired through the involvement of a single person. Indeed, an ICO in our sample of 933 ICOs needed 52 people to run their business.

Role	***Average***	***Std. Deviation***	***Max***	***Min***
Team member	*9,14*	*5,99*	*52*	*1*
Advisor	*3,26*	*3,72*	*21*	*0*

Table 5. Roles statistics

Another important statistic is related to the business sector of the venture launching the ICO. The table 6 shows the main sectors of our sample and the percentage of success in the relative industry. As suggested by Allen et al. (2018) and Tapscott & Tapscott (2017), the sectors in which it is possible to exploit the strong potential of Blockchain are finance and economics. Being the Blockchain disruptive in fields where there is the opportunity of disintermediation, the ICO proponents were attracted by the potential gains of these two macro topics. Indeed, the majority (18,86%) of the ICO launched in the time horizon selected entered the marketplace and exchange business. It follows just behind the finance sector (18,76%), very interested in the elimination of many intermediation costs too. The miscellaneous sector (13,29%) was designed for those projects that merged more sectors and tried to define a new industry. It is quite common in context where a new technology arises that entrepreneurs try to create a new business, exploiting the cost reduction and the new functionalities that create value for the customers. As for the first two typologies, the High-tech services (10,72%) is mainly referred to project that want to exploit the Blockchain to disrupt current industries eliminating costs and intermediation. Finally, the Smart contracts field (4,61%) is a very important evolving market that in the future would allow to automate many processes, from the insurance ones to the legal ones, as affirmed by many experts (Cong et al., 2017; Hsiao, 2017).

Sector	***Observations***	***%***	***Success***
Marketplace and exchange	*176*	*18,86%*	*69,32%*
Finance	*175*	*18,76%*	*81,14%*
Miscellaneous	*124*	*13,29%*	*70,97%*
High-tech services	*100*	*10,72%*	*81,00%*
Smart contracts	*43*	*4,61%*	*81,39%*
Gaming	*42*	*4,50%*	*61,90%*
Media and entertainment	*41*	*4,39%*	*58,53%*

Gambling	*24*	*2,57%*	*75,00%*
Advertising	*20*	*2,14%*	*80,00%*
Charity	*8*	*0,86%*	*25,00%*
Other	*180*	*19,29%*	*41,11%*
Total	***933***	***100%***	**-**

Table 6. Top 10 sectors for number of ICOs and relative percentage of success

Thanks to the 685 successful campaigns, the sample ICO raised $9,3 billions. Figure 10 shows the fundraising distribution from the first year of the ICO since February 2018. It is evident the huge increase of the 2017 and the good trend of the first months of the 2018.

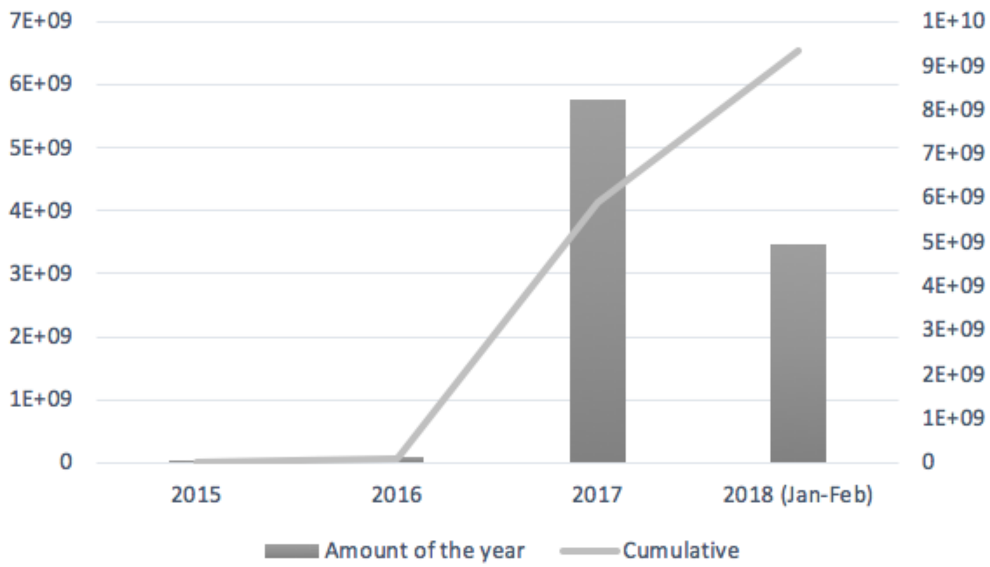

Figure 10. Amount raised in dollars

The largest offering was the Tezos one with $230 millions raised. Tezos is a Swiss company whose aim is to create an alternative to the Ethereum smart contracts. In table 7, it is possible to see the top 10 ICOs for amount raised. These are the only token sale able to reach $100 millions (excepted Kin with $98 millions). In our sample, other 22 campaigns raised between the $50 millions and $95 millions and all the top 100 are over the $29 millions. These are impressive figures, considering that the biggest crowdfunding campaign is Pubble Time with “just” $20 millions raised.

Company name	USD Raised	ICO end date
Tezos	230.450.000	July 2017
Filecoin	205.000.000	September 2017
Sirin Labs	157.886.000	December 2017
The Bancor Protocol	153.000.000	June 2017
Bankera	150.950.000	February 2018
Polkadot	144.347.000	October 2017
QASH	108.175.000	November 2017
Status	107.665.000	June 2017
Envion	100.012.000	January 2018
Kin	98.500.000	September 2017

Table 7. Top 10 ICOs for amount raised

Then, table 8 shows some statistics about the disclosure of important information of the projects: the white paper and the code. These are the main elements through which an investor can evaluate the project in its completeness; from the business model to the practical operation on the Blockchain. As we can expect, most of the team provided a white paper to the investors, but only 64% published the code.

Info disclosed	Observations	%	Success
White Paper	886	94,96%	75,29%
Code	597	63,99%	72,86%

Table 8. ICO with White Paper and Code disclosed

Instead, table 9 and 10 show some statistics about two ICO's proceedings decisions of the team and advisory board: the choice to give bonuses and which typology, and the choice of the Blockchain. The Early Bird bonus is the concept of "first come, first served"; the price of the token increases according to the time or the previous token sold. Table 9 shows that it is the most used type of bonus. As described in paragraph 1.1.4, the introduction of the ERC20 standard token drove many teams in the choice of developing the project on the Ethereum platform and, in fact, it is the most used platform to run an ICO, as shown in table 10.

Bonus	***Observations***	***%***	***Success***
Early Bird	*538*	*57,66%*	*74,35%*
Major Contributor	*23*	*2,47%*	*52,17%*
Early Bird & Major Contributor	*55*	*5,89%*	*70,91%*
Other	*25*	*2,68%*	*76,00%*
None	*292*	*31,30%*	*73,63%*
Total	***933***	***100%***	***-***

Table 9. Statistics for type of bonus used

Blockchain	***Observations***	***%***	***Success***
Ethereum	*770*	*82,53%*	*73,25%*
Waves	*34*	*3,54%*	*58,82%*
Bitcoin	*12*	*1,29%*	*66,67%*
Neo	*9*	*0,96%*	*88,89%*
Private (own)	*74*	*7,93%*	*77,03%*
Other	*28*	*3,00%*	*89,29%*
N.A.	*6*	*0,64%*	*50,00%*
Total	***933***	***100%***	***-***

Table 10. Statistics for type of Blockchain used

Now, we want to observe some statistics about the core matter of this study: the centrality. The table 11 shows the differences between the roles held by people in the ICO: team member vs advisors. For those people who worked in both roles in different campaigns, we have decided to treat them as advisors. The difference in the data is relevant and appears in every metric. The most significant differences are the Betweenness Centrality and the Eigenvector Centrality.

Metric	Team members	Advisors
Mean Degree Centrality	*16.4*	*39.02*
Mean Betweenness Centrality	*2174*	*141150*
Mean Eigenvector Centrality	*0.0007*	*0.001*
Mean Efficiency (nodal)	*0.101*	*0.145*

Table 11. Means of centrality metrics for individuals

Table 12 describes some general statistics of the overall network of individuals. The network resulted extremely sparse, as already happened in other studies (Suominen et al., 2016; Takes & Heemskerk, 2016). The network is composed of 407 components. The largest connected component, the sub-graph with the highest number of nodes, consists of 66% of the overall network in terms of nodes. The network has a low assortativity, which is the correlation degree for graphs, that means nodes poorly tend to create links among their peers. The transitivity, which is the number of triplets fully connected (Barrat ar al., 2004), is not much relevant because the teams have their members linked.

Measure	Data
Nodes	*10298*
Edges	*91785*
Assortativity	*13.34%*
Density	*0.17%*
Transitivity	*74.09%*
Number of connected components	*407*

Table 12. Statistics of the individual network

The ICOs' network is composed of 933 different nodes linked by 224 edges. Of course, it is segmented in the same 407 non-connected sub-graphs, but the density is five-time superior. The network is also more assortative. Since we are observing ICOs, the interconnection within teams are not reported and therefore it is reasonable the decrease in transitivity.

Measure	Data
Nodes	*933*
Edges	*2214*
Assortativity	*40.97%*
Share of the LCC	*54.3%*
Density	*0.5%*
Transitivity	*44.8%*
Number of connected components	*407*

Table 13. Statistics of the ICO network

3.3.2 Variables univariate statistics

In this paragraph, we provide some univariate statistic related to the variables explained previously whose results determined our multivariate model.

ICO variables

First of all, we want to show those variables referred to the ICO proceedings that we used as control variables in our regression model, in order to clear furtherly the ideas about the concept of Initial Coin Offering. In table 14, we have also inserted the dummy variable *succ* that indicates if an ICO had success (1) or failed (0), then used as dependent variable in the multivariate analysis. The most interesting data from this table is that 73% of our sample was successful, the 83% used the Ethereum Blockchain to implement the ICO (in line with what told about ICO history in the sub-paragraph 1.1.3), and the 84% of the tokens ensured the right of access to the venture's platform.

ICO variables	*Mean*	*Standard deviation*	*Median*	*Max*	*Min*
succ	*0,73*	*0,44*	*1*	*1*	*0*
eth_block (dummy)	*0,83*	*0,38*	*1*	*1*	*0*
code (dummy)	*0,64*	*0,48*	*1*	*1*	*0*
duration	*32,30*	*24,91*	*30*	*189*	*1*
supply (mln)	*187.430*	*3.513.750*	*100*	*101.000*	*0,0002*
tokdistr (mln)	*62.804*	*963.165*	*60*	*20.000*	*0,001*
curr (dummy)	*0,09*	*0,28*	*0*	*1*	*0*
utility (dummy)	*0,84*	*0,36*	*1*	*1*	*0*
govern (dummy)	*0,12*	*0,33*	*0*	*1*	*0*
profit (dummy)	*0,22*	*0,41*	*0*	*1*	*0*
contrib (dummy)	*0,08*	*0,27*	*0*	*1*	*0*
price	*$37,88*	*$609,38*	*$0,27*	*$13.128*	*$0,000035*
soft (dummy)	*0,37*	*0,48*	*0*	*1*	*0*
hard (dummy)	*0,70*	*0,46*	*1*	*1*	*0*
softcap	*$2.812.975*	*$26.609.427*	*$0*	*$750.000.000*	*0*
hardcap	*$61.563.346*	*$983.698.435*	*$10.000.000*	*$30 billion*	*0*
endbtc	*$8.615*	*$4.924*	*$8141,43*	*$19.343,04*	*$230,20*
endeth	*$540*	*$325*	*$421,15*	*$1.397,48*	*$0,68*

Table 14. ICO variables main statistics

<u>*Static centrality measures*</u>

Now, we can see in table 15 the centrality measures calculated for the static network. We can see that only 54% of the ICOs are part of the largest connected component of the whole network. The average number of links for an ICO is almost 5, but as we can see from the standard deviation, this number is very variable. The median value says that 50% of the ventures have one or zero nodes. Indeed, there are some ICOs with more than 5 links (the ICO with the highest number of links has 51 connections) and many other with few or zero links (384 ICOs have zero connections). So, we can state that the centrality measures are really dispersed just observing the values of mean, standard deviation and median.

Static centrality measures	***Mean***	***Standard deviation***	***Median***	***Max***	***Min***
largest_component (dummy)	*0,54*	*0,50*	*1*	*1*	*0*
degree	*4,74*	*8,20*	*1*	*51*	*0*
betw	*396,30*	*1.018,66*	*0*	*12.717,55*	*0*
eig	*0,01*	*0,03*	*5,2x10^{-5}*	*0,22*	*0*
eff	*0,08*	*0,08*	*0,11*	*0,25*	*0*

Table 15. Static centrality measures main statistics

Dynamic centrality measures

From table 16, we can observe the main statistics for the centrality measures calculated in the dynamic network. Being the network basically the same, we can see the same dispersion of the previous measures.

Dynamic centrality measures	***Mean***	***Standard deviation***	***Median***	***Max***	***Min***
dyn_degree	*2.049,81*	*3.544,71*	*438*	*24.228*	*0*
dyn_betw	*494,35*	*2.479,95*	*0*	*58.958*	*0*
dyn_eig	*0,01*	*0,03*	*3,38x10^{-5}*	*0,226*	*0*
dyn_eff	*2,52x10^{-4}*	*2,45x10^{-4}*	*3,05x10^{-4}*	*7,96x10^{-4}*	*0*

Table 16. Dynamic centrality measures and statistics

Success variables

Finally, table 17 represents the statistics for the success variables. We can observe that only 23% of the campaigns had at least one member of the team or advisory board that had conducted a previous ICO with success.

Success variables	***Mean***	***Standard deviation***	***Median***	***Max***	***Min***
succ_index	*1,00*	*2,64*	*0*	*26,31*	*0*
prev_succ (dummy)	*0,23*	*0,42*	*0*	*1*	*0*
unsucc_index	*0,16*	*0,50*	*0*	*5,5*	*0*
prev_unsucc (dummy)	*0,17*	*0,37*	*0*	*1*	*0*

Table 17. Success variables main statistics

3.3.3 Means difference comparison and T-tests

Before doing the T-tests for our variables of interests, we consider appropriate to show the mean differences between the population composed by the successful ICOs and the one constituted by the failed ICOs. In order to have a significant indicator for the difference, we show the difference in percentage points from the failed mean to the successful mean.

From these first rough analysis, we can expect that the T-tests will show a significant difference in means for the variables referred to the largest connected component of the whole network, measures of success and the unique measure of experience.

In table 18, we analyze the centrality measure in terms of means. We can observe that the relevant differences in terms of magnitude are referred to the largest connected component ("*largest_component*") and the eigenvector centrality ("*eig*").

Static centrality measures	***Successful mean***	***Failed mean***	***Difference %***
largest_component (dummy)	*0,62*	*0,33*	*+87,88%*
degree	*4,65*	*4,98*	*-6,63%*
betw	*393,09*	*405,15*	*-2,98%*
eig	*0,009*	*0,012*	*-25%*
eff	*0,087*	*0,085*	*2,35%*

Table 18. Difference in centrality measures means

Instead, table 19 refers to success measures. The numbers show a strong difference for all the success measures from the failed ICOs to the successful ones. As we expected the previous successes were more present in the successful ICOs population, but unexpectedly the previous failures were as present as the successes. In the same way, both the number of successes, calculated through the success index and the number of failures have a very strong difference from the two populations and the difference increase in the successful population. Again unexpectedly, the number of previous failures seems to have a positive effect on the success of the ICO.

Success measures	***Successful mean***	***Failed mean***	***Difference %***
succ_index	*1,25*	*0,30*	*316,67%*
prev_succ (dummy)	*0,29*	*0,09*	*222.22%*
unsucc_index	*0,20*	*0,07*	*185,71%*
prev_unsucc (dummy)	*0,20*	*0,08*	*150%*

Table 19. Difference in successful measures means

These results led us to a perspective change. We asked ourselves if it was more a matter than previous experience than previous successes and failures. So, in this phase, we introduced the dummy variable referred to the previous experience, *prev_exp.* We calculated the difference of the means also for this variable. As shown in table 20, the difference was comparable to the success measures ones.

Experience measure	***Successful mean***	***Failed mean***	***Difference %***
prev_exp (dummy)	*0,291*	*0,096*	*203,12%*

Table 20. Difference in experience measure mean

The basic aim of the T-tests is to know if there are statistically significant differences between the average values of the independent variables, considering two cases, the one when the fundraising campaign was successfully completed and the one when the ICO failed. It allows to better perceive the data sample and variables' characteristics and to help us in the construction of the regression model.

Table 21 indicates the results of the T-tests performed. In particular, it shows the p-value and the confidence intervals of the means differences from success to failures with a confidence level of 95%.

Specifically, the largest connected component obtained a very small p-value, so the two means are statistically different. Moreover, remembering that is a dummy variable and the differences can be expressed in percentage, the confidence interval (95%) tells us that the maximum difference could be 31,7% and the minimum 17,9%.
For the degree, betweenness, eigenvector and efficiency centralities the p-values are very high, and hence we can affirm that there is no significant difference between the means. Also, the confidence intervals at 95%, positive but also negative in the other side, confirm the non-statistically significance.

Contrarily, talking about the measures of success we obtained low p-values, in particular for the success index and the occurrence of previous successes by the proponents of the ICO with values very near to zero. This result is confirmed also by the confidence intervals.

Finally, the T-test results (table 21) referred to the occurrence of previous experience by the proponents of the ICOs give a further proof of the perception had before. The p-value for this variable is very low; it is the second lowest p-value observed in this analysis. The extremes of the confidence interval tell us that the occurrence of previous experience in the case of successful ICO is more frequent than in the case of failure, at 95% of confidence level. Exactly, the mean in case of success could be at maximum 24,4% and at minimum 14,3% higher than the one in case of failure.

Static centrality measures	***P-value***	***Confidence Interval***	
largest_component (dummy)	*5,66 x 10 $^{-16}$ ****	*-0,364*	*-0,226*
degree	*0,5935*	*-0,916*	*1,60*
betw	*0,8675*	*-147,54*	*393,09*
eig	*0,2534*	*-0,002*	*0,007*
eff	*0,7067*	*-0,015*	*0,009*
Success measures			
succ_index	*6,79 x 10 $^{-12}$ ****	*-1,221*	*-0,683*
prev_succ (dummy)	*7,91 x 10 $^{-15}$ ****	*-0,248*	*-0,149*
unsucc_index	*4,17 x 10 $^{-6}$ ****	*-0,183*	*-0,074*
prev_unsucc (dummy)	*5,76 x 10 $^{-7}$ ****	*-0,162*	*-0,071*
Experience measure			
prev_exp (dummy)	*1,25 x 10 $^{-13}$ ****	*-0,244*	*-0,143*
* p<0.1; ** p<0.05; *** p<0.01			

Table 21. T-test result

As expected from the results of the difference analysis, also according to the T-tests, the statistically significant differences are those of the largest connected component of the whole network ("*largest_component*"), success measures ("*succ_index*", "*prev_succ*", "*unsucc_index*", "*prev_unsucc*") and the experience measure ("*prev_exp*"). Moreover, the negative confidence intervals for these measures tell us that the means, in case of failed ICOs, are lower than the ones in case of successful fundraising campaign.

Anyhow, from this analysis we expect in our regression model that the centrality measures (except for "*largest_component*") will not be statistically significant, but to be sure we will search for some interaction effects between the variables performing the multivariate analysis.

3.4 Multivariate analysis with static network

3.4.1 Purpose of the first models and model specifics

After the first analysis, in which we observed the results from some univariate statistics, we performed a multivariate regression model using our variables of interest and the control variables.

The first step of analysis was aimed at approaching the statistical significance of the centrality measures and the success measures. Conversely, in this phase we want to test directly our research hypotheses described in chapter 2, regarding the relations between our measures and the success for Initial Coin Offerings, supporting with quantitative and statistical proof.

The regression model used was the logistic one because of the dichotomous nature of the dependent variable. We regressed the variable *succ*, indicating the success of the fundraising campaign, over our variable of interest, referred to centrality, previous success and previous experience, and over the control variable, referred mainly to the ICO characteristic and crypto-environment.
We selected these variables according to the research hypothesis this work aimed to support and to the results of the T-tests.
We used the pseudo-R^2 of Cox-Snell and, mainly, of Nagelkerke to evaluate the goodness of the models while we evaluated the statistical significance of the independent variables with the p-value. We exploited the standard error of observations as a proxy of their dispersion. Moreover, we built a classification table for each model in order to calculate the percentage of the correct predictions.

Afterward, we have built the correlation matrix (table 22), from which we have seen a strong correlation between most of the static centrality measures.
Thus, we chose to add sequentially the centrality measures one at a time, to check the relevance of every single variable on the whole model and to avoid the multicollinear effect. We develop the models in a progressive way. The base model is constituted by all the control variables and the measures that resulted most significative from the T-tests, namely largest connected component and the occurrence of previous successes.
Moreover, for each model, we will show the classification table related to the observation of how many times our model predicted correctly the ICO outcome.

Before showing the results, we provide an explanation of the variables used.

Dependent variable

As mentioned above, we esteemed the success of an Initial Coin Offering on the basis of the achievement of its soft cap and, when it was not set by the team, the non-event of the money-back process. Therefore, the dependent variable, called "*succ*" is a binary variable equal to 1 if the ICO achieved the success and to 0 if it failed. In our data sample, we observed 685 successes and 248 failures.

Independent variables

We considered a set of variables to measure the effect of the network relationships (social capital) and the previous successful experience of the members launching the ICO (human capital).

Starting with social capital, we considered the belonging to the largest component of the whole network as a measure of the social capital because of the higher level of knowledge developed and the easier access to resources in a larger community (Nicholson et al., 2004). The variable for this concept was called *largest_component* and it was constructed as a binary variable. This is referred to the hypothesis *H1*. Kim (2019), studying the effect of firm's centrality in the innovation performance, used a dummy variable just to indicate the belonging to the largest component of the whole network.

Still in relation to the social capital, we exploited the variables "*degree*" (standing for degree centrality), "*betw*" (standing for betweenness centrality), "*eig*" (standing for eigenvector centrality) and "*eff*" (standing for efficiency) to measure the level of centrality of the ICO, basically given by its members, in the static network, in relation to the research hypothesis *H2.a, H2.b, H2.c* and *H2.d.*

The utilization of these variables is inspired by many past studies applied in several different fields. The degree, betweenness and eigenvector centralities were used by Cheng et al. (2019), studying the effect of firm's position in the network on the informed short selling events. The same measures were also exploited by Bajo et al. (2016), analyzing the effect of the position of a lead IPO underwriter in its network of investment banks on different IPO characteristics.

The work of Georgieva et al. (2016) was aimed at evaluating the effect of the CEO's position within the hierarchy of all worldwide business executives on the IPOs outcomes, using as explanatory variables the degree and the eigenvector centralities.

Instead, Latora & Marchiori (2003) used the efficiency to observe how well information spreads in a network.

We continue the independent variables description with the human capital variables. For human capital, we intend the capacities developed by individuals during the execution of past ICOs. In particular, we distinguish the simple experience in past crypto-funding campaigns and the experience with success.

Regarding the success, we have included in our base model the occurrence of past ICOs conducted with success by individuals. The variable used is a dummy variable and is named "*prev_succ*". A similar variable was used by Butticè et al. (2017) with the difference that they took into consideration the number of previous successes. We considered such factor in our success index that is not included in the base model, but in the robustness checks explained in paragraph 3.6. We applied this methodology to avoid the multicollinear effects between the variables. The variable "*prev_succ*" is referred to the research hypothesis *H3.a.*

<u>*Control variables*</u>

Now, we explain the control variables used in our base model. They are mainly variables related to the ICO characteristics, except for two variables used to consider the crypto-environment situation at the moment of the ICO. Most of these variables were introduced after the reading of the papers written by Adhami et al. (2018) and Fisch (2019).

The first control variable explained is the utilization of the Ethereum Blockchain for the ICO realization. In this work, we exposed more times the usefulness given by the creation of the ERC20 token standard in the diffusion of the ICO phenomenon. Fisch (2019) introduced in his work a dummy variable that indicated if the project was Ethereum-based or not, finding a statistical significance for the ICO success. In the same way, we have introduced a dummy variable, called *eth*.

The second control variable indicates if the code was made public by the team or not and it is called simply *code*. Both Adhami et al. (2018) and Fisch (2019) found a statistical significance for the ICO success. Taking inspiration by these works, we have used a dummy variable equals to 1 if the code was published and 0 if not.

Fisch (2019) observed a significance also in the duration of the ICO expressed in days, and hence we used the same variable called *duration*.

Next, Adhami et al. (2018) introduced in their model all the right's typologies given by the token, founding a statistical relevance for the utility right and the profit right. Following their work, we have introduced all the five rights using five dummy variables equal to 1 if the right was given by the token and 0 if not, called *contrib* (the right to contribute to the project), *profit* (the right to receive profit distribution), *govern* (the right to vote for certain decisions about the project), *utility* (the right to access to the project platform), *curr* (the right to use the token as a mean of payment or store of value).

Fisch (2019) introduced in his model the fundraising goal both as dummy variable both as number. Unlike from his study, we have specified the type of fundraising goal as it is done in most of the ICOs. In particular, we exploited two dummy variables indicating the presence of a soft cap and a hard cap, we called them respectively *soft* and *hard* and, when present, we have also used two continuous variables indicating the targets in dollars of the soft cap and of the hard cap, called respectively *softcap* and *hardcap*.

Linked to the concept of the fundraising goal, the token supply and the token distribution were considered in our model. When Fisch (2019) observed a statistical significance in the number of tokens issued by the company for the ICO success, he defined the finding "surprising, as the number of tokens sold can be freely decided upon by the venture and should thus not infer any reference to its underlying quality". So, we introduced the variables *supply*, to indicate the whole number of tokens supplied by the venture, and *tokdistr*, to indicate the number of tokens destined for the crowd sale.

Unlike from the works mentioned, we have decided to insert the variable *price*, referred obviously to the price of the token.

Finally, we decided to use two variables able to explain the general situation of the crypto-environment. As explained in sub-paragraph 1.1.2, the Bitcoin price influence strongly the whole crypto-environment and it is a good indicator of its general situation. For this reason, we added the variable *endbtc* that indicates the Bitcoin price the day after the end of the ICO. Moreover, unlike from Fisch (2019) that used only the Bitcoin price, we have exploited also the Ether price with the variable *endeth,* given the importance of the Ethereum Blockchain for the ICO phenomenon.

Tables 14, 15, and 17 show the main descriptive statistics for the variables used in our models.

3.4.2 Results of the first models

In this part, we show the main results of our regression models, as we can see in table 28, exploited to give an answer to our research questions. Table 28 reports the estimated coefficients and the standard error in parenthesis. As explained by the legend under the table, the symbols "***" is used when the p-value is under 0.01, the "**" when it is under 0.05, and "*" when it is under 0.1.

The first column of the table refers to the regression including all the control variables and the independent variables for each category (centrality measures/social capital and success measures/human capital) that obtained the lowest p-values from the T-tests.
As we have seen in table 27, these variables are *largest_component* and *prev_succ*, that were used to test respectively the hypothesis *H1* and *H3.a* (Model I).

Then, we have constructed the correlation matrix, table 22. From this table, we can make some observations.
Another validation of the T-tests results is the significance of the correlation among the variables *largest_component* and *prev_succ* with the ICO success.
All the static centrality measures have a high correlation between themselves, and hence we have decided to analyze them one at a time in order to avoid the multicollinear effects.

		(A)	(B)	(C)	(D)	(E)	(F)	(G)
(A)	degree	1	0,798***	0,856***	0,706***	-0,024	-0,031	-0,018
(B)	betw		1	0,566***	0,503***	-0,055	-0,049	-0,006
(C)	eig			1	0,465***	-0,016	-0,018	-0,041
(D)	eff				1	0,003	-0,01	0,012
(E)	largest_component					1	0,452***	0,219***
(F)	prev_succ						1	0,207***
(G)	succ							1

* p<0.1; ** p<0.05; *** p<0.01

Table 22. Correlation matrix for the first multivariate analysis

The subsequent columns are referred to the models used in order to evaluate the impacts of the centrality measures one at a time.
The second column introduces the variable *degree* that represents the degree centrality of the ICO projects, to test the hypothesis *H2.a* (Model II).
Similarly, the Model III introduces the variable *eig*, referred to the eigenvector centrality, to verify the hypothesis *H2.b.*
Then, the Model IV uses the variable *eff*, measuring the efficiency, to test hypothesis *H2.c*.

Finally, the Model V concludes the analysis of the centrality measures done one at a time, introducing the variable *betw*, the betweenness centrality, to test the hypothesis *H2.d*.

All the models present a pseudo-R^2 according to Negelkerke in line with the work of Fisch (2019), even if he used a linear regression instead of logit regression, and almost double compared to the work of Adhami et al. (2018), that used the logit regression like us.

<u>*Model I*</u>

The result of Model I are very interesting. Indeed, the p-values of *largest_connected* and *prev_succ* tell us that these two variables are significant. Specifically, the *largest_connected* is significant at 99.9% confidence level while *prev_succ* at 99%. Both are positively related to the ICO success. This result verifies the hypothesis *H1* and *H3.a.* Moreover, the results of the other regression confirm the robustness of these two variables, giving more support to *H1* and *H3.a.*

Regarding *H1,* the result allows us to affirm that the belonging of the ICO to the largest connected component is a strong signal of the venture's social capital quality for entrepreneurs. According to the work of Kim (2019), a venture forms part of the main component can exploit better information because the knowledge is connected between the nodes. Talking of ICOs, the teams can exchange information between them and may reach, independently from the path, an individual that could help them. Moreover, in accordance to the paper of Nicholson et al. (2004), we can affirm that being in a larger network allows projects to access to greater resources, the innovation, and hence also the knowledge, is potentially deeper and also experts are more relevant than the ones in smaller networks.
This result may be very useful for future ICO proponents that can easily contact an advisor (at least) that has relationships with the main component of the whole ICO community, to exploit his relationships in order to reach the most updated best practices and the deepest knowledge about the ICO proceedings.
Another aspect to consider is the word of mouth effect. Indeed, the bigger the network the higher the number of potential nodes reached. In this way, a newcomer can exploit the

already existing relationships, instead of creating new ones, in order to increase the information circulation about the project in the ICO community. Hence, the marketing costs may decrease, and consequently also the soft cap and the probability to reach it.

Passing to hypothesis *H3.a*, the results of our models are a great evidence that “success makes success”. As studied by Butticè et al. (2017) in the crowdfunding field, the presence in the team of individuals that have led at least past successful campaign, is a signal about the skills owned in the ICO conduction. Thus, investors may use this indicator as a form of evaluation of the team capacities.

Table 23 shows the classification table for the Model I. As we can see the model predict correctly the 83,2% of the ICOs outcomes and when it predicts the ICO success it has a probability of being right of the 92,7%. This result could be very interesting for the decision-making process of potential investors that may exploit our model.

Expected		*0*	*1*	***% of correctness***
Observed	*0*	*141*	*107*	*56,9*
	1	*50*	*635*	*92,7*
Global percentage				*83,2*

Table 23. Classification table of Model I

<u>*Model II*</u>

As explained above, the Model II was used to test the effect of the degree centrality on the ICO success to test the hypothesis *H2.a*. Unfortunately, the result of this model confirmed the perception had from the T-test: the degree centrality has not a statistical significance on the ICO success. It means that the number of links is not related to the probability of success. However, the classification table shows that the results of the model are correct in 83,2% of the predictions.

Expected		0	1	% of correctness
Observed	0	139	109	56,0
	1	48	637	93,0
Global percentage				83,2

Table 24. Classification table of Model II

Model III

The Model III is aimed at analyzing the effect of the eigenvector centrality on the success of the token sale. Again, the result showed no statistical evidence and we had to reject the hypothesis *H2.b*. As for the degree centrality, the T-test for the eigenvector centrality showed that there was no difference between the means of successful and failed ICOs, and the Model III confirmed that there is no statistical significance for this measure.
Still, the classification table shows an important percentage of correctness, particularly in case of prediction of success.

Expected		0	1	% of correctness
Observed	0	140	108	56,5
	1	50	635	92,7
Global percentage				83,1

Table 25. Classification table of Model III

Model IV

Unlike with all the other models, the Model IV showed a statistically significant positive relationship between the efficiency, *eff*, and the ICO success. However, the significance was not very high (confidence level of 90%) and this single result is not enough to verify the existence of a link between the centrality and the outcome of the funding campaign. Nevertheless, this result gave us more motivation in the continuing of the research.

Moreover, the classification table shows again a good level of correctness, particularly when the model predicts success.

Expected		*0*	*1*	*% of correctness*
Observed	*0*	*138*	*110*	*55,5*
	1	*50*	*635*	*92,7*
Global percentage				*82,9*

Table 26. Classification table of Model IV

Model V

Finally, also the Model V showed the same results of the first two models. The betweenness centrality is statistically not related to the ICO success, too. Below is reported the classification table of this model.

Expected		*0*	*1*	*% of correctness*
Observed	*0*	*140*	*108*	*56,5*
	1	*49*	*636*	*92,8*
Global percentage				*83,2*

Table 27. Classification table of Model V

The results of this analysis have not satisfied our research hypothesis, but they have not destroyed our motivation that has been strengthened by the result of Model IV referred to the efficiency.

Thus, at this point, we decided to ignore the simultaneity assumption and we re-design the network in order to consider also the time factor. We called it dynamic network.

	Model I	Model II	Model III	Model IV	Model V
prev_succ	0.792	0.798	0.792	0.810	0.795
	(0.318)**	(0.319)**	(0.318)**	(0.320)**	(0.318)***
largest_component	1.428	1.436	1.426	1.437	1.439
	(0.227)***	(0.227)***	(0.227)***	(0.227)***	(0.227)***
degree		0.011			
		(0.011)			
eig			-0.343		
			(2.936)		
eff				1.926	
				(1.127)*	
betw					0.000
					(0.000)
endbtc	0.000	0.000	0.000	0.000	0.000
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
endeth	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
soft	-1.779	-1.789	-1.779	-1.811	-1.787
	(0.232)***	(0.233)***	(0.232)***	(0.234)***	(0.232)***
softcap	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
hard	0.178	0.172	0.179	0.158	0.172
	(0.235)	(0.236)	(0.235)	(0.237)	(0.236)
hardcap	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
supply	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tokdistr	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
price	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
curr	0.506	0.521	0.505	0.533	0.526
	(0.406)	(0.407)	(0.406)	(0.409)	(0.407)
utility	0.132	0.144	0.132	0.141	0.144
	(0.301)	(0.302)	(0.301)	(0.303)	(0.301)
govern	0.010	0.017	0.009	0.006	0.019
	(0.292)	(0.293)	(0.292)	(0.294)	(0.293)
profit	-0.224	-0.226	-0.224	-0.206	-0.231
	(0.266)	(0.267)	(0.266)	(0.268)	(0.267)
contrib	-0.492	-0.505	-0.492	-0.512	-0.501
	(0.337)	(0.338)	(0.336)	(0.339)	(0.337)
duration	-0.005	-0.005	-0.005	-0.006	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
code	-0.094	-0.085	-0.095	-0.088	-0.084
	(0.201)	(0.202)	(0.202)	(0.202)	(0.202)
eth	0.037	0.035	0.037	0.030	0.026
	(0.296)	(0.296)	(0.296)	(0.297)	(0.296)
_cons	1.322	1.258	1.328	1.192	1.279
	(0.443)***	(0.448)***	(0.446)***	(0.451)***	(0.445)***
R^2(Cox-Snell)	0.310	0.310	0.310	0.312	0.310
R^2(Nagelkerke)	0.451	0.453	0.451	0.455	0.452
N	933	933	933	933	933

* p<0.1; ** p<0.05; *** p<0.01

Table 28. Regression models for the first multivariate analysis

3.5 New analysis with the dynamic network

The results of the first multivariate analysis led us to continue our work, neglecting the simultaneity assumption used to build the first network (the static one).

3.5.1 Dynamic network construction

We have built the dynamic network starting from the static one. Taking from our database the date of the end of each ICO, we determined the weight for the i^{th} edge as the delta from the first day observed (so the date of the end of the first node in absolute) in our sample to the day of the end of the i^{th} ICO. In this way, we have penalized the oldest ICOs whose edges have a lower weight. We did it for two reasons:

- Cost of building a new network and benefits from a large one: as stated by Nicholson et al. (2004), the benefits provided by a large network are more and more efficient than the ones provided by a small network. Talking of the same network with the same people and the same matter of interest (ICO), we can make a comparison between a first period of development and a second period of maturity.
  In the development period, the ICO proponents had to build their knowledge about the proceedings with a trials and errors approach. Indeed, there were not best practices to follow and neither resources to exploit; for example, there were not experts of the phenomenon. Moreover, the new projects could not count on the opportunity of spreading the information in a community (no word of mouth effect), and hence they could not hope in marketing costs reduction from it. Obviously, it is true that, being few projects, the attention of the investors was more concentrated but it is also true that the investors were very few, too.
  On the contrary, a large and mature network can provide to the newcomers many benefits. Newcomers can exploit the best practices developed before, and generally the knowledge of experts. Finally, they can exploit the word of mouth effect to diffuse in the community the information about their project, hoping to reach investors interested in their work.

- Phases of the ICO phenomenon: the two time-windows have another important difference. In the first phase the hype for the Initial Coin Offerings was very low because most of the people do not believe in the crypto-world; it was known that the Bitcoin (the first and sole cryptocurrency at the time) was used for many illegal reasons, particularly in the so-called "deep-web" (Wu, 2013).
  Today we can count on an even larger community of people that believe in cryptocurrencies and in the Blockchain potential, and hence it is also easier for projects to find interested investors.

If we assume that the level of knowledge of the network is positively related with the time, the weight calculated as the number of days passed by the first day observed is a measure of the level of knowledge developed that the project members can exploit to run their ICO.

3.5.2 Dynamic centrality measures

In this section, we provide an explanation of the dynamic centrality measures and how they were calculated.

First of all, we have to remember that in case of weighted networks, the adjacency matrix is not filled by only 1 and 0 to represent the link between two nodes, but the 1 is substituted by the weight of the link. For example, if the edge that links the nodes i and node j has a weight equals to 2, the element a_{ij} of the adjacency matrix in row i and column j will be 2.

Defined the weighted adjacency matrix, we provide an explanation for the calculus of the dynamic centrality measures and the relative name given to the variables used for our analysis.

- Strength centrality (the equivalent of the degree centrality in weighted networks), *dyn_degree*: Defined a_{ix} as the adjacency matrix element in row i and column x, it is calculated as: $C_{dynS}(x) = \sum_{i=1}^{n} a_{ix}$.

In this way the strength centrality is a measure of the level of knowledge that could be exploited by a node.

- Betweenness centrality, *dyn_betw*: the explanation for the betweenness centrality is a little more complicated. We remember to the reader the static definition of the betweenness centrality. Defined g_{ij} as the number of shortest paths, the static betweenness centrality is: $C_B(x) = \sum_{i=1,i\neq j}^{n} \sum_{j=1,j<1,j\neq x}^{n} \frac{g_{ij}(x)}{g_{ij}}$

  In our case, we prefer that the path from a node to another one passes in the edges with higher weights (and hence with a higher level of knowledge). Thus, we define the shortest path, h_{ij}, as the path with the highest average of the weights. Then, we can calculate the betweenness centrality as: $C_{dynB}(x) = \sum_{i=1,i\neq j}^{n} \sum_{j=1,j<1,j\neq x}^{n} \frac{h_{ij}(x)}{h_{ij}}$

- Eigenvector centrality, *dyn_eig*: its calculation is the same as the static one because it considers the adjacency matrix with the weights.

  Defined $v_j = (v_1, \ldots, v_n)$ referring to an eigenvector for the maximum eigenvalue $\sigma_{\max}(A)$: $C_{dynE}(x) = \frac{1}{\sigma_{max}(A)} \sum_{j=1}^{n} a_{jx} * v_j$

- Efficiency, *dyn_eff*: we remember to the reader the definition of the static efficiency. It is the inverse of the sum of the distance, $d(x,i)$, between the node x and all the nodes in the network and if two nodes are not connected their distance will be $d(x,i) = +\infty$. Defined $e_{xi} = \frac{1}{d(x,i)}$ and considering that if $d(x,i) = +\infty$, it implies $e_{ij} = 0$, $C_{EFF}(x) = \sum_{i\neq x} e_{ix}$.

  The dynamic efficiency is calculated in the same way, but e_{xi} is raised to the power of the inverse mean of the weights of the edges, m_{ix}, between the node x and the node i. It is the inverse because e_{xi} is lower than 1. The dynamic efficiency is calculated as: $C_{dynEFF}(x) = \sum_{i\neq x} {e_{ix}}^{\frac{1}{m_{ix}}}$

3.5.3 Univariate analysis for dynamic centrality measures

As done in the first analysis, we perform the difference in means and the T-tests for the new variables calculated as explained in paragraph 3.2. Being the same network on a graphical point of view, it is useless performing again the analysis for the *largest_connected* variable because the projects belonging to the largest connected component of the whole network are the same.

Just from the table 29, we can observe encouraging results. For all the measures the difference between the group composed by the successful ICOs and the one by the failed ICOs have a strong difference in the means in terms of magnitude. It was a first proof that the new way of building the network is more appropriate to catch information about the centrality.

Static centrality measures	***Successful mean***	***Failed mean***	***Difference %***
dyn_degree	*2459,54*	*918,09*	*+167,90%*
dyn_betw	*579,30*	*210,00*	*+175,86%*
dyn_eig	*0,0115*	*0,0037*	*+210,81%*
dyn_eff	$2,92x10^{-4}$	$1,41x10^{-4}$	*+107,09%*

Table 29. Difference in means for dynamic centrality measures

Then, we have performed the T-tests in order to affirm if there are statistically significant differences in the means for the dynamic measures.

Table 30 reports the results. We can immediately observe that the p-values are all as much small as to say that all the means are different at the 99,9% of confident level. Moreover, we can say that the means in the case of successful fundraising campaign are always higher than the ones in case of failed campaigns, given the negative confidence interval. It is a further step forward to the validation of our research hypothesis.

Dynamic centrality measures	*P-value*	*Confidence Interval*	
dyn_degree	$2,67x10^{-13}$	*-1.947,65*	*-1.135,25*
dyn_betw	$1,76x10^{-3}$	*-629,61*	*-145,00*
dyn_eig	$02,14x10^{-5}$	*-0,011*	*-0,004*
dyn_eff	$2,2x10^{-16}$	$-1,83x10^{-4}$	$-1,19x10^{-4}$

Table 30. T-test results for dynamic centrality measures

3.5.4 Multivariate analysis with dynamic centrality measures

To have the confirmation that our research questions are correct, we have done for a second time the multivariate analysis considering the dynamic measures of centrality and using the same indicators to see the goodness of the model (p-values and R^2 by Cox-Snell and Neglkerke).

Except for the static centrality measures, in the second multivariate analysis, we have used the same variables of the first one. Moreover, the same speech done for the static centrality variables is valid for the dynamic ones. In particular:

- The strength centrality (*dyn_degree*) substitutes the degree centrality and needs to validate the hypothesis *H.2.a*.
- The new eigenvector centrality (*dyn_eig*) is used to test the hypothesis *H2.b.*
- The new efficiency *(dyn_eff*) is used to test the hypothesis *H2.c.*
- The new betweenness centrality (*dyn_betw)* is used to test the hypothesis *H2.d.*

From the matrix of the correlation (table 31), we can see that all the independent variables are significantly correlated with the ICO success. It is an important proof of the goodness in the utilization of the dynamic network.
However, it shows also a lot of correlation between the independent variables, and hence a high probability of the multicollinear effect. For this reason, we decided to use one variable at a time in our models.

		(A)	(B)	(C)	(D)	(E)	(F)	(G)
(A)	dyn_degree	1	0,374***	0,811***	0,674***	0,512***	0,627***	0,192***
(B)	dyn_betw		1	0,253***	0,253***	0,183***	0,262***	0,069**
(C)	dyn_eig			1	0,412***	0,275***	0,432***	0,110***
(D)	dyn_eff				1	0,944***	0,625***	0,273***
(E)	largest_component					1	0,509***	0,262***
(F)	prev_succ						1	0,201***
(G)	succ							1

* p<0.1; ** p<0.05; *** p<0.01

Table 31. Correlation matrix for the second multivariate analysis

Thus, we have built six models, one for variable, in which we have included the same control variables of the previous analysis. Table 38 shows the results of the regression. Now, we are going to analyze the models.

Model VI

In the Model VI we have used the variable *prev_succ* that measure the effect of the participation in previous successful ICO. This model confirms what we said for the first multivariate analysis: the presence of members in the team or advisory board that have done a previous ICO successfully has a positive effect on the success of the new campaign. Again, this result is in line with the previous work about crowdfunding done by Butticè et al. (2017). The pseudo-R^2 for this model is lower than the ones of the first multivariate analysis, but it is still greater than the ones observed by Adhami et al. (2018).
The classification table shows a poorer predictive ability than the previous models, but the correctness percentage of the success predictions equals to 91,7% is still a good result.

Expected		*0*	*1*	***% of correctness***
Observed	*0*	*125*	*123*	*50,4*
	1	*57*	*628*	*91,7*
Global percentage				*80,7*

Table 32. Classificaton table of Model VI

Model VII

The Model VII uses the variable *largest_connected* that tells if a project belongs to the largest connected component of the whole network. As we expected, the results confirmed the previous models and the belonging to a larger network has a positive effect on the ICO outcome and confirms again what previously said by Kim 2019). The pseudo-R^2 is closer to the ones of the first multivariate analysis; it is a measure of the effect of this variable on the ICO success.

The classification table provides us a further attestation of the importance of this variable. Indeed, the global percentage of correctness is higher than the previous models.

Expected		*0*	*1*	***% of correctness***
Observed	*0*	*141*	*107*	*56,9*
	1	*47*	*638*	*93,1*
Global percentage				*83,5*

Table 33. Classification table of the Model VII

The following models introduce the dynamic centrality measures, the reason of this second multivariate analysis.

Model VIII

The first dynamic centrality variable introduced is the strength centrality, *dyn_degree*, that represent the number of links of a node multiplied by the weight of the edges representing the factor time. It is a measure of the knowledge available from the direct links for a node. The regression result shows that this variable has a very high statistical significance but the effect on the ICO outcome is very near to zero ($2{,}65x10^{-4}$). In any case, even if small, the effect is positive, and the small coefficient is due to the fact that this variable has very big values (the maximum value is equal to 24.228 while the mean is 2.048) and the effect is muffled by the small coefficient. This result allows us to accept the hypothesis *H3.a* and confirm as said in the study of Rost (2011) that linked the strength of the ties with the exchange of knowledge and particularly with the tacit characteristics of innovation, knowledge recognition and knowledge realization.

The pseudo-R^2 is coherent with those of the previous models and then, the classification table confirm the goodness of the model.

Expected		***0***	***1***	***% of correctness***
Observed	*0*	*136*	*112*	*54,8*
	1	*57*	*628*	*91,7*
Global percentage				*81,9*

Table 34. Classification table of the Model VIII

<u>*Model IX*</u>

The model IX uses the eigenvector centrality, *dyn_eig*, that is a measure of the level of knowledge reached by a node exploiting both the direct links both the connections of the near nodes. The result shows again a strong statistical significance and, this time, a high coefficient because the eigenvector centrality assumes values smaller than the strength centrality. In any case, it is a valid proof of the intuition had at the beginning of this work that was the existence of positive relation between the eigenvector centrality as a measure of knowledge diffusion and of the word of mouth effect (hypothesis *H2.b*). It is in line with the works of Bajo et al. (2016), Cheng et al. (2019) and Kim (2019) that all linked the eigenvector centrality measure to the information exchange and already existing knowledge learning within a network.
The pseudo-R^2 (0,369) is the lowest of the models done and indeed, it has an effect on the classification table with the global percentage of correctness equals to 80,2%. However, the percentage is quite high when it predicts the ICO success (93%).

Expected		***0***	***1***	***% of correctness***
Observed	*0*	*111*	*137*	*44,8*
	1	*48*	*637*	*93,0*
Global percentage				*80,2*

Table 35. Classification table of Model IX

Model X

The Model X introduces the efficiency, *dyn_eff*, that as the other centrality measures have a very low p-value that means that its significance is very high. The coefficient is very big, and it is due to the fact that this measure has very low values; its median value is equal to $3{,}05\text{x}10^{-4}$. Again, this result tested our hypothesis *H3.c*. Indeed, this measure is an indicator of the efficiency in the exchange of information. The positive relation with the ICO success link is a signal that a higher efficiency has the effect of faster learning of the best practice to conduct an ICO. Cheng et al. (2019) and Kim (2019) using the "sister" of the efficiency, the closeness centrality, arrived at the same conclusions regarding the role of this measure on the capability of the spread of knowledge.
The pseudo-R^2 (0,455) is the highest of the models of this second multivariate analysis and it is confirmed by the classification table that reaches a global percentage of correctness equal to 83,1%.

Expected		*0*	*1*	***% of correctness***
Observed	*0*	*141*	*107*	*56,9*
	1	*51*	*633*	*92,6*
Global percentage				*83,1*

Table 36. Classification table of the Model X

Model XI

Finally, the last model introduces the betweenness centrality, *dyn_betw*, that concludes our analysis, again, with a strong significance. As for the strength centrality, it reaches very high value (maximum value equals to 58.958) and its coefficient ($3{,}97\text{x}10^{-4}$) dampens it. However, this result verifies also our last research hypothesis *H2.d* regarding this measure. Similar results were found by Bajo et al. (2016) and Cheng et al. (2019) that tested the importance of this measure in terms of brokerage role for the diffusion of information and knowledge.

The pseudo-R^2 is similar to the one of Model IX, the lowest one. However similarly to the Model IX, its classification table shows a very high percentage of correctness when it predicts the success of the ICO (92,8%).

Expected		*0*	*1*	***% of correctness***
Observed	*0*	*115*	*133*	*46,4*
	1	*49*	*636*	*92,8*
Global percentage				*80,5*

Table 37. Classification table of Model XI

	Model VI	Model VII	Model VIII	Model IX	Model X	Model XI
prev_succ	1.652 (0.280)***					
largest_component		1.715 (0.203)***				
dyn_degree			0.000 (0.000)***			
dyn_eig				16.104 (5.209)***		
dyn_eff					3875.316 (447.275)***	
dyn_betw						0.000 (0.000)***
enbtc	-0.000 (0.000)	0.000 (0.000)**	0.000 (0.000)*	0.000 (0.000)	0.000 (0.000)**	0.000 (0.000)*
endeth	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.000)	-0.001 (0.000)	-0.001 (0.000)
soft	-1.610 (0.220)***	-1.805 (0.231)***	-1.630 (0.220)***	-1.617 (0.216)***	-1.799 (0.232)***	-1.611 (0.215)***
softcap	-0.000 (0.000)***	-0.000 (0.000)***	-0.000 (0.000)**	-0.000 (0.000)***	-0.000 (0.000)**	-0.000 (0.000)***
hard	0.192 (0.226)	0.177 (0.234)	0.187 (0.227)	0.240 (0.223)	0.195 (0.235)	0.197 (0.222)
hardcap	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
supply	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
tokdistr	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
price	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
curr	0.507 (0.391)	0.478 (0.405)	0.468 (0.389)	0.409 (0.383)	0.499 (0.407)	0.467 (0.388)
utility	0.086 (0.296)	0.150 (0.300)	0.078 (0.296)	0.084 (0.292)	0.131 (0.302)	0.084 (0.293)
govern	0.000 (0.286)	0.019 (0.292)	0.060 (0.287)	0.054 (0.283)	0.029 (0.294)	-0.002 (0.282)
profit	-0.205 (0.261)	-0.205 (0.266)	-0.163 (0.260)	-0.125 (0.258)	-0.225 (0.266)	-0.171 (0.257)
contrib	-0.401 (0.334)	-0.514 (0.335)	-0.372 (0.332)	-0.395 (0.325)	-0.495 (0.336)	-0.367 (0.326)
duration	-0.005 (0.004)	-0.005 (0.004)	-0.005 (0.004)	-0.004 (0.004)	-0.005 (0.004)	-0.005 (0.004)
code	-0.106 (0.196)	-0.065 (0.201)	-0.088 (0.196)	-0.060 (0.192)	-0.099 (0.202)	-0.067 (0.192)
eth	0.070 (0.284)	0.002 (0.294)	0.032 (0.284)	0.050 (0.279)	0.018 (0.296)	0.014 (0.279)
_cons	1.772 (0.432)***	1.290 (0.440)***	1.661 (0.433)***	1.819 (0.425)***	1.301 (0.441)***	1.946 (0.425)***
R^2(Cox-Snell)	0.276	0.305	0.280	0.253	0.312	0.254
R^2(Nagelkerke)	0.402	0.444	0.409	0.369	0.455	0.370
N	933	933	933	933	933	933

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 38. Regression results of the second multivariate analysis

3.6 Robustness checks

In this section, we will describe some further analysis mainly done to confirm the results of the previous models, but also to better understand them, particularly we found some interesting results from the analysis of the variable *prev_exp,* referred to the occurrence of past experiences in ICOs by at least one member of the proponents.

<u>*Introduction of robustness checks*</u>

To perform the robustness check analysis, we had to introduce some new variables. The first of the variables used for robustness checks is the dummy variable "*prev_exp*" that considers if at least one member of the team or advisory board had past experience in an ICO. As explained in paragraph 3.3.3, this variable was introduced during the phase of analysis in the difference of the means between the population composed of successful ICOs and the one constituted by failed ICOs. It was useful to understand that the past experience may be a good signal for investors, but in the base model its utilization created an overlap with the variable related to the previous successes, "*prev_succ*". For this reason, we introduced it in the model only in the robustness checks.

Moreover, we have exploited other variables, already introduced above. We have used the variable *succ_index*, a measure of the number of successful ICOs done by all the proponents, *unsucc_index*, a measure of the number of failed ICOs done by all the proponents, and *prev_usucc*, a dummy variable equals to 1 in case of occurrence of at least one failed ICO in the proponents' past experience and 0 otherwise.

Then, we have verified the quadratic effect of the centrality measures. Specifically, we wanted to understand if the square of the variables continued to have a positive effect or it changed in a negative one. Practically, we wanted to test if being too central may have a negative effect. In the case, it may be due to the spillover of information, moral hazard, and exploitation of advantages by more central nodes.

Finally, we added the direction to the edges of the network in order to allow the exchange of information and knowledge only from older ICOs to the younger ones

3.6.1 Success, unsuccess and experience measures

First of all, we did the correlation matrix for the measures of success identified. The table shows a strong and high significant correlation between the variable used in the previous models, *prev_succ*, and the selected variables for the check. Thus, we have decided to approach this check as well as we did in the multivariate analysis, analyzing one at a time the variables. We have to evidence that the variables related to previous failed campaigns are positively related to the ICO success.

		(A)	(B)	(C)	(D)	(E)	(F)
(A)	prev_succ	1	0,779***	0,685***	0,524***	0,988***	0,207***
(B)	prev_unsucc		1	0,617***	0,713***	0,796***	0,138***
(C)	succ_index			1	0,622***	0,677***	0,159***
(D)	unsucc_index				1	0,568***	0,112***
(E)	prev_exp					1	0,201***
(F)	succ						1

* p<0.1; ** p<0.05; *** p<0.01

Table 39.Correlation matrix for the robustness checks

Table 40 shows the results of the regressions. In line with our expectations, the number of previous success has a significant and positive effect on the ICO success. However, as anticipated by T-Tests explained in paragraph 3.3.3 and the correlation matrix, the variables, *prev_unsucc* and *unsucc_index*, related to the previous ICOs failed by the members of the team or advisory board, have a positive effect on the success of the ICO, counter-intuitively. We expected a sort of black-sheep effect, and hence a negative coefficient for these measures. The explanation to this strange result is given by the last variable used in this robustness check, *prev_exp*. Indeed, it confirms the idea that it is not important the outcome of the previous campaigns, but it is the participation and the opportunity to have direct contact with the world of the ICOs. In a certain sense, this result gives more emphasis to the

concept of centrality, to the importance of the relationships built, and to the knowledge learned.
Anyhow, the positive outcome of previous ICOs is still important. Thus, we want to compare the Model VI, which introduced *prev_*succ, and the Check IV, which introduced *prev_exp*.

The two pseudo-R^2 are comparable, so both the models are equally good in the explanation of the ICO outcomes. However, if we see the two coefficients we can see that the one referred to *prev_succ* (1.652) is a little higher than the one referred to *prev_exp* (1.601).

To conclude this section, making a comparison between the variable related to the success, *prev_succ,* and the variable related to the experience, *prev_exp,* it is possible to affirm that the previous successes are a better, even if little, signal for investors than the previous experiences.
Nevertheless, this robustness check allowed us to understand the importance of having experience in the ICO field that can be translated in the importance of being in the network. In fact, it opens the doors of the crypto-world and may provide to the individuals the access to the knowledge necessary to launch a campaign, the opportunity to build the own network of relationships to exploit for future projects, and moreover may be a signal for investors about the social capital of the venture.

At this point, we continue the robustness check with the analysis of the quadratic effects of the centrality measures.

	Check I	Check II	Check III	Check IV
prev_unsucc	1.416 (0.303)***			
succ_index		0.337 (0.077)***		
unsucc_index			1.067 (0.315)***	
prev_exp				1.601 (0.274)***
enbtc	0.000 (0.000)*	0.000 (0.000)	0.000 (0.000)*	0.000 (0.000)
endeth	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
soft	-1.627 (0.218)***	-1.618 (0.217)***	-1.611 (0.215)***	-1.597 (0.220)***
softcap	-0.000 (0.000)***	0.000 (0.000)***	-0.000 (0.000)**	0.000 (0.000)***
hard	0.218 (0.224)	0.214 (0.220)	0.236 (0.222)	0.196 (0.226)
hardcap	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
supply	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
tokdistr	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
price	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
curr	0.474 (0.388)	0.445 (0.388)	0.504 (0.387)	0.512 (0.392)
utility	0.085 (0.296)	0.079 (0.294)	0.103 (0.294)	0.088 (0.296)
govern	-0.049 (0.284)	0.011 (0.286)	0.003 (0.283)	-0.002 (0.287)
profit	-0.186 (0.259)	-0.223 (0.260)	-0.174 (0.257)	-0.198 (0.260)
contrib	-0.370 (0.330)	-0.418 (0.332)	-0.385 (0.326)	-0.400 (0.334)
duration	-0.005 (0.004)	-0.005 (0.004)	-0.004 (0.004)	-0.005 (0.004)
code	-0.058 (0.193)	-0.074 (0.194)	-0.018 (0.192)	-0.102 (0.196)
eth	0.031 (0.282)	0.059 (0.282)	-0.036 (0.280)	-0.064 (0.284)
_cons	1.834 (0.429)***	1.840 (0.430)***	1.813 (0.426)***	1.768 (0.431)***
R^2(Cox-Snell)	0.262	0.267	0.253	0.274
R^2(Nagelkerke)	0.381	0.389	0.369	0.400
N	933	933	933	933

* p<0.1; ** p<0.05; *** p<0.01

Table 40. Regression results of the robustness checks referred to the measures of success

3.6.2 Quadratic effect of the centrality measures

In this section of the robustness checks, we want to analyze the quadratic effects of the centrality measures in order to understand the behavior of the variables. In particular, we want to explore if over a certain level the effect of the variable on the ICO outcome changes and, if yes, how.

To achieve our objective, we have performed other regression analysis including in each model a centrality measure and its squared.

Then, we used the coefficients to understand the behavior of each variable, defining their parabolas, specifying the concavity, the vertex and the intersection with the axis. In fact, these elements are crucial to understand the effect of the variables on the success of the ICO.

In essence, we want to extrapolate a formula like the following:

$$y = \alpha x^2 + \beta x + (control\ variables) + \varepsilon$$

Where:

- y is the dependent variable (success / failure)
- x is the centrality measure considered;
- α and β are the coefficients obtained by the regression models;
- $control\ variables$ are the overall effect of the control variables that would not be considered in the parabola because we want to know only the effect of the centrality measure x;
- ε is the error that we supposed to be zero.

Thus, we are interested in the coefficients of the centrality measures and their p-values to understand the statistical significance of the behaviors. In table 41, we have reported the analysis of the regression models and we can see that the coefficients are all significant except for the efficiency, and so we would not consider reliable the behavior.

In order to simplify the understanding of the reader, we provide some figures, created with the software GeoGebra 5, that represent the effects of the centrality measure to vary their values.

	Check V	Check VI	Check VII	Check VIII
dyn_degree	5.19×10^{-4} (0.000)***			
dyn_degree^2	-2.16×10^{-8} (0.000)***			
dyn_eig		81.428 (18.336)***		
dyn_eig^2		-375.819 (91.572)***		
dyn_eff			2958 (1648)*	
dyn_eff^2			1825000 (3252000)	
dyn_betw				4.59×10^{-4} (0.000)***
dyn_betw^2				-7.22×10^{-9} (0.000)**
enbtc	0.000 (0.000)*	0.000 (0.000)*	0.000 (0.000)**	0.000 (0.000)*
endeth	-0.001 (0.000)	-0.000 (0.000)	-0.001 (0.000)	-0.001 (0.000)
soft	-1.672 (0.224)***	-1.618 (0.217)***	-1.789 (0.232)***	-1.611 (0.216)***
softcap	0.000 (0.000)***	0.000 (0.000)***	-0.000 (0.000)***	0.000 (0.000)***
hard	0.166 (0.230)	0.206 (0.224)	0.197 (0.235)	0.194 (0.222)
hardcap	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
supply	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
tokdistr	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
price	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
curr	0.515 (0.395)	0.433 (0.387)	0.499 (0.407)	0.472 (0.388)
utility	0.086 (0.298)	0.079 (0.294)	0.125 (0.302)	0.084 (0.293)
govern	0.043 (0.291)	0.014 (0.288)	0.032 (0.295)	-0.004 (0.282)
profit	-0.192 (0.261)	-0.110 (0.258)	-0.229 (0.267)	-0.173 (0.257)
contrib	-0.380 (0.334)	-0.343 (0.329)	-0.489 (0.337)	-0.363 (0.327)
duration	-0.006 (0.004)*	-0.005 (0.004)	-0.005 (0.004)	-0.005 (0.004)
code	-0.091 (0.198)	-0.103 (0.194)	-0.104 (0.202)	-0.067 (0.192)
eth	0.029 (0.288)	0.040 (0.282)	-0.021 (0.296)	-0.014 (0.279)
_cons	1.549 (0.437)***	1.764 (0.427)***	1.316 (0.442)***	1.941 (0.426)***
R^2(Cox-Snell)	0.293	0.269	0.311	0.255
R^2(Nagelkerke)	0.427	0.392	0.453	0.372
N	933	933	933	933

Table 41. Regression results of the robustness checks referred to the quadratic effects of centrality measures

Figure 11 shows the behavior of the strength centrality, *dyn_degree*. Both the strength centrality and its square are significant at the 99% of confidence level and so, we can assume that the behavior is reliable.

The point B is the vertex of the parabola, while point C is the intersection with x-axis.

It means that the strength centrality will have an increasingly positive effect on the ICO success since its value is lower than 12.013,89 (point B), where the effect on the success will be maximum. After this value, the effect will decrease since arriving at the value of 24.027,78 (point C), where the effect will be zero. Over this point, the effect on the success will be negative.

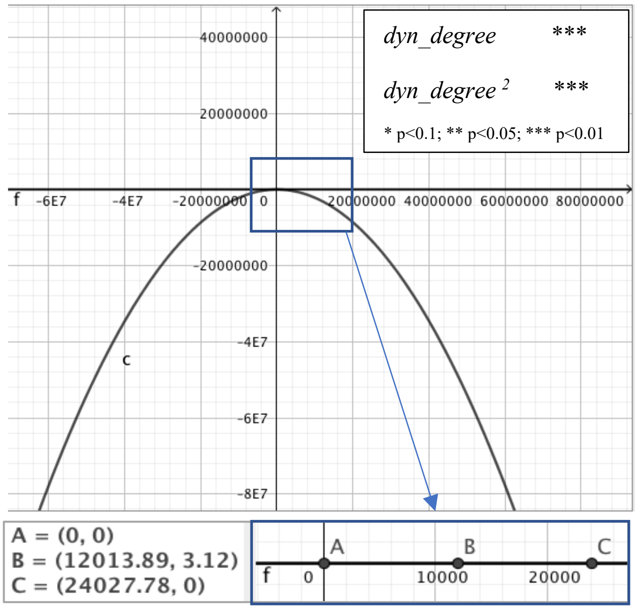

Figure 11. Behavior of strength centrality

Practically, the level of knowledge received has an optimal level, and beyond its effect will decrease. It may be due to the incapability to process the information, but also to the possible spillover of information about the project and moral hazard practiced by advisors with a lot of links, and hence with more control on the information flow. Another explanation of the behavior may be the fact that the links are created when an advisor or team member participate in more projects: it could be possible that the participation is simultaneous and hence the individual is not able to concentrate enough effort on each fundraising campaign causing its failure. Moreover, advisors with a central position in the network may ask for higher retributions and it could increase the soft cap of the ICO. In doing so, it is possible that the cost to build the relationships overcomes the benefits, having a negative effect on the outcome of the fundraising campaign. A similar study done by Horton et al. (2012) linked the centrality of CEOs and executive directors with their retribution. It is an important basis for our suggestion.

In any case, we observed that only one ICO has a strength centrality over 24.027,78 (point C), so the negative effect given by this measure is very rare.

Passing to the eigenvector centrality, we can see again that the significance of this variable and its square is strong. We must specify that the values of this measure are between 0 and 1; for this reason, we have set a vertical line passing from the value 1 of the x-axis representing the highest constraint of the eigenvector centrality. We can observe a behavior similar to the strength centrality, even if the numbers are considerably lower because of the different values of the two measures. The effect of eigenvector centrality increases since the value of 0.11 (the vertex, point B) and then decreases since the value of 0.22 (point C) where its effect is equal to zero. Beyond this point, it has a negative effect on the success of the ICO.

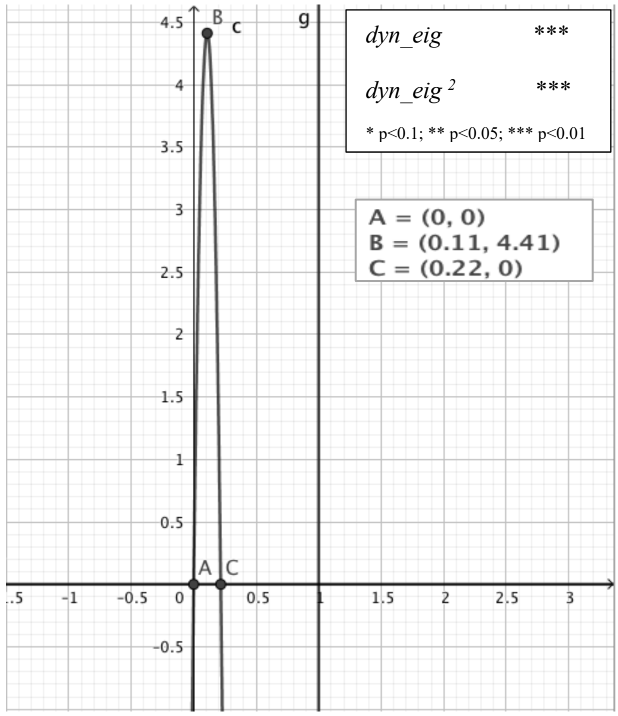

Figure 12. Behavior of the eigenvector centrality

We remember to the reader that the eigenvector centrality is a measure of how many links the nodes near to the analyzed node have. Conceptually, it measures the information exchange capability with the indirect nodes.

The possible explanations of the strength centrality's behavior are valid also for the eigenvector centrality's one, except for the poor commitment of the advisors because this measure does not consider the direct link, and hence the shared projects of the advisors and team members. However, the possibility of the spillover of information and moral hazard increases because it is logical to speculate about the exploitation of the information related to the project from people more distant from the advisor in bad faith that works for the venture in order to avoid direct connection with him. Anyhow, we observe that only 3 projects of our sample composed by 933 ICOs are over 0.22 (point C), and hence we have a very small number of ventures that suffer the negative effect of high eigenvector centrality.

About the efficiency, we can see from the regression (table 41) that this variable is not very significant when its square is included in the model, and the same square is totally nonsignificant for the ICO success. So, we can suppose that the quadratic effect of the efficiency is irrelevant, and no particular quadratic behavior could be analyzed.

Finally, we can see from the regression that the betweenness centrality is significant at the 99% confidence level while its square at 95%. Thus, we have plotted its behavior and observed its characteristics. In this case, it is similar to the strength centrality both in behavior and in numbers. Indeed, it has a positive trend since it reaches the value of 31.786,7 (the vertex, point B) where its effect is optimal. Then, the effect decreases since the value of 63.573,41 (point C). Beyond this point, the effect on the ICO success is negative.

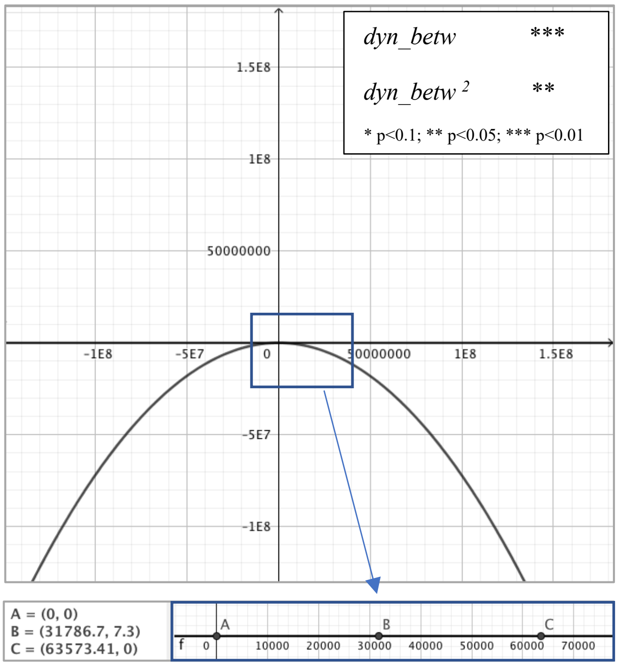

Figure 13. Behavior of the betweenness centrality

Practically, the betweenness is a measure of the quality of the node and its links in the exchange of information. So, the node and its links are seen as channels for information. It is reasonable to assume that high-quality knowledge circulates in high-quality channels. The decrease of the effect related to the increase of the variable may be due to the difficulty in managing the information received, but also as said for the strength centrality, may due to the elevate retribution asked by advisors with a high brokerage power. Again, this supposition is in line with the work of Horton et al. (2012) that affirmed that CEOs and executive directors with a brokerage role receive higher compensation. However, in our sample no ICO reaches a betweenness centrality level higher than 63.573,41 (point C), so all the observations have a positive effect.

3.6.3 Network with directed edges

Our last robustness check wants to explore deeply the goodness of our network design. Understood the importance of the network building from the first to the second analysis, we tried a different approach to do it. Indeed, we added another characteristic to the edges of the network: the direction. In particular, we set the direction from the older to the younger nodes in order to avoid that the model allowed the older projects to receive knowledge and information by the younger ones. Then, we calculated the centrality measures and performed other logistic regressions to observe the change from the previous model.

Table 43 shows that the direction variation did not add relevant information to the previous models. Indeed, the Check XII is exactly the same of Model XI; it means the betweenness centrality, as conceived in this work, is not affected by the direction.

To simplify the comparison to the reader, table 42 shows the differences between the network without direction (used for the second multivariate analysis) and the one with the direction (used for the robustness check). As we can see by R^2, the two models are comparable, and it means that the weights are a good way to measure the different time periods. Finally, the results of these regressions give again more strength to our research questions as showed by the p-values.

	No Direction			***Direction (robustness check)***		
	R^2(Nagelkerke)	*Coefficient*	*Std. error*	*R^2(Nagelkerke)*	*Coefficient*	*Std. error*
dyn_degree	*0.444*	*0.000*	*(0.000)****	*0.412*	*0.000*	*(0.000)****
dyn_eig	*0.369*	*16.104*	*(5.209)****	*0.373*	*18.141*	*(5.497)****
dyn_eff	*0.455*	*3875.316*	*(447.275)****	*0.450*	*3953.225*	*(464.871)****
dyn_betw	*0.370*	*0.000*	*(0.000)****	*0.370*	*0.000*	*(0.000)****
* p<0.1; ** p<0.05; *** p<0.01						

Table 42. Comparison of the centrality measures calculated with and without directed edges

	Check IX	Check X	Check XI	Check XII
dyn_degree	0.000			
	(0.000)***			
dyn_eig		18.141		
		(5.497)***		
dyn_eff			3953.225	
			(464.871)***	
dyn_betw				0.000
				(0.000)***
enbtc	0.000	0.000	0.000	0.000
	(0.000)*	(0.000)	(0.000)**	(0.000)*
endeth	-0.001	0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)
soft	-1.635	-1.614	-1.778	-1.611
	(0.221)***	(0.216)***	(0.231)***	(0.215)***
softcap	0.000	0.000	0.000	0.000
	(0.000)**	(0.000)***	(0.000)**	(0.000)***
hard	0.198	0.236	0.174	0.197
	(0.228)	(0.223)	(0.234)	(0.222)
hardcap	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
supply	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
tokdistr	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
price	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
curr	0.472	0.404	0.497	0.467
	(0.390)	(0.384)	(0.406)	(0.388)
utility	0.084	0.078	0.126	0.084
	(0.296)	(0.292)	(0.301)	(0.293)
govern	0.045	0.045	0.056	-0.002
	(0.289)	(0.284)	(0.293)	(0.282)
profit	-0.176	-0.130	-0.215	-0.171
	(0.261)	(0.258)	(0.265)	(0.257)
contrib	-0.378	-0.392	-0.473	-0.367
	(0.332)	(0.327)	(0.335)	(0.326)
duration	-0.005	-0.004	-0.005	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)
code	-0.086	-0.062	-0.097	-0.067
	(0.196)	(0.192)	(0.201)	(0.192)
eth	0.025	0.046	0.032	-0.014
	(0.285)	(0.279)	(0.295)	(0.279)
_cons	1.650	1.815	1.302	1.946
	(0.433)***	(0.426)***	(0.441)***	(0.425)***
R2(Cox-Snell)	0.283	0.256	0.308	0.254
R2(Nagelkerke)	0.412	0.373	0.450	0.370
N	933	933	933	933

* p<0.1; ** p<0.05; *** p<0.01

Table 43. Regression models for the robustnes check referred to the directed network

4 Conclusions

In this last chapter of the thesis, we will discuss deeply the results of our analysis, including the models of the second multivariate analysis and the robustness checks. We will provide also some suggestions extrapolated from the results for investors and ventures that want to approach the phenomenon of the Initial Coin Offerings.
Finally, we will explain some limitations of our work that may be overcome in future research.

4.1 Discussion of the main results

Who knows if when Satoshi Nakamoto was writing its paper (Nakamoto, 2008), would he (or she or they?) have imagined that those words would become the manifesto of the cryptocurrency and the Blockchain? Indeed, many innovative projects have evolved from that paper. Cryptocurrencies and, mainly, Blockchain attracted the interest of many actors in several different fields: the supply chain, the public administration, healthcare, industry 4.0 and, clearly, the finance.
In particular, a phenomenon linking Blockchain, cryptocurrencies and finance was boomed in 2017: The Initial Coin Offering.
The ICO allows those projects inspired, also indirectly, by the work of Satoshi, to receipt the funding necessary for their growth in a decentralized manner, in line with the basic idea of the Bitcoin creator. The ICOs permit exactly to collect money by people from any corner of the world with the only requirement of an Internet connection, democratizing the access to financing.
These features have been a crucial element for its development so much that the whole number of funding campaigns was able to reach more than \$22 billions basically in just 2 years. This huge increase in the numbers led many scholars to study the phenomenon (Adhami et al., 2018; Amsden & Schweizer, 2018; Catalini & Gans, 2018; Conley, 2017; Fisch, 2019; Flood & Robb, 2017; Kaal & Dell'Erba, 2017). A consistent stream of the literature focuses on the recognition of the determinants of success of the ICOs. Most of the authors investigate the features of the funding campaign, the characteristics of the team launching the projects (so, the social capital and the human capital) trying to find elements

signaling the goodness of the project, as previously done for other financing methods as crowdfunding, IPOs and VC (Ahlers et al., 2015; Busenitz et al., 2005; Colombo et al., 2015; Williams et al., 2010).

Our work is based on this literature, but it uses measures and methodologies totally innovative in this field coming from the Social Network Analysis. SNA is the study of the relationships between people and their network. This matter was applied in many fields in which human relationships play a decisive role (da Silva et al., 2019; Ma et al., 2019; Song et al., 2018; Suominen et al., 2016). In particular, an important element of this theory is the centrality, that is a measure of the position of an individual (or node) in its network of social contacts. The centrality was studied by many scholars also to understand some dynamics related to entrepreneurial and economics theory (Bajo et al., 2016; Horton et al., 2012; Kim, 2019; Nicholson et al., 2004).

The aim of this work is to continue the previous literature about the determinants of success in ICOs using the approach of the SNA in an innovative way. In a certain sense, our efforts want to create a link with the virtual world, an environment in which often the human side is given up, and real humans relationships.

In economic terms, we want to evaluate the importance of the social capital and human capital of the ventures for the outcome of the token sales. In doing so, we consider some measures of centrality (for social capital) and the past experience of the ICO proponents in previous crypto-funding campaigns (for human capital). To our knowledge, there are no other works that exploit the SNA instruments and the history of people's success to understand the determinants of the ICOs' success and we believe that our study will be useful for the growing number of investors in cryptocurrencies and the teams that want to finance their project with this innovative method of funding. Moreover, we hope it can help regulators to understand better the dynamics of this phenomenon, providing them a study that can stimulate ideas for future regulations able to consider positively the ICO's human side.

In performing this empirical analysis, we have used a sample of 933 ICOs, occurred from October 2015 to February 2018, and another one of 10297 proponents, divided into team members and advisors. The second sample was used to build the people social network that then, mixed with the first sample, was used to build the ICO social network from which we

have calculated the centrality measures. In the beginning, we built a (static) network without taking into consideration the time factor, assuming the time horizon was enough thin (first ICO relationship built in March 2017) to do not influence the centrality. After a set of analysis, where we applied some classic centrality measures, this assumption was revealed inconsistent, and hence we built a new (dynamic) network. Specifically, we assigned a weight to the edges of the network in order to have a measure of the age of the relationships. This system was also useful for assessing the level of knowledge accumulated over time in the ICO community. So, we did the analysis for both networks. The ultimate centrality measures applied are the strength centrality (the equivalent of the degree centrality for weighted networks), the eigenvector centrality, the betweenness centrality and the efficiency (the equivalent of the closeness centrality for disconnected networks). We used other measures to evaluate the effect of the ventures' social capital and human capital to the ICO success (as the belonging to the largest connected component of the whole network and occurrence of past successful ICO conducted by the advisors or members of the team).
For each measure, we performed a T-test in order to understand the difference in means in case of ICO's success or failure. Then, we built our regression models to test our research hypotheses. Moreover, we performed some robustness checks to better understand the results of our models.

The regression models verified our research hypotheses. We found that the ICO's centrality, calculated on the basis of the team members and advisors' relationships, is positively related to its success. Indeed, all the centrality measures have resulted statistically significant for the ICO success and this result leads us to do some considerations. It is reasonable to assume that a more central project has higher opportunities to receive more information about the environment and the best practices for the ICO proceedings. Then, the social contacts of its members allow advertising easily the campaign within the crypto-community, exploiting the word of mouth effect. It may be a crucial element for fundraising because the information is directly addressed to the most interested typology of investors. Moreover, it may have a direct implication in a specific ICO feature: the soft cap. Indeed, a common practice of the phenomenon is to include in the soft cap the marketing cost of the campaign. In this way, the word of mouth within the community can help to reduce the marketing cost, and, hence, the soft cap. Specifically, a lower soft cap could be reached easily, increasing the ICO's probability of success. This is not only a reasonable assumption, but it was also tested through our models, showing that the size of the soft cap is negatively related with the ICO success with a level of confidence of the 99.9%.

Now, we will talk of each specific centrality measure used and the findings of them. To do so, we will explain how we conceived and intended these measures in order to allow the reader to better understand the implication given by the results both of the regression models both of the robustness checks:

- *Strength centrality*: it measures the amount of knowledge that can be absorbed from the adjacent nodes. The positive relation with the success represents an evidence of the importance of the direct relationships in the exchange of best practices about ICO proceedings and knowledge development. This result is in line with the work of Rost (2011) who demonstrated that the strong relationships in a non-structured network (as the ICO one) are a driver for innovation and knowledge creation. Another point of view is the word of mouth effect given by the direct relationship that can spread information about the campaign reducing the marketing costs and the soft cap. In the robustness check, we verified the quadratic behavior of this measure and we saw that over a certain value this measure affects negatively on the probability of success of the ICO. It may be due to the difficulty in processing the information received, or to the spillover of relevant and secret information about the project. Another aspect of its negative relationship could be the low commitment of advisors engaged at the same time in too many projects. Anyhow, we evidence that only one ICO in our sample suffered this negative pattern.

- *Eigenvector centrality*: it measures the level of knowledge available to the connected nodes of the reference node; in other words, it is the amount of knowledge in the area near to the node. The eigenvector centrality is positively related to the ICO success. The same concepts expressed for the strength centrality are valid also for this measure; diffusion of best practices and exploitation of the word of mouth effect. The relation between this measure and the spread of information was already founded by Bajo et al. (2016), Cheng et al. (2019) and Kim (2019). Studying its quadratic behavior, we found a negative relationship once exceeded a certain value, too. In this case, the spillover of information may be more credible. Indeed, the moral hazard of an advisor is more probable because he can exploit “more distant” colleagues to spread secret information about the project in order to be not directly linked with the most visible source of spillover (the distant colleague).

- *Efficiency*: it measures the efficiency in the exchange of information from the reference node. Again, the regression shows a positive relation with the ICO success. In a certain sense, the efficiency is a direct measure of the potential word of mouth effect because it is more related to the outflow of information than the inflow. It implies that the efficiency may reduce consistently the marketing costs and, as explained before, also the soft cap increasing directly the probabilities of success. The robustness check of this measure did not show statistical significance for its square, and hence we can suppose a linear behavior for efficiency.

- *Betweenness centrality*: it measures how many times a node is in the path with the highest level of knowledge between two different nodes. In a certain sense, it is a measure of the quality of the information channels. Finally, this measure is positively related to the success of the token sale. Bajo et al. (2016) and Cheng et al. (2019) demonstrated the importance of this measure in terms of brokerage role for the diffusion of the information and knowledge. In the same way, we can affirm that ICOs with a higher betweenness act as a broker for the information exchange. Then, assuming that better-quality knowledge circulates in better-quality channels, teams with higher betweenness centrality receive high-quality information through which they can better do the ICO proceedings. Studying the quadratic behavior, we found that also this measure has a negative association with the outcome, over a certain level. This may be due to the difficulty in processing the amount of information, but also to the high retribution asked by advisors with an important brokerage role. This suggestion is coherent with the work of Horton et al. (2012) who argue that the compensation of CEOs and executive directors is related to their betweenness centrality.

Our results showed also that the belonging to the largest connected component of the whole network has a positive relationship on the success of the fundraising campaign. It is due to the fact that the larger the network the higher the knowledge developed within. This concept was demonstrated also by Nicholson et al. (2004) that affirmed "the larger the network, the greater access to resources for a firm". Then, Kim (2019) studied directly the belonging to the main group of a network and verified that this characteristic allows firms to be updated about the latest trends in innovation. Moreover, he did the example of Silicon Valley, where many of the world's most innovative firms are established, enabling them to exploit immediately the knowledge created. Our work is perfectly in line with the previous literature regarding the size of the network and the belonging to the largest connected component.

Our results show also a relation between the past ICO conducted successfully by the proponents of a new ICO and its success. The "success makes success" concept was also previously studied in the crowdfunding by Butticè et al. (2017). It demonstrates the strong similarity between these two funding methods. However, in the robustness checks, we tried to go in deep regarding this relation. Indeed, we expected to find a negative relation with past failures and future successes, a sort of black sheep effect. We have found that the previous failures were unexpectedly positively related with the ICO success, and we thought that it was more a matter of previous experience; actually, we supposed it doing the T-tests. We found a positive relationship between the previous experience in past projects, independently by the campaign outcome, and the ICO success. It is reasonable to assume that this relation is linked with the knowledge acquisition about the ICO proceedings through social relationships. In fact, the simple participation in an ICO, regardless of the result, implies the creation of relationships with the other participants through which the assimilation of knowledge on best practices takes place.

Finally, in the last robustness check, we added the direction to the edges of the network to allow the information flow only from the older ICOs to the newer ones, and not vice versa. The result of this check confirmed the previous results without adding relevant insights. It demonstrates that the weights assigned are a good measure, not only of the knowledge accumulated over time, but also of the time periods. In fact, it further confirmed us that we were on the right path, and it gave also a stronger validation to our innovative application of Social Network Analysis in the ICO context.

4.2 Limitations and future research

A limitation of our work is that the data was collected manually without any automatic process, and hence the human error may be present in the compilation process. Moreover, the most trusted ICO data providers not always disclose the necessary data, and sometimes a complete ICO misses. In those cases, the data search was done on different websites and blogs, which provided different information between themselves. Hence, a further limitation of our work is the scarce reliability of a share of the data we collected. Furthermore, the time horizon under analysis stops in February 2018, and it will be interesting to continue the work in order to understand the future development of the phenomenon. Indeed, it may be newsworthy to study the quadratic behavior of the centrality measures using a larger sample, in order to find if the negative effect occurs in very few cases, as happened for our sample, or if it is a more widespread phenomenon.

Another future research may take into consideration a different way to build the network, giving a different meaning to the weights or build as many networks as the time periods, even if our model goodness was validated by the robustness checks.

Regarding the network, many analyses could be done for the social network to study the relationship of the individuals in the community. For example, a study can search for a relationship between the advisors and sector to find the existence of relevant sub-networks and of sector's experts. We always consider worth remembering to the reader that many ICOs turned out to be scams, and hence it would be interesting and important (especially for regulators) to study the possible relationship between centrality measures and post-ICO performances.

Finally, the ICO environment is constantly evolving, and it is certainly relevant to continue the monitoring and the studying of the phenomenon. There are still many questions marks about the future of ICOs and cryptocurrencies, mostly regarding their future regulations, but the high potential of these instruments and their underlying Blockchain technology is unexceptionable. We hope that our efforts may be useful for future scholars, that will deepen the matter. Furthermore, our biggest hope is towards ICOs' investors and proponents, that can use our findings to develop new best practices and to screen future projects; giving more emphasis to human relationships in terms of knowledge spreading and creation, but also of availability of benefits and resources for projects. This research could boost the development of this fundamental topic, that (we hope) could become the future of fundraising.

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