POLITECNICO DI MILANO

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Initial Coin Offering and Economic Complexity.

An Experimental Study

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Abstract

English Version

The Initial Coin Offering (ICO) is an innovative fundraising campaign based on the Blockchain technology.

Through a digital token offering on the internet, start-ups or consolidated companies can collect funding without relying on intermediaries. This allows companies to enter the financial market in a short time, and without large investment. Operational costs are impressively reduced and moreover, every person in the world is reached by the fundraising campaign, thanks to the internet.

This new way of alternative financing reached its peak during the years 2017- 2018, when thanks to it, more than $25 billion were raised.

The ongoing research aims at analysing factors that lead to a successful ICO. This work wants to follow this trend utilizing the Economic Complexity toolbox, introduced by Hausmann and Hidalgo, and that was never used before in this financial sector.

The Economic Complexity framework measures the quality of the structure of an entity through a deep analysis of its connection inside the network.

Our objective, with this work, is to measure the level of complexities related to people that organized the fundraising campaigns and search if a correlation exists with the success of the campaign itself.

We want to asses if the social capital owned by the people organising the fundraising is determinant on the final output of the ICO.

Abstract

Versione Italiana

Le Initial Coin Offering (ICO) sono una forma innovativa di campagna di raccolta fondi basata sulla tecnologia Blockchain. Attraverso un'offerta di token digitali su Internet, le startup o le società già affermate possono raccogliere finanziamenti senza fare affidamento ad intermediari.

Ogni azienda è così in grado di entrare nel mercato finanziario in breve tempo e senza ingenti investimenti essendo i costi operativi notevolmente ridotti; inoltre, le campagne sono accessibili ad ogni persona nel mondo purché abbia un accesso ad internet.

Questo modo innovativo di finanziamento alternativo ha raggiunto il suo apice negli anni 2017 - 2018, periodo in cui sono stati raccolti oltre $ 25 miliardi.

Gli studi nella letteratura in corso mirano ad analizzare i fattori che portano ad un ICO di successo.

Il lavoro segue questa tendenza volta ad utilizzare i concetti introdotti della Economic Complexity di Hausmann e Hidalgo, che non sono mai stati applicati in questo campo finanziario.

L'Economic Complexity ha l'obiettivo di misurare la qualità della struttura di un'entità attraverso un'analisi approfondita delle sue connessioni all'interno del network.

Il nostro obiettivo è misurare il livello di complessità relativo alle persone che hanno organizzato le campagne di raccolta fondi e vedere se esiste una correlazione con il successo della campagna stessa. Vogliamo quindi valutare se la qualità del capitale sociale delle persone è determinante per la riuscita finale dell'ICO.

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Executive Summary

The great recession marked irredeemably the world. After 2008 difficulties to raise funds were so remarkable that all the economy was stuck. Entrepreneurs were not able to access funding to launch their innovations or found new companies. Traditional financial systems were no longer able to respond to their needs.

This crisis, as already happened in the past, challenged the ability of the humankind to address problems and to come up with solutions.

As a matter of fact, new technologies allowed the emergence of novel disruptive approaches that contributed to overcome the barriers settled by the traditional financing instruments. Alternative ways to rise funds appeared in the financial market.

Thanks to crowdfunding, going to a bank to ask for fund to start a new business project was no longer necessary. People started to collect money from their home, opening a campaign on the crowdfunding platforms available on the net. Billions of dollars have been collected and thousands of projects funded.

But the innovation did not stop, pretty much at the same time Satoshi Nakamoto published a paper, where the blockchain paradigm was described, introducing the peer-to-peer network and the concept of cryptocurrencies. Based on the development and application of these concepts, Satoshi Nakamoto introduced soon after the Bitcoin, revolutionizing the entire financial world.

This disruption opened the way, some year after, to the Initial Coin Offering (ICO), an alternative way of financing companies.

An ICO can be 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” (Adhami et al., 2018).

ICO has similarities with crowdfunding, both rely on an “open call”, the possibility of all types of investors to participate via Internet in the collection of funds.

At a first look there also similarities with an IPO: both processes are aimed at collecting funds from people. But an IPO calls for the necessity of having stable revenues, a good reputation on the market, a formal document, the prospectus and of being compliant with regulations.

The literature on ICOs discusses different topics. One of the most interesting field of study is the information asymmetry theory and the signaling theory with their central role to understand the potential success of an ICO. (Akerlof, 1970; Spence, 1973).
Information asymmetry creates three main challenges for the ICO world are: the reluctance at the innovation, the risk propensity of people and the little information available on projects.
The “signaling theory” was applied to address this information asymmetry to address the so-called intellectual capital, a key ingredient for the success of the investment.
Investors started not to consider just the little information available on the projects but to give more importance to the members composing the team responsible to the development of the project.

Social capital became a central element of evaluation for the financial world and also for ICOs. This Evidence of this trend is given by the development of the literature in the field of Social Network Analysis.
Several authors focused their work on the relationships of the social capital with different aspects of a business project. A correlation between compensation of executives and the characteristic of their social connections was observed (Horton et al., 2012).
Social Network Analysis was also performed on the IPOs, acknowledging that IPOs, conducted by more than one central lead underwriter, are associated with biggest absolute values of IPO price offer. (Bajo et al., 2016).

Our work follows this direction aiming at evaluating the importance of the social capital that each individual has inside the network of the ICOs’ world and its impact on the final results of a fundraising campaign.
The novelty of our work is related to the use of the framework of analysis: the Economic Complexity to address this topic.

Hidalgo and Hausmann, defined the Economic Complexity as an index that is based on the study of the structure of the system and on the relationships present inside. This index has a predictive power in terms of future development of an entity inside the systems. Within Economic Complexity, the Method of Reflections is a tool to analyze the structure of the system considering two different entities: diversity, defined as the number of products made by a nation, and ubiquity, being the the number of countries that make a product.
The Method of Reflections can measure the complexity level of each node in a system, starting from diversity and ubiquity, by iterating them and using one to adjust the other until they converge to a final value that represents the economic complexity level.

Once we framed our work on ICOs with a comprehensive literature analysis, we stated our research hypothesis, based on the capability of the Economic Complexity.
Our first two hypotheses, in fact, are related to the applicability of Economic Complexity on the ICOs field and on its capability to better analyze a system compared to the measures of the Social Network Analysis.
Once assessed the appropriateness of the Economic Complexity, we defined of our third hypothesis, that concerns the predictive power of this conceptual framework, taking into consideration the correlation of the level of complexity obtained for each individual with their ICO performances.

To define a working roadmap to develop our work, we researched the existent literature the methodologies of application of the Economic Complexity.

To assess our hypothesis, we created the foundation of our analysis: the bipartite network, that represents the ICOs network relating the member *m* with the ICO *i*; there is a correlation when one member *m* is part of ICO *i*. The result is a matrix of 9362 members related to 856 ICOs.
After formulating the bipartite network, we could apply the Method of Reflections and introduce the concepts of diversity of a member *m*: how many ICOs the member *m* did, and ubiquity of an ICO *i*: how many members there were into the team of the ICO *i*.

With the Method of Reflections, we assessed the complexity level of each member iterating diversity and ubiquity to get an higher order of analysis of the system improving the previous one.
At the same time, we performed the Social Network Analysis on the members' network of 9362 people. Applying the main measures of the Social Network Analysis, degree, betweenness and eigenvector centrality, on the 9362 x 9362 matrix we obtained for each vertices the value of centrality.

Obtained all centrality values we started to analyze if Economic Complexity is appropriate for assessing the social capital of a person, following a path similar to the one used by Hidalgo and Hausmann in their work.
We analyzed the measures of complexity together with the measures of centrality to see if higher levels of iteration of the Method of Reflections generate a higher fitting with centrality measures. This fitting was evaluated seeing if increasing the level of iteration there is an evolution on the correlation of Method of Reflections' measures with centrality measures.
From this first analysis we could find some first evidence: the evolution of the correlation of the measures of complexity was observed only with the degree centrality. Betweenness and eigenvector centrality were not able to measures properly the network of members, not being able to highlight the quality of the position of a person inside a network that is poorly dense, full of vertices, but with few edges.
A first confirmation come from this passage: Economic Complexity framework can better catch the actual interconnections and their quality inside the ICOs world through the bipartite network than the centrality measures in the simple network of members.

We then repeated the same analysis, but considering a downsized network made only of members that participated to more than one ICO; these lead to a new bipartite network of 494 ICOs and 547 members and the relative member network.
We considered this further step to verify if there is an improvement on the relationship between complexity measures and betweenness and eigenvector centrality. There was an improvement but only in respect to the eigenvector centrality. For betweenness centrality the correlation was still null, because the members' network is characterized by a high

distance between the different members, due to the rareness to find themselves in the same ICO.

This approach allowed us to prove that the Economic Complexity framework can be applied in the field of ICOs, moreover we saw that it is able to catch the quality of interconnection of a person and quantify the social capital in this field of the financial world, better than the measures of centrality.

After having validated this aspect, we develop our model with the aim of demonstrating that there is a correlation between the level of complexity, as indicator of social capital of each individual, and his capability to raise funds.

We performed our analysis adding to the model control variables are referred to the members characteristics such as being her/him an advisor or a member and being or not an expert in a particular sector.

Values obtained in terms of level of confidence and correlation, validated our hypothesis: team members with a higher level of complexity are able to raise more funds, meaning that human relationships play an important role during the ICO campaigns.

Furthermore, setting different models with different levels of iteration, we have seen that the adjusted R-squared increased with the increase of the levels of iteration.

These models demonstrate that higher orders of iteration of complexity are better informative on the capability of a person to raise funds.

With our model we contribute to create a better information analyzing the social capital referred to each actor and assessing their position and their relevance inside the network.

In the alternative finance industry, characterized by a strong information asymmetry, our model provides a tool to better assess the quality of an ICO before its first collecting round.

1 Literature Review

1.1 Blockchain

Today the financial system involves trillions of dollars and billions of people on a daily base. The existing financial system is not any more efficient in facing the economic challenges, due to an increasing number of operational problems such as rising costs, fees and delays, onerous paperwork and opening up opportunities for fraud and crime.
This inefficiency depends mainly on systems that are: first, antiquated, paper-based; second, centralized, difficult to change and subject to failures and attacks; third, exclusionary, disclaiming the access to basic financial tools to several people.

1.1.1 Why Blockchain?

To solve these issues a new technology has emerged: blockchain.
Blockchain is defined by Stanciu, A., (2017) as:

"A distributed database of records, or public ledger of all transactions or digital events that have been executed and shared among participating parties."

This technology sustains any digital interactions and records transactions, securely and transparently, verified by the consent of the majority of participants in the networks.
It encloses some relevant characteristics:

1. Immutability: after an agreement on a transaction and its recording, nothing more will be changed.
2. Decentralization: it solves the problem of the traditional model, increasing the nodes, reducing the effect of failure, and ensures scalability.
3. Anonymity: the identity of users is hidden.

4. Better Security: no more single point of failure that locks down the entire network.

5. Increased Capacity: several servers working together, as a whole, are better than a few centralized.

The blockchain is a database that stores all the transactions in blocks. To set up a new transaction, the sender forwards it in the communication channel to all the nodes in the network; only when it arrives at the receiver, it is validated and recorded with the creation of a new block.
This block, after the authorization, becomes a non-reversible part of the blockchain. It, now, contains some new metadata and also the hash value of the previous block, so it has a point of contact with its parent block. This is the link between different blocks, creating a chain of blocks called blockchain.
The distributed ledger is available for everyone, but the anonymity is guaranteed by the identification through a public key. Moreover, the transactions are encrypted.
Due to the continuous changing of the transaction, attacks and frauds are more complex, they need several modifications, not only of the information that arrives at the receiver nodes but at all the other in the chain. This attempt is unfeasible, unless the majority of the nodes are fraudulent.

1.1.2 Bitcoin and Blockchain Technology

The commerce on the Internet channel relies completely on financial institutions, representing the trusted third parties to process electronic payments. This system works well for the majority of transactions, but some of them, such as non-reversible and small casual ones are not possible since financial institutions cannot avoid mediating disputes that increase the fees and costs.

To solve this problem a purely peer-to-peer version of electronic cash has been introduced, giving the possibility to send directly the payment, without passing from a third party.

But a problem persisted: the double spending, the possibility to cheat using the coin for making more than one transaction.

A solution was found by Satoshi Nakamoto, the developer of Bitcoin, who introduced the peer-to-peer network, becoming the first person to solve this big issue.
The system is a P2P distributed timestamp server that acts as a generator of the computational proof of the chronological orders of transactions.
An electronic coin is represented by a chain of digital signatures and each transaction by a set of a digitally signed hash of the previous transaction and by the public key of the next owner. The private key is used for signing the transaction while the public one for verification. The latter is kept from the wallet and implemented online.

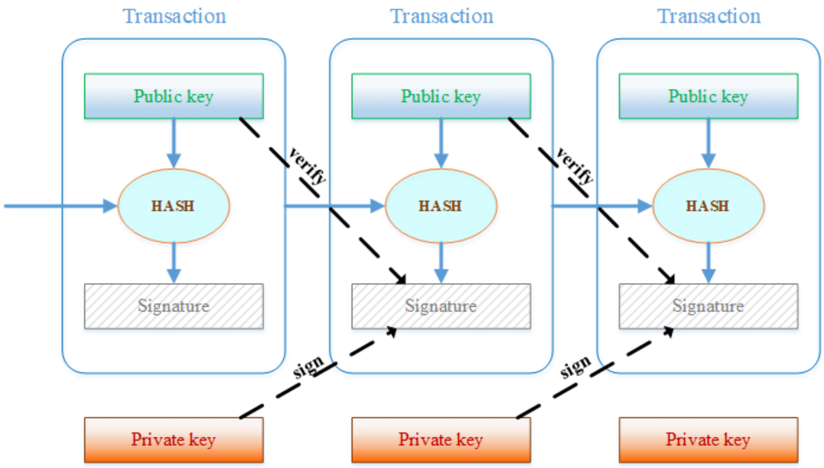


Figure I – The Structure of Transaction in a Bitcoin Blockchain

The Bitcoin ledger represents the ownership status of all existing bitcoins and the transition function. The result is a successful transaction or an error, depending if the sender has enough bitcoins or not to make the deal.
A fraudulent user can try to cheat the system and use the same coin twice (double-spending problem), but the situation is minimized thanks to the Bitcoin network by demanding a proof-of-work from each node that verifies the transaction. This is possible thanks to the higher computational power of honest nodes respect to the attacker ones. In fact the rule leading the system is that, the longest chain with higher consensus is the right one, and it cannot be changed by attackers given the higher number of voting of the honest nodes.

1.1.3 Cryptocurrencies

Nowadays cryptocurrencies have become very popular and used everywhere; their success was possible by blockchain technology, which guarantees security through strong cryptography keys, anonymity, trust and a decentralized system with lower risk of possible paralysis.
Cryptocurrency can be easily dispatched between two parties, independently where they are, without the support of an intermediary and are characterized by the velocity of transaction. For these reasons, cryptocurrencies become ideal for crowdfunding purposes giving the birth to the so-called Initial Coin Offering (ICO) phenomenon.

To provide an overview of this world, today still not yet well known, it is necessary to start from the first cryptocurrency created: the Bitcoin.
Bitcoin is the first digital currency created and it is based on Blockchain technology as described in the previous paragraph.
With the developing of the technology, more than 2000 cryptocurrencies were created, called alternative coins respect to the Bitcoin (or altcoins), but still remaining strictly linked to the value of the Bitcoin; in fact, in the majority of the cases, the value of the other cryptocurrencies is derived from the Bitcoin one.
The Bitcoin, still today, is the most famous cryptocurrency ever created. Nakamoto (2008) its founder was the first person to develop a system of decentralized payment, without any type of intermediary with a direct peer-to-peer transaction.

The Figure II below, shows the evolution of the value of the Bitcoin, which was not considered at all until the 2017, due to the lack of the capacity of understanding the real potential usage of this type of coin.
At the end of the 2017, it reached its maximum surpassing a value of 20,000 USD per Bitcoin, due to the multiple speculations behind the stock on the exchange market for cryptocurrency.

For this reason, many trading companies around the world banned the possibility to their analysts to make trading on this specific stock, due to the strong presence of a bubble. From the beginning of 2018, after some months of raising prices, the value of the Bitcoin started to quickly decline, losing up to 75% from its maximum value.

Today the price seems to be quite stable when compared with the market of reference.

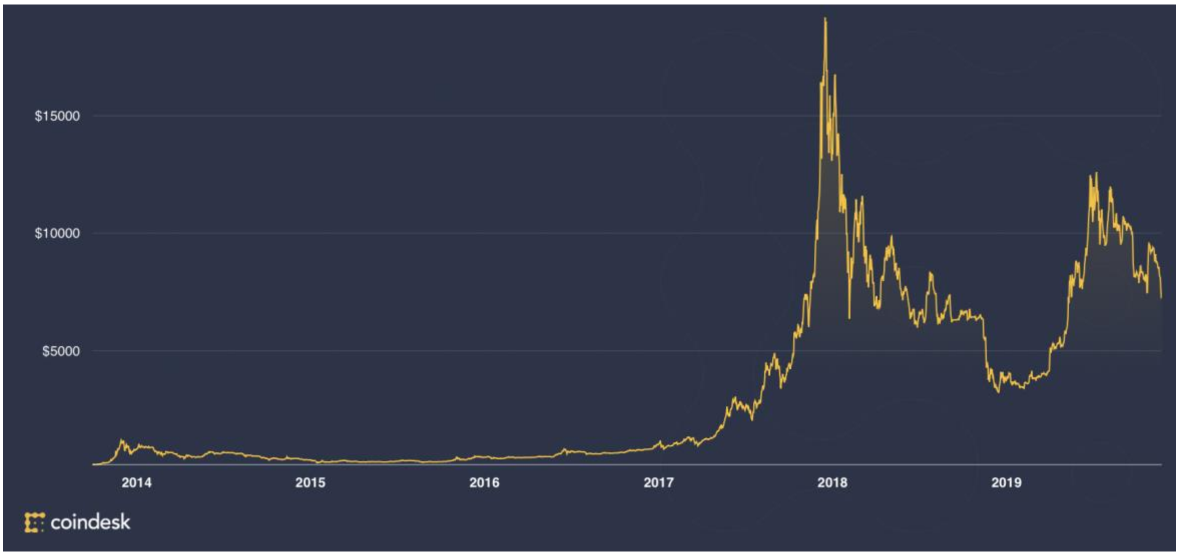


Figure II – Bitcoin Price Index

For the sake of clarity, it is important to repeat the difference between Bitcoin and Blockchain: they are two separate entity, even if correlated. Bitcoin is the coin that permits the transaction, Blockchain is the underlying technology, needed to assure the right exchange, the affordability and the anonymity of the transaction.

Only with the introduction of the Ethereum cryptocurrency it was possible the development and the implementation of a programmable blockchain as Boreiko & Sahdev said in their work.

This type of blockchain has automated protocols to act in a predefined way when some specific event happens.

This type of procedure, defined as “smart contract”, is based on an open software able to create own tokens on the Ethereum blockchain without any type of effort in terms of time spending. The improvement of the underlying technology and of the generation method of new tokens is called ERC20 token standard contract.

This new standard contract, thanks to its simplicity respect to the previous blockchain, is the reason why the ICOs' world start to be known and to rise.

This new method for tokens creation and to the possibility to use the new Ethereum blockchain platform, allows a new stage of blockchain financing.

Other projects were then developed and implemented such as NEO, WAVES, and Bitshares, but none of those is known as the Ethereum and Bitcoin platforms.

1.2 Initial Coin Offering – ICO

ICOs may be 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” (Adhami et al., 2018).

1.2.1 Main Features

ICOs are in continue evolution, being a new phenomenon, but it is possible to find a structural pattern and define a roadmap where the principal steps of a fundraising project are shown in a timeline sequence (Kaal & Dell’Erba, 2018):

1. The Pre-lunch announcement of the investment project through crypto-fora, like Bitcoin Talk and Reddit.

2. An “executive summary” for explaining the project to possible investors, and also to collect suggestions for the implementation (“comments on the project” are taken in consideration by the management during drafting).

3. A “white paper”, fundamental document that characterizes all ICOs, with information on the project, the strategy, the returns to facilitate the decision of the investors.

4. A “yellow paper” explaining in detail the functionalities of the underlying technologies.

5. A possible “Pre-ICO” or “Pre-Sale” offer, for specific investors only (i.e. ventures capital and funds); sometimes the money collected are sufficient and the public lunch is cancelled.

6. The ICO public relation campaign to address broad small investors.

7. The ICO lunch.

8. The quotation of digital tokens; they are “listed on cryptocurrency exchanges for trading”. There is the opportunity for of a secondary market to trade the tokens acquired and liquidate the investment.

As mentioned before, a key document is the “white paper”: it includes many information about the ICO. It is important to underline that this document is not approved by anyone, and that there are no certifications by the authorities. It contains a detailed project description, information on the team and advisory board, funding target (hard and soft cap), token characteristics and the underlying blockchain, offering period, if there is a pre-sale period and also some clarifications about jurisdiction, guarantees and risks of the investment. This document has three main objectives: first, provide the reader all the above information; second, influence his decisions; third, put him in contact with other possible clients.

To better understand the general framework, it is important to describe the principal features of an ICO.

Token

One of the key concepts of an ICO is the “token”. It represents a sort of share of the company. There are different types of tokens distinguished by different characteristics and rights (A. Lielacher, 2017):

1. Currency tokens: they are cryptocurrencies used to buy and sell goods and services and are also a store of value.
   The main difference with the digital version of fiat money is that they are decentralized and not controlled by the authority, they are independent by the Central Bank, there is no financial intermediaries using a peer-to-peer network and cryptography to protect the transaction.

2. Equity/Security tokens: they represent shares of a company after a token sale. The characteristics are control and ownership of the company according to the percentage owned. They are regulated by global regulators.

3. Utility tokens: they provide access to a company platform, product or service; they are not considered like an investment and for this reason they don't have any type of regulatory restrictions.

4. Asset tokens: they refer to a physical asset or product. A good example is tokenized gold, allowing investor to buy it without the difficulty of storing it. Asset tokens are not so popular due to the impossibility to have a high upside potential with the price of the asset usually not exceeding the real value.

5. Reputation/Reward tokens: they give to the owner some rewards or good reputation respect to the activeness of him on the platform. Is difficult to define a value of this type of tokens, for this reason they are not frequently used.

Underlying Blockchain

Today the majority of the ICOs are managed trough Smart Contract using Ethereum blockchain with its ERC-20 Token Standard Contract. Its major characteristics are the simplicity of new tokens' creation, compared to the Bitcoins ones, and the possibility of trading them with Ethers, Ethereum cryptocurrency, which embeds a monetary value (Fenu et al., 2018).

Code

It is necessary to implement a computer code for smart contract that will support the entire project and the collection of funds. The code is often published on GitHub, allowing investors a possible analysis helping them in their choice.

Token Supply

During an ICO it is important to choose the overall amount of token supply. It is possible to identify two different situations: first, capped ICO with a maximum possible collection of tokens guaranteeing that the percentage of ownership of the company by the investor is known in advance. Second, uncapped one with the possibility to collect more funds to work with and satisfy all interested investors, but probably reducing the original estimated value of the token.

Hard and Soft Cap

Hard and soft cap can be considered as two fundraising goals: the first one represents the upper limit, defined by the team of the ICO, over this limit the funds are completely returned to the investors; while, the soft cap is more important in terms of success of the ICO, a non-goal for that amount of funds means a failure with the consequent total reimbursement of money.

Token Distribution

The team is always the entity who decides how and to who distribute the tokens: the major quantity is reserved for the crowd, but there are also other several subjects to be served: going from the team to the advisors, from community to funds for future improvement and development, from liquidity necessity to airdrop and bounties.

Airdrop and Bounties

Two from to reward the users of a network are airdrop and bounties. The first one is easier in term of work and consists in an extra allocation of tokens in a free-way to the user that helps the spread of the project (i.e. using social networks and publicize it); the second type of reward is more complex and deals with the capability to fix some bugs or to translate in different languages the “white paper” and sometimes to improve, also, the quality of the code.

Bonus

Rewards designed to increase the collection of tokens. The team can set different types of bonuses between two categories:

- Early bird: it is a discount applied on the first N tokens; it is made for selling in a faster way part of the tokens and reward, trough the discount, earlier investors.
- Major contribution: it is a discount related with the quantity bought, higher the quantity, higher the discount.

The two categories can be both set in the same ICO, can be only one or none.

Duration

The duration is very variable depending on different ICOs and projects. It is influenced by the capacity of collecting funds in short time; less is the time needed to reach the upper limit, the hard cap, less is the duration of the ICO.
Considering only the time spent during the effective sale of tokens, the crowdsale, the horizon can go from only one day to several months, or in particular cases more than one year.

Use of Funds

The team can or cannot, according to their preferences, make public information regarding the uses of funds collected. This information, if any, is written in the “white paper” and, usually, is split into five categories:

- Funds for software development: it is one of the most important use and it is due to the fact that an ICO is based on blockchain technology, with the possible need of future improvements on the code.

- Funds for business development: such as in any type of investment and projects it is key to increase the basic operative functions, to better match the market and keep up with the competition at global level.

- Funds for marketing: money necessary for marketing campaign, advertising, public relations…, it increased in importance nowadays due to the growing relevance of customer satisfaction, the known "customer experience".

- Funds for legal costs: costs generated by the activities of the projects and by the alignment with the restrictions and regulations on the market.

- Funds for reserves: money set aside for unexpected events or losses.

1.2.2 History of Initial Coin Offering

For understanding the development of ICOs trough time, it is necessary to start from the 2008 financial crisis. During those years, banks undertook excessive risks, in particular investing in subprime mortgages, not considering the concrete possible risk of a depreciation of the real estate market.
With the explosion of the bubble, several banks faced important economic problems. The banks, having liquidity problems, started to divest their assets, not only just the worst, but also the profitable ones and reduced the supply of loans to the market, with the consequence of leaving part of demand unsatisfied.
The crisis was about the reduction of the supply of loans by the banks and not due to the demand, which didn't decrease. This problem also arose from more restrictive compliance parameters, which resulted in lower funds for small medium enterprises (SMEs) and start-ups.

An alternative to bank funds, SMEs and start-ups could rely only on risk capital by venture capitalists (VCs). Equity financing where the investors are expert in the specific sector and help the process of development not only through funds, but also with knowledge, guidance, experience and managerial competence.
Only in the last five years, the contact between the borrowers and the financial markets is reduced, starting from crowdfunding platforms, passing to peer-to-peer (P2P) platforms and arriving at the Initial Coin Offering, thanks to technology that allowed to bypass financial intermediaries. All these new types of financing represent the so-called Alternative Finance (AF) sector, A sector measured to be, in 2016, over €5bn in Europe and $35bn in US (Boreiko & Sahdev, 2018).

Boreiko & Sahdev describe the evolution of the ICO in five phases:

1. Prototype phase: the first use of blockchain technology to collect money was attempted by J.R. Willet in 2013, when, during the San Jose Bitcoin conference, decided to promote his idea of building a new versatile protocol layer on top of bitcoin. The contributors, in that case, would have received, instead of Bitcoins, new coins, representing the ownership stake of this new technology.
   The announcement was made in a forum, bitcointalk.org, without any advertisement, intermediaries and legal entity. The funds collected were used to develop the original idea and the coins were traded on the market, possibility to have a liquid exit from the investment.
   One of the bigger issues of this type of collection was the anonymity, only the virtual identity of the founders was known, in fact all was based on the credibility of those people, well known by the community. Nothing about the project, nor details on future plans, the presence of the "whitepaper" would be necessary for sustainability of the ICOs.
   In the summer of 2014, for a forty days collection campaign, an exception was found: the Ethereum donation campaign. This was the first legal ICO with the formal registration of the investors, better transparency on third parties, avoiding moral hazard ex post; moreover, characterized by a well-defined strategy and development plan, later called "Roadmap".

2. Initial start-up phase: from the first stage of ICO the majority of them stayed based on Bitcoin technology and only after a full year some of them used the Ethereum one.
   The major evidence was that 46% of the cases had a legal advice within a purchase agreement differently from the first ICOs.
   In this phase some start-ups had the support of VCs, other undertook a pre-sale phase; more than 50% of them offered deep discounts to early buyers, ICOs seemed to be successful and of interest. Moreover, the majority were capped, and the price could be fixed or determined at the end of the sale.

3. Late start-up phase: one year later, there was a rapid internationalization of ICOs, passing from 27 to 112, raising up to $300m, in 23 different countries.
   The increasing pressure by legal entity, forced the ICOs to choose their governing jurisdiction and, also, discouraged and prohibited some type of investment.
   During this phase was given a great importance to marketing campaigns, introducing jointly the "bounty campaigns", rewarding active private promoters.

4. Early growth phase: having discovered this new method of collecting money in a quickly and cheaply way, in 2017, many start-ups decided to run their token sales, arriving to count 169 ICOs, for a total of $2.5bn.
   Given the strong increase in the phenomenon, the regulators started to restrict the possible ICOs: many countries, such as China, decided to ban them. For this reason the majority of jurisdiction were settled in Switzerland and Singapore, countries with lower restrictions.
   From now on, the ICOs became the model which we know today.

5. Late growth stage: up to now the participation of VC and private sales is continuously increasing, with different stage of fundraising, before the pre-sale and sale phase.
   In 2017 the total ICOs, according to icodata.io, were 875 with a total collection near to $6.3bn, In 2018 there was a growth in ICOs of 45%, but raising only $7.8bn.

Looking at date available in different websites on funds raised in 2018 ICOs, the overall amount can vary from 22bn to something less the half of that amount, as from data on bloomberg.com. This incongruence is due the lack of reliable data, as says Alex Buelau, “At the end of the day, there’s no way to really agree on the information based on provable facts,”, and moreover, “It’s early days. The question is how can the industry create an incentive for these guys to report accurate numbers? At this point there’s no incentive.”

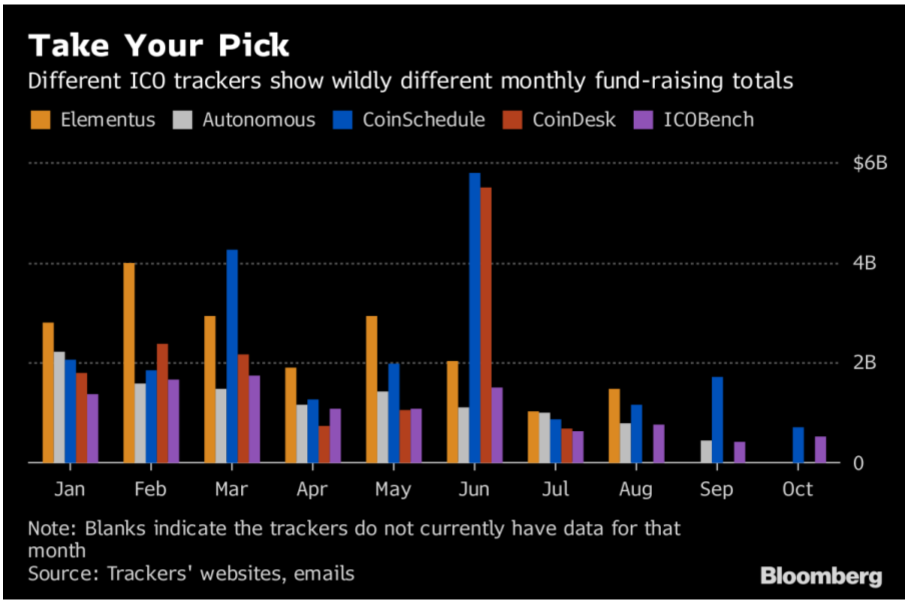


Figure III – 2018 ICOs Raised Funds, According with Different Websites

1.2.3 ICO and Other Form of Fundraising

ICO vs. Crowdfunding

Crowdfunding was born some years earlier with respect to ICO, but at the same time it was also based on Internet technology. The word “crowdfunding” was introduced in 2006 by Michael Sullivan, defined such as a specific type of crowdsourcing (acquisition of source to give back services), based on collection of funds and peer-to-peer finance.

In a more formal way, it is possible define “crowdfunding” as: “a collective effort by people who network and pool their money together, usually via the internet, in order to invest in and support efforts initiated by other people or organizations.” (Ordanini et al., 2011).
Moreover the European Crowdfunding Network (2012-2013) affirms that: “Crowdfunding is the mechanism of pooling and distributing relatively small financial investments from a large audience of supporters in exchange for equity or liabilities carrying financial returns or other non-financial rewards, where supporters are people or organizations who network, usually via the internet, to jointly support other people or organizations.”

Comparing the definition of an ICO, mentioned in paragraph 1.1.4, and of crowdfunding, included here above, it is possible to notice similarities and differences starting from the general structure of the investments: the major similarity is the “open call”, the possibility of all types of investors to participate via Internet in the collection of funds, but at the same time this is also the biggest difference, with the distribution of “tokens” in one case and of a “reward” in the other, in terms for example of equity or the final product/service.
Though being both “open call”, there are different geographic limitations: for crowdfunding campaign the limitation is defined by the area in which the platform operates, while in an ICO there is no limit, due to the Ethereum platform, with its ability to generate and trade in easily way new tokens, with a blockchain platform guaranteeing a worldwide network and connection. Some geographical restrictions can be found in ICOs due to limits in specific countries like China.

Crowdfunding can be divided in four different categories (Hossain & Oparaocha, 2017):

- Donation-based crowdfunding: there is no material reward but only gratitude from the founders; usually for no-profit organization (i.e. charity and social initiatives), but no only.

- Reward-based crowdfunding: the reward is usually the final product with a discount, but there is no a monetary reward or ownership of shares of a company so there are no interests and dividends.

- Equity-based crowdfunding: it is like a profit-sharing model, the investors will receive shares of the company, with the possibility to get profits and dividends.

- Lending-based crowdfunding: the investors lend money for interest return; they will receive back their money with a percentage interest on the amount.

Making a comparison with the "tokens" of the ICO again similarities and differences are evident: the most clear similarity is regarding equity-based crowdfunding and utility token, both guaranteeing control and profit sharing; for reward-based crowdfunding it is possible to find a link with the utility token: in the first case, the investor will receive the product with a discount respect to the non-participating people, in the ICO's case, the investor will have the access to a service or product on the platform, with a discount respect to pay it through "fiat" money and not trough the token sailed during the ICO.
On the other hand, reward token is completely different from reward-based crowdfunding; in this case the concept in ICO is related with the reputation on the platform.
Moreover, currency and asset token have no equivalents in the crowdfunding model, such as the lending-based crowdfunding has in ICOs.
Regarding donation, both ICO and crowdfunding are used to finance some ethical and social projects, but in the first case there are always tokens in exchange.

Another important difference is in terms of platform used: a crowdfunding campaign needs the support of an intermediary, needs an online platform to collect money from the investors, guaranteeing also a higher safety, respect to the ICO, in terms of frauds.

The ICO is based on blockchain technology, with no centralized control and no need of a platform. Thanks to cryptocurrency the exchange is made directly with the counterparty.

Moreover, the ICO is characterized by two rounds while of crowdfunding ends after the conclusion of the investment; ICO is envisages also a second round where "tokens" are traded on the market; there is the presence of a secondary market after the investment, the so-called "cryptocurrency exchanges", where the "tokens" are exchanged such as a normal share of a company on the traditional market exchange.

ICO and IPO

An Initial Public Offering (IPO) is a process of selling shares of a private company to the public for the first time. It is a process to collect money in exchange of part of control of the company. The company, for the first time, passes from to be a private company to a public one; now shares are exchanged in a stock exchange of reference.

At a first look it is possible to identify a similarity with the ICO process: both processes are aimed at collecting funds from people, but the reason behind and the timing are not the same. For an IPO the motivations are linked with the necessity to have more funds to invest in a new project or to reduce the existing debt, or, in another case, such as an "exit strategy" for the liquidation of the capital of Venture Capitalists (VCs) and Business Angels (BAs).
To go public with an IPO is necessary to fulfill requirements of different type: first, it is strictly required to publish an IPO "prospectus" which must be approved by public agencies (i.e. CONSOB in Italy and SEC in US) and it must contain at least a minimum of information such as the history of the company, information about the business, the governance, the future strategies and all the characteristics, risk and probability of success of the company. Second, how Collomb says, the company must "demonstrate a certain level, and stability, of revenues – which can only be achieved through a certain maturity in the issuer's operations"; third, the transparency must be increased to guarantee a higher credibility raising the possibility to have better possibility of success during and after the IPO process.

With an ICO usually the primary aim is the development of the idea, of the business because, as in crowdfunding, the collection of the money is needed for the initial events and for the first stages of the life cycle of the company. Often and mainly always it is not about existing companies, but start-ups in their earlier phases, still not well developed and characterized by a higher risk respect to an IPO.
Furthermore, an ICO has not a certificated document such as the prospectus of an IPO but has a “white paper” which is composed by different sections, that provides information similar to that in the IPO prospect, but without the validation by the authorities.
Moreover, in the case of an IPO, an underwriter is requested who can diversify institutional and retail investors. In ICO this is not possible, due to the fact that the entrepreneur manages the whole process.
It is evident that an ICO is far more risky from the point of view of the investment, respect to an IPO, and from the other in terms of scams.

Other differences can be seen in the shares distributed in an IPO and tokens distributed in an ICO. In the latter case “tokens” represent a right-of-use usually for digital services and access to the respective platform, if it is referring to utility tokens, as described above. It is also possible to find different type of access and rights according to different tokens. For “shares” the concept is far distant from the previous ones, they represent a valuable asset, part of ownership of the company and embed voting rights.

1.2.4 Regulations and Limitations

One of the biggest points of criticism for the ICOs' funders and investors are the regulations and limitations that are spreading worldwide, due to several negative effects observed in the last years during the process of fundraising like fraudulent and terroristic activities, scams and money laundering.

There are different levels of limitations for the ICOs around the world, that depend on the specific country and legal authority of reference.

In East Asia, the biggest country to have banned ICOs is China; the People's Bank of China decided to forbid completely all types of activities that involve cryptocurrencies considering both business and private investments. The authority, also, stated that all the past and finished ICOs money collected should be refunded to the investors. Now, legally, people have the possibility to hold altcoins, but all types of violation of the rules will be investigated by the central authority of China.

Following the same footsteps were South Korea, Nepal, Bangladesh all for the themes regarding money laundering and terroristic activities.

Another important country to be looked at is The United States of America with extremely different regulations by state to state. Here we go from absence of regulations to strong restrictions with a requirement of a license to engage in altcoins activities, up to full ban.

The European ICOs' market, is nowadays still unregulated. The European Commission published in 2018 a document describing the entity of the ICOs, defining it such as an innovative method of collecting money, in easily and cheaply way, but at the same time characterized by high risks for the investors.

Singapore, Honk Kong, Switzerland and the Baltic Republics are friendly countries to ICOs, with less restrictive requirements and limitations.

Singapore developed a guide of *Digital Token Offering*, issued by the Monetary Authority describing the treatment between the altcoins and the current security laws.

Looking at Italy, at the beginning of the 2019 the CONSOB developed a document on the crypto-exchange market. It encloses the guidelines for the market and define a competitive framework to favor the return of the ICOs investments, gone abroad in the last years. The document also states the best approach on how protect the investors in the crypto market, based not only on the process, but also on the trading activities with the possibility to liquidate the investment in a properly way (Negri Della Torre & Bosisio, 2019).

1.2.5 The Recent Developments of ICO

To solve some limitations and issues derived from ICOs, starting from 2018 two new finance alternatives were developed: the Security Token Offering (STO) and the Initial Exchange Offering (IEO).

<u>Security Token Offering – STO</u>

Security tokens create a link between the blockchain technology and physical assets. These tokens are different from the cryptocurrencies, they are digital currencies, representing a sort of share of a company with the possibility to be traded.

The sale of the security tokens is finalized to collect money from the investors on the market to develop a new business area inside the company.

To better understand their essence, it is useful to compare a STO and an ICO.

STOs are like an investment contract, the "security" tokens represent part of equity of the company, with voting rights and profit sharing; ICOs are generally characterized by "utility" tokens giving the access, after the conclusion of the ICO, to a platform or to a particular service.

STOs are subjected to security laws, generating a rapid switching from "utility" to "security", knowing well the high probability of scams occurred in different past ICOs.

STOs, differently from ICOs, are regulated crowd-sales having the necessity of a specific protocol called "Know Your Customer – (KYC)", protocol that verifies the identity of the clients and investors, protecting them from frauds.

This new type of instrument is seen as the opportunity for everyone to invest in a company that has been approved by regulators and to list their cryptocurrency as a security, having now part of ownership of the company thanks to the coins acquired; for this reason it is also called "everyman's IPO" as in fintech podcast of *Crypto and Blockchain Talk*. STO gives the possibility of an investment not just to high net worth participants, but to everyone.

A research by PWC (2019), shows an important growth in 2018 respect to previous year: the number of STOs passed from only 2 with a raised amount of USD 22m to 28 per a total of USD 442m. The expectation of growth in 2019 and 2020 is very positive, due to the probable adoption of new funding method; however, it is still not clear if there is a concrete possibility of a replacement of the ICOs by STOs.

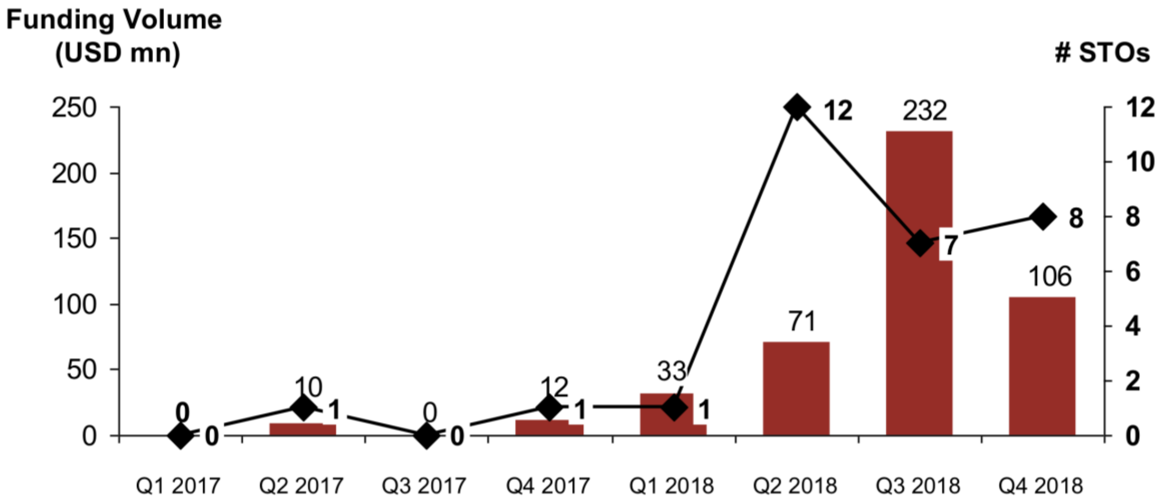


Figure IV – Growth of STOs from 2017 to 2018

<u>*Initial Exchange Offering – IEO*</u>

The Initial Exchange Offering (IEO) is a fundraising stage administrated by an exchange; differently by the ICO, it is not the team who conducts the fund raising, but it is a well-known fundraising platform, where the registered users can use their wallet to buy tokens of different companies.

One of the most important benefit is the simplicity to participate to an IEO; the only prerequisite is having an account on the exchange platform with some funds; the user can buy tokens through the trusted website's interface. Thanks to usage of a reputable platform, the security of the investment increases, reducing possibility of scams respect to an ICO. For

ICOs there is no restriction regarding limitations on people and companies who want to conduct the fundraise; for IEOs is the exchange platform that screens the companies before allowing the collection of funds on it.
The advantages of an IEO are not only for the users, but also for the funders. The latter have the possibility to reduce marketing campaign, costs, timing and efforts thanks to the engagement of an existing trusted platform with a portfolio of users who can see the product on the exchange. This allows funders to focus more on the development of their project.
A last difference is the automatic process of listing tokens of an IEO on the market exchange after the ended event, in opposite with the ICO which shall reach out to exchange its tokens.

As reported by *Icobench* (2018), the IEOs market is not well developed; it is possible to find approximately 60 IEOs with a total raised of USD 266m. The majority is concentrated between Hong Kong and Singapore with an amount of USD 124.5m raised.
The most popular platform is *Exmarkets Launchpad*, with 11 IEOs; the most important in terms of amount raised is *Binance Launchpad* with USD 79m raised.

1.3 Success of ICO

The information asymmetry theory and the signaling theory play a central role to better understand the potential success of an ICO.

The information asymmetry theory was introduced in 1970 by Akerlof in his work “The Market for Lemons”.

In his work Akerlof relates quality and uncertainty and develops its research for the “car market” for its concreteness and for the easiness of understanding, not for its importance.

Let’s suppose to have four kinds of car: new car, could be a good car, a lemon (the bad one), and also this is true for the used cars. The ones who want to buy a car don’t know its quality, neither for the new nor for the used cars, what they know is the probability of distribution: q if it is a good car, $(1 - q)$ if it is a lemon. After using the car for a certain period of time, the car owner can redefine its value, increasing the accuracy of the valuation.

At this moment an information asymmetry emerges: the owner has more information respect to the buyer, he can make a better valuation having a better understanding if his car is good or not. Being the owner the only one to have the information, the price of good and bad cars remains the same, resulting in an “exit” from the market of the good cars, remaining only the lemons traded to an excessive price (Gresham’s law).

The theory of signaling was introduced in 1973 by Spence in his work “Job Market Signaling”.

In his work Spence tries to identify, for the job market, the right “signals” to predict if an employee could be a good investment for a company or not, before hiring him.

This theory can also be linked to the “car market” substituting the car with the employee; it tries to fix this relevant problem of information asymmetry and this theory can be generalized for the entire market categories.

Spence wants to analyze the signals from the job candidates to understand if these are real or fictional, because the candidates want to spread their signals either they have it or not. They do this for catching the attention of the recruiters and obtain a job.

In this specific case Spence analyses the level of education to better define the quantity of salary to pay for different employees.

An important role is represented by the cost of signaling, the cost related to the possibility to make adjustments, through the manipulation, by the job applicant. At this point it is impossible to distinguish an applicant from another, up to the cost of signaling has a negative correlation with productive capability.
Having this negative correlation, the worst applicants shall spend a lot of money to look like the best ones, resulting in a cost higher than the effective increase in salary.
At this point, education becomes a credible signal permitting to firms to decide how much to pay their employees.

It is relevant to affirm that the preceding two theories are decisive for the description of the process of success of an ICO.

One of the main hurdles of an ICO is the information asymmetry. It is emphasized by three different aspects: first, the technical environment that requires a deep knowledge or propension to technology innovation; second, the investment risk because ICOs are usually situated in early stages of life cycle and their tokens have not a counter value in real world and there is also an high possibility of fraud. Third, the absence of disclosure requirements and anonymity, in fact the ventures prefer to disclose few information or nothing at all and in another case some teams want to remain anonymous, not reveling nothing about them, using pseudonymous making impossible the tracking of their account.

To mitigate this big issue, we can adopt the framework of the signaling theory: studying the entrepreneurial finance we know that, investors want to find a team with strong technological capabilities, or also called "intellectual capital", that is considered crucial for the success of the investment. For an ICO, this leads to a higher possibility of a higher value of the token, higher utility, dividends or return that are the major motivation of an ICO investor, who can sell the tokens on the secondary market at the conclusion of the ICO period.

To define the quality of a venture, looking at the "intellectual capital", we need to create a link with some observable features that can be used to assess the underlying quality.
To signal this quality there are three indicators (Fisch et. al., 2019):

1. Patents: they are considered, as already seen in prior research in entrepreneurial finance, an effective signal. First of all, they are published publicly and communicated by the venture and, moreover, they are costly to acquire considering the effort of the ventures that increase with the inability. For this reason, patents become a strong signal of quality, due to the impossibility of the low-quality venture to develop patents in an easy and cheaply way.

2. Technical white paper: it is a key document, a standard for all ICOs, containing the technical description of the project, its implementations, functions and uses, needed to show the level of the technological expertise. Sometimes potential investors are not able to clearly and completely understand the underlying technology and its applications, assigning, in this way, a high capability and proficiency to the ventures. Also in this case, such as for the patents, the costs are directly linked with the technological capabilities of the ventures; for this reason, this type of document becomes crucial in the overall valuation.

3. High-quality source code: the code is a standard for ICOs, so at first sight, it doesn't show nothing of relevant importance, but, analyzing it deeply, different types of quality can be identified, linked with the possible success of the investment. To understand it, not being the investors an expert in programming codes, they can find a collection of codes on GitHub platform, organized in repositories by different quality and complexity.

1.4 Social Network Analysis

Social Network Analysis is the process of studying social structures using the theory of network and graph. It sees the world as a set of nodes, that represents people or other entities, and edges linking them that take into account interactions among everyone.
The fundamental assumption is that every individual relates to others and this interaction shapes and changes the behavior of both.

This field of study has gained a relevant significance in the last decade.
Thanks to the creation of the internet, people are now able to keep relationships with everyone around the world, having interaction is never been easier. Networks are really developed, branched and widespread and be able to correctly analyze them lead to a strong competitive advantage.
That is why more and more companies are now using Social Network Analysis, they want to study their customers and understand their behavior, extrapolating information that can drive future product development and help the understanding of people's needs.

1.4.1 History

The actual Social Network Analysis is developed from the studies of Jacob L. Moreno, a psychiatrist that in 1930, introduced this methodology to support a group of sociologists, who wanted to study people. In his work, J.L. Moreno sees person, organization or other entities not as stand-alone structures, but analyzing their relationships in the network it is possible to find out how they behave.
The scientific attention regarding this study lasted only for a few years even if during the years, similar versions were also repurposed. One, in 1936 by the German psychologist, Kurt Lewin, that analyze social psychology using a social network approach.
In the same period also in the field of anthropology, it was conducted social network research by W. Lloyd Warner, that used the approach for studying two American communities.
However, these two studies didn’t have the same relevance as the first one and they were not able to improve the visibility of the social network analysis in the scientific community.

The theme returned popular in 1970, when a professor of Harvard, White, together with his students defined a generalized framework of the research topic, going to structure a clear line of studies.

Thanks to their provision, Social Network Analysis started to be considered and defined as a field of research.

In 90s, Social Network Analysis started to be recognized and appreciated also in the Physic world; indeed first D. Watts and S.H. Strogatz with their studies on the small world and then A.L Barabàsi and R. Albert with their studies on the distribution of the degree centrality, enlarged the relevance of Social Network Analysis.

With the advent of the internet, researchers found new applications of Social Network Analysis, using it to study the network of computers for example, Freeman in 2005, or to find the influencers inside the network like De Valck in 2009.

1.4.2 Main Concepts

A social network is a social structure composed by nodes that are linked among each other through edges. Each node represents an entity and each edge represents a type of connection, that can be friendship, marriage, common interest, money transaction...

According to Haray and Barnes, Social Network Analysis has a strong relationship with the Graph theory, in fact it considers and analyzes the social connection through the presence of nodes and edges. Moreover, Social Network Analysis can measure the social capital of an entity inside the network.

The social capital is the value of the person or of the companies inside the world of reference. With the Social Network Analysis it is studied how entities relate among each other and the quality of their relationships instead of looking at their characteristics.

In order to better explain basic concepts of Social Network Analysis, it is necessary to introduce how the graph theory works.

K. Ruohonen, in his work "Graph Theory" (2013) defined a graph as a set of vertices V and a set of edges E that are used to connect vertices.

The graph obtained can be expressed also in matrix form: a graph G formed by V,E can be represented in a "n x n" adjacency matrix $F = f_{ij}$, with n that is the number of V and f_{ij}, gives the number of links between node i and node j.

Now it will be introduced the most important definition that referred to Social Network Analysis:

- Centrality: it gives a first measure of the social power of a node. It is based on the capacity of an entity to well connect the network.

- Centralization: it indicates how much centralized is a network. The more is centralized, the more the edges come from one or a few nodes.

- Degree: it is the sum of links that an entity has with others in the network.

- Bridge: a tie is a bridge if its presence makes possible to connect two entities that otherwise would be into two different group.

- Betweenness: it measures the importance of a node within the network, and its ability to have control over information passing between others.
  High level of betweenness means that a node is essential due to its removal could disrupt the communications between the other vertices.

- Closeness: it measures how much vertices are near each other. It gives the capability to have information through the ramifications of the structure of the network.

- Density: Network density is the proportion of edges of the node on the possible total number of edges.

- Prestige: it is the centrality of a node but referred to a direct graph.

- Radiality: it is a measure of the capability of the nodes to provide new information to the network and take into account its capability to influence other nodes.

- Structural cohesion: it is the minimum number of members required, in order to have a group, under its value there would be a disconnection of the cliques.

1.4.3 Measures of Centrality

The social network analysis is conducted through the application of its centrality measures. It will be listed the main centrality measures, their characteristics and their application

The degree centrality Deg_{cen} is a simple measure that counts how many links a node has. It can be split in two measures if the network considered is a directed network: in one hand there is the in-degree centrality, number of incoming links, in the other, out-degree, number of outcoming links. So, it is possible to define the degree centrality as:

"A node is important if it has many neighbors, or, in the directed case, if there are many other nodes that link to it, or if it links to many other nodes."

The formula for the degree centrality for a node *i* is:

$$Deg_{cen(i)} = \sum_{j} a_{ij} \quad \forall j \neq i$$

Equation I – Degree Centrality Formula

<u>The Eigenvector Centrality</u>

The eigenvector centrality Eig_{cen} is a natural extension of degree centrality. Regarding the in-degree centrality, it counts one centrality point for every link a node receives, considering all nodes with the same weight and importance. The eigenvector centrality makes this distinction between the nodes and it is defined as:

"A node is important if it is linked to by other important nodes."

The main difference between the in-degree centrality is that a node which receives many links does not means that has necessarily a high eigenvector centrality, due to these links could have low or null eigenvector centrality; moreover, a node with high eigenvector centrality is not necessarily linked with an high number of links, few links but very important.

This type of centrality, considered as a ranking measure, is an old method used for the first time by some pioneers such as Leontief, W., W., and Seeley, J., R., in the first half of 19th century.

The formula for eigenvector centrality, considering λ the largest eigenvalue, is:

$$Eig_{cen(i)} = \frac{1}{\lambda} \sum_{j} a_{ij} * Eig_{cen(j)} \quad \forall j \neq i$$

Equation II – Eigenvector Centrality Formula

The Betweenness Centrality

The betweenness centrality Bet_{cen} analyzes the relations between vertices: vertices with high betweenness centrality may have a particular influence and importance within the network, thanks to their control over information passing between others. These vertices are essential due to a removal of one of them could disrupt the communications between the other vertices.

This type of centrality differs from the other measure: a vertex can have quite low degree and could be connected with other low degree vertices, but still have high betweenness. To explain better the mean of this sentence it is possible to define it through an example: if a vertex A has low degree and the relative connections are with other low degree vertices, but it represents a “bridge” between two different groups in a network, so every nodes to communicate shall go through this bridge, node A acquires high betweenness centrality even though it is not well connected.

The betweenness centrality formula is:

$$Bet_{cen(i)} = \sum_{s \neq v \neq j} \frac{\sigma_{s,t}(i)}{\sigma_{s,t}}$$

Equation III – Betweenness Centrality Formula

It represents the sum of the ratios between the number of shortest paths $\sigma_{s,t}$ connecting every pair of nodes *(s, t)* in the network and the number of those that transit through an edge linked to node *i*. The role of this measure is also seen such as the figure of a "broker" , that connects between others the nodes in the network.

Nodal efficiency

To explain in a clear way the nodal efficiency it is necessary to pass before from closeness centrality: it measures the mean distance from a vertex to other vertices, considering the shortest path possible present in the network. To use correctly this type of measure is necessary to have a completely connected network, for this reason we shift to the nodal efficiency Eff_{cen} defined such as the inverse of the average length of all the shortest paths from a certain node to all the others in the network, here defined as $d_{i,j}$. Where the connection is not present, the distance would be infinite, but in the specific case the inverse is set to zero. The formula for nodal efficiency is:

$$Eff_{cen(i)} = \frac{1}{1-N} \sum_{j} \frac{1}{d_{i,j}} \quad \forall j \neq i$$

Equation IV – Nodal Efficiency Formula

Page Rank

Page Rank was introduced by Google Search in order to classify web pages and apply it to their search engine. It is their first and most famous algorithm.

It is based on the classic measures of Social Network Analysis, indeed it could be considered as a variant of the eigenvector centrality.

It asses the importance of a web page counting the number of links that it receives from other website and checking their quality.

1.4.4 Main Application

How already seen, in its life the Social Network Analysis has been applied in various and diversified fields.
It will be presented now the most recent works, that highlight how this methodology is still now very used and of relevance.

In 2004 Nicholson et al published research about the board's structural social capital created as a consequence of interlocking directorates. Applying the Social Network Analysis and its measures, they compare the network of the executives of the best 250 companies in the US and Australia.
In the United States, the network is much larger and more connected than its counterpart. They understand that the use of measures of interpersonal links and traditional measures of inter-firm links are important when scholars study the resource dependence role of boards

As a consequence of the comparison, three important points are evidenced for the study of the network.
First, larger network is able to provide more connections in respect to the smaller one, giving a higher level of potential opportunities.
For example, larger network means greater access to knowledge for a company, moreover, information and innovation could spread along the network faster, leading to a strong reduction in information asymmetries and in innovation competitive advantages.
Second, in the larger network of the United States, directors can rely on a network with a greater level of potential that make him/her able to build and exploit human capital.
Last, the work suggests that it is the human relationship that board members make with board members of other companies that significantly improve the social capital of the firm. In fact, it is the interlock between firms that make possible the rise of interpersonal network.
If the network is full of links, it becomes so dense, large and centralized that directors find themselves in a single communication network. For directors, this is a possibility to improve the social capital of boards and so enhancing the firm performances.

Horton et al in 2012 applied the Social Network Analysis to measure how much directors are connected in the director network.
The paper shows that compensation is related to the characteristic of their social connections. Chiefs and outside directors, that have a brokerage position (with a high level of betweenness centrality) reach higher level of compensation.
Moreover, the results highlight that the aggregate connections are positively correlated with future performances.
Nevertheless, these results are inconsistent if managerial power is taken into account, while are relevant with executives receiving compensation for the resources, they are able to add to a firm.

To sum up, connections are beneficial to the executives but also to their firm.
Some clarification needs to be done:
First, the social network of reference is not complete, indeed social ties that represent directors' interlocks do not represent all the possible ways of relation through which an executive can have important information like for example political activities.
However, these ties add confusion to the network leading to a potential reduction of the network effect.
Second, authors have studied how human capital can predict social capital measure, but the other way round has to be considered: directors with higher abilities have a higher probability of arrive in a better network position.
And last, there could be the common mistakes that happen in this type of study, such as a missing variable that could change the results.

In the last years, new articles about how some IPO characteristics are correlated by the location of its underwriter in the network of investment banks have been conducted using Social Network Analysis.

Bajo et al. in 2016 created a network of underwriters where the edges are given by a previous syndicate underwriting.
In the paper is developed the hypothesis that investment Banking network helps IPO underwriters to spread disclosure information during the IPO process.

This has to induce authorities to pay attention to the firms that are going to be listed for two main reasons:

The lead underwriter could spread information through its relationship to transmit signals about its IPO companies to institutional investors; moreover, on the other way round, the network can assist the main underwriter to get useful information to correctly price the company.

The main evidences of this work are:

IPOs conducted by more than one central lead underwriter are associated with biggest absolute values of IPO price offer.

Second, IPOs conducted by more than one central lead underwriter are linked with Higher IPO initial returns and better secondary market valuations

Third, IPOs conducted by more than one central lead underwriter are able to attract more people and make a strong participation from financial market players.

Lastly, IPOs conducted by more than one central lead underwriter are characterized by a higher probability to have a higher level of secondary market liquidity and greater iso long-run returns

1.5 Product Space

After making a general overview about the ICOs' world and the importance of the Social Network Analysis, here below we are going to explain the main study that we have applied in our work.

1.5.1 What is the Product Space?

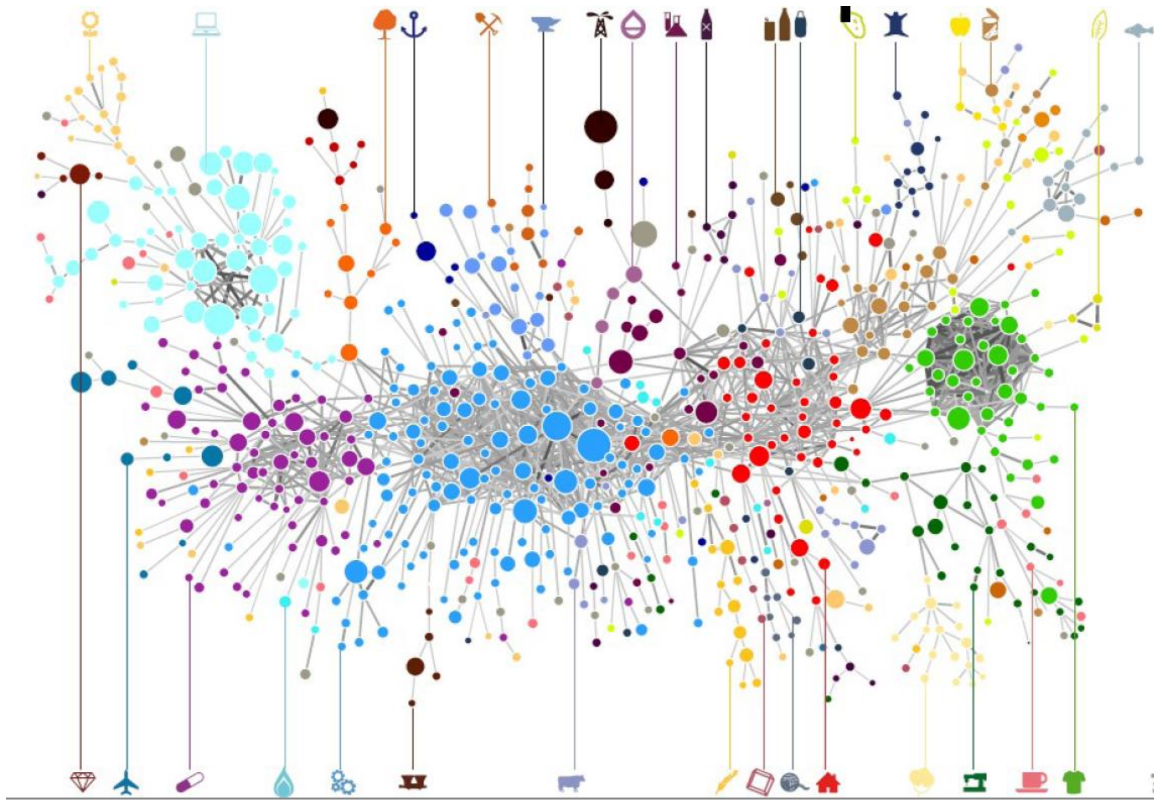


Figure V – Product Space

The product space is a representation of all products exported in the world.
Nodes represent products and their size is proportional to world exchange of that asset. Connected products are characterized by a high probability of being co-exported.
The space reveals that many assets group naturally into communities where there are lot of connection. This can lead to the idea that products in these communities are based on similar capabilities.

Already at a first glance the product space appears highly heterogeneous, its main characteristics are the presence of a central nucleus, with a lot of connection, and a periphery, in which there are few connection between less sophisticated products. This can explain the difficulty of the poorest countries to converge towards the productivity levels of other countries.

The product space can be seen as a forest in which each tree represents a product. Each country is made up of companies that produce goods. We assume that companies are like the monkeys, that inhabit the forest, live on trees and exploit them.

Often the forests are not homogeneous, they are composed of areas where the trees are thick and rich of fruit and areas where the vegetation is sparse and poor.

In this analogy, the economic development of a country can be seen as the ability of monkeys to jump to the best areas of the forest and settle where it is possible to find more food.

If apes are companies, every jump from one tree to another involves a redistribution of human and physical resources and of the productive factors used by the organization.

This redistribution is between the goods that were initially produced, before the jump, and the new assets.

If the same analogy is applied to traditional development theories, the structure of this forest should not be very important, and all trees should be equally reachable by the apes.

But we know that these animals can only jump up to a certain distance, so it is not just important to know the structure of the product space, but also to identify the position of each country (of its monkeys).

This can avoid the risk that the economy of the country remains blocked in poorly connected parts of the forest.

With the purpose of finding relationship between products, Hausmann and Hidalgo adopted a novel ex-post approach, starting from the results: since two goods are produced in tandem, then they will be more likely to be linked. This approach was different than connecting two products ex-ante, investigating on the factors that determine the connection between the various products such as the similarity between inputs involved during the process..

The entity that considers this type of ex-post connection is *Proximity*.

Proximity is the measure that formalizes the intuition the country's ability to produce a good depending on its ability to fabricate another.

A useful example to understand this has been made by Hausmann in 2007: if we take a country that exports apples, it certainly will have the land and the climate suitable for apples' growth and maturation, it will have the packaging technologies and proper transportation system and it will have several qualified agronomists. It seems very likely that this country could have all the necessary conditions to export pears as well. Instead looking at a completely different product space, appliances for example, most of the skills developed for the apple market would be totally useless.

Formally the proximity ϕ_{ij} between two products *i* and *j* is calculated as the minimum of the conditional probabilities that a country has to export a good, since it exports the other.

$$\phi_{ij} = \min\{P(RCAx_i | RCAx_j), P(RCAx_j | RCAx_i)\}$$

Equation V – Proximity Formula

It is essential to take the minimum of the two values returned by the probabilities; indeed, in the case of countries that are the only exporters of a given product, the conditional probability of exporting any other good, since it exports that, is always equal to one. But since the opposite is not true, thanks to this passage, the error is avoided.

In the formula, RCA stands for Revealed Comparative Advantage. It is the Hungarian economist Bela Balassa who suggested calculating the comparative advantage of a nation with a new method: instead of trying to predict what countries will export by analyzing the opportunity costs of countries ex ante, it will be enough to simply observe the trend of international exchanges ex-post since they reveal what are the comparative advantages of the various States.

$$RCA_{ci} = \frac{\frac{X_{ci}}{\sum_c X_{ci}}}{\frac{\sum_p X_{ci}}{\sum_{c,i} X_{ci}}}$$

Equation VI – RCA Formula

$RCA_{c,\,i}$ tells us if a country c exports a quantity of good i, expressed as a fraction of its total exports (to the numerator), greater than the average share of global trade (in the denominator).

1.5.2 How Product Space is Developed

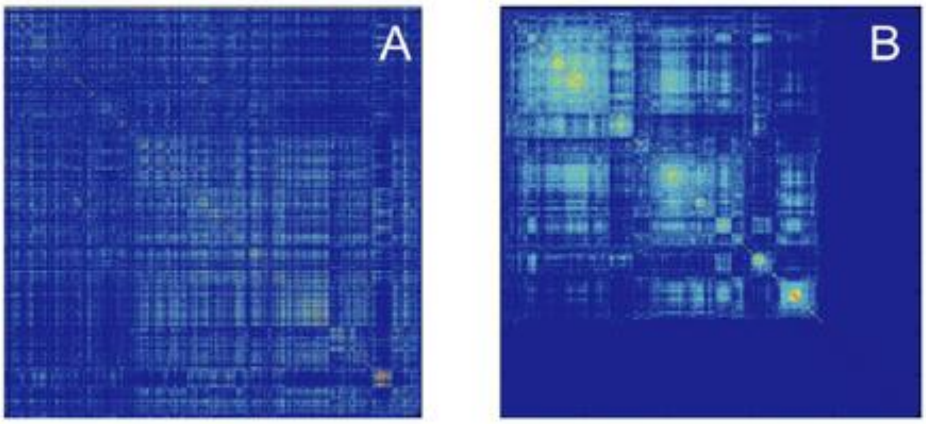


Figure VI – Product Space Matrix.
A: Product Ordered Following the SITC. B: Product Grouped into Communities

The product space can be represented by a matrix built using the proximity ϕ_{ij}:
Each row and each column represent a product, while all the intersections measure the proximity of the pairs of goods to which they correspond.
On figure A the order of the products is given by the Standard International Trade Classification (SITC). SITC is a classification of exported goods conceived by the United Nations and used to recognize and trace goods in international trade.
On figure B the matrix is re-organised and re-arranged to create homogeneous clusters by medium connection. It was noted that only 775 of products are really part of the product space, while the others, which correspond to empty rows and columns, are not traded.
A blended and homogeneous product space should imply uniform values of ϕ_{ij}, indicated with homogeneous colors, whereas the product space in the figure seems to be modular, with some very connected goods and others independent.

The distribution of proximity values reveals that ϕ_{ij} assumes very different values and moreover the 5% of its observations is equal to zero, 32% lower than 0.1, and 65% equal to 0.2, revealing a generally sparse product space.

The next step is to generate a network representation of the matrix, in order to visualize it and investigate the structure of the product space and the dynamics of the countries within it.

To insert all the products in a single connected network, avoiding island of isolated good, it is necessary to calculate the maximum spanning tree (MST) on the proximity matrix.

MST is formed by the links that connects all the nodes in the network employing the minimum connections' number and the maximum possible sum of proximities.

Thus, the output is the set of N - 1 connections that connect all the N nodes so that the sum of the proximities is maximized.

After that, the primary structure is formed, all the stronger connections that are not already in the MST and that are higher than a certain threshold are then added. Setting a proximity of 0.55 as threshold, it is obtained a network with all 775 nodes and 1525 connections.

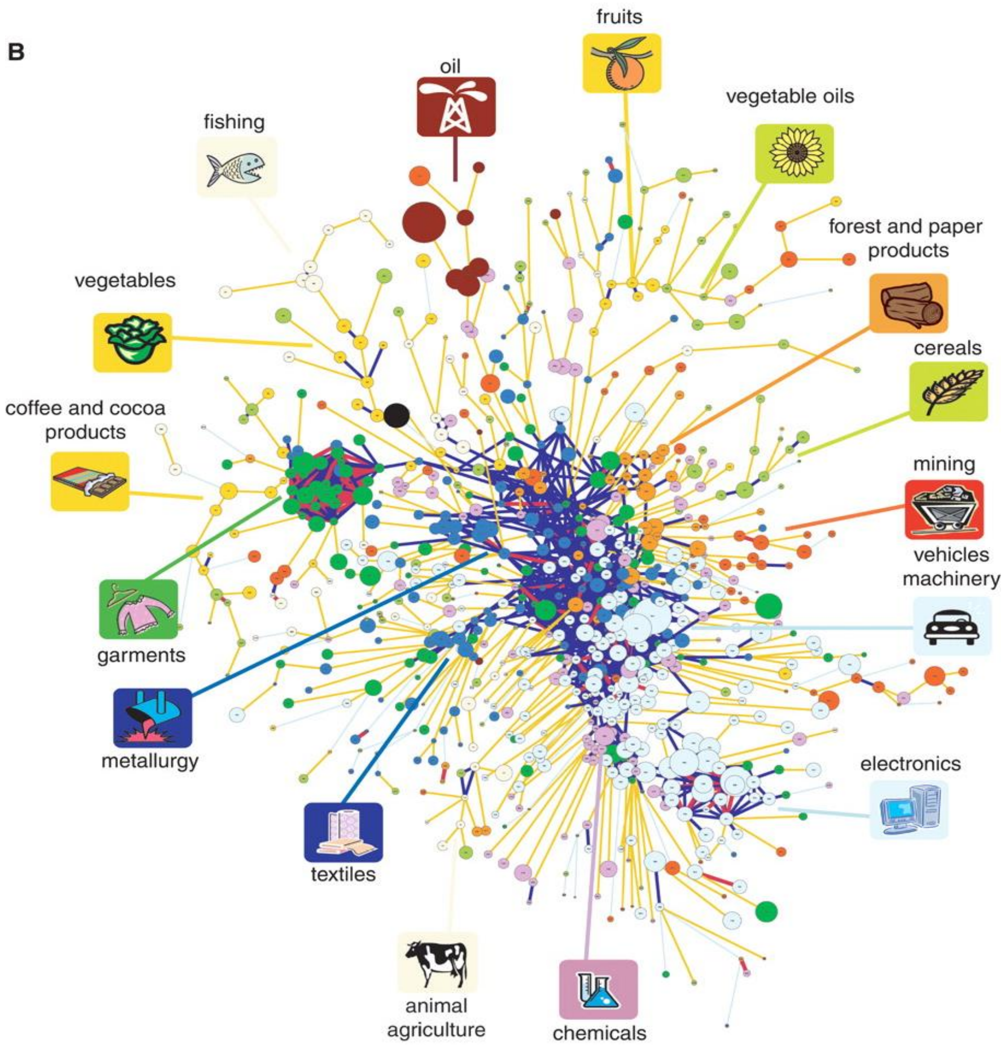


Figure VII – Product Space

Describing how the various goods tend to be arranged inside the space:

- in the core there are metal products, machinery and chemicals,

while the periphery is made up of all the other classes of goods:

- in the upper part of the periphery there are products related to fishing, tropical agriculture and cereals,

- in the area on the left, there is an important agglomeration on clothing, followed by that of textiles and cattle breeding,

- the bottom of the periphery is composed by the large cluster of electronics,

- in the right-side there are mining and forestry products.

The first feature of the network tested Hausmann was its ability to group products into clusters. For this purpose the nodes of the network have been marked with different colors, according to the division into ten classes proposed by Leamer (1984) (the first and second classes are composed by primary products, from the third to the sixth there are various types of crops and livestock of livestock, while the last four categories concern different types of products in the manufacturing sector).

Products belonging to the same class are close together and tend to form clusters. It is interesting to observe that, even if the Leamer classification had been completed with a different methodology, when investigating the quantities of production factors, capital, work and skills needed for the producing goods, there is a high similarity between its results and the structure of the product space.

Moreover, the product space seems to offer a more detailed division for some product classes.

For example, machinery is naturally divided into two agglomerations, one consisting of vehicles and heavy machinery and another that belongs to electronics.

1.5.3 How is Positioned a Country in the Product Space

In order to analyze which is the position of a country inside the product space, it is necessary to introduce a new measure to describe the position of an element in the space.

What is used is based on the work of Hausmann, Hwang et al. (2005), which involves a two-stage process.

First, for each product it is assigned a value, called PRODY:

$$PRODY_k = \sum_j \frac{\frac{x_{jk}}{X_j}}{\sum_j \frac{x_{jk}}{X_j}} Y_j$$

Equation VII – PRODY Formula

where x_{jk} are the total exports of the good *k* from of the country *j*, X_j are the total exports of of the country *j* and Y_j indicates the per capita GDP of nation j.

We could therefore say that PRODY is a weighted average of the GDP per capita of those countries that export that good, where the weights reflect RCA that each state has for that product. Usually, most sophisticated goods are exported from richest countries. From the definition of PRODY, we can understand that fluctuations in its value over time are connected to a plurality of causes: countries that export k can change, but also the GDP of these countries or their degree of specialization.

Secondly, it is calculated the average of the PRODYs of the first N products to which a country access after M repetitions at ϕ_0 and indicated it with $< PRODY >^N_{M\phi_0}$.

From product space studies, it is emerged that:

- Countries are divided into two categories: rich ones, producing goods located in the core of the network and poor ones, whose products are in the periphery.

- Not all countries have the same development opportunities: these differences, present also among countries with similar levels of exports, can be attributed to their different production structures. Some of them are on the path of structural transformation and economic growth, while others are stuck in a blind alley.

1.6 Economic Complexity

Nowadays societies can achieve large amounts of productive knowledge thanks to the fact that this knowledge can be divided into bits and pieces and given to many.

But, to use this knowledge, capabilities have to be put back together using organizations and markets.

Our society is wiser, not because people are smarter, but because we have a diversified know-how and we are able to combine it in a larger variety of product.

During the last decades however, even if models of economic growth have taken into account that the variety of input used for the production of goods by a nation has an impact in its overall productivity, there have been few efforts to transform this intuition into data (Hausmann, Hidalgo et al., 2007).

1.6.1 What is Economic Complexity

All the goods that are produced have been made with the use of machinery, raw materials and labor. These elements alone, however, would not be sufficient to justify their large variety.

Equally important elements, are the knowledge and the set of knowledge necessary to design, develop and implement new assets.

To act as intermediaries between the products and the information required for their realization, there are engineers, chemists, physicists, doctors, mechanics, people who know how this knowledge can be translated into practice.

Only by relying on the specialization of each of them in the related branch of the sciences, society can access to an amount of knowledge that it could not be reached individually.

If the products are seen as vectors of this knowledge, then the market, the place where these products are exchanged, acts as a connector of competences and information available around the world and guarantees free access to them.

Through the presence of products in the market, the knowledge by a few can reach many. In a society, the more different pieces of information are present, the more you can combine them, make use of them and make them interact as in a network, the greater is the degree of knowledge that society can incorporate.

Knowledge can be codified or tacit. The first is certainly easier to transmit and teach: it is available in books, ready to be read or listen to.

The differences in production would be erased in a short time if only this type of knowledge existed.

However, most knowledge is tacit, and therefore difficult to transmit and absorb.

The crucial point of both the process of growth and development of knowledge converges here: not transmit it would mean letting it disappear together with people or products that contain it, but incorporating it is an expensive and time-consuming path.

Constantly notions and sciences expand in the world.

The easier strategy that we learned and adapted from Adam Smith to face this expansion is the division of labor and the consequent specialization of people.

Therefore, it is important that the “blocks” of knowledge, each individual specialized in, are coherent among each other, so that he can best achieve his work.

To refer to these “blocks”, the Hausmann and Hidalgo used the term *capabilities*.

Given the complexity of many of the products, the collaboration of several individuals is often required, so that their capabilities can interact for the production.

Rarely a couple of people is enough, sometimes it is needed a hundred or even more; this is why networks of people were born. A network is the organizations of people, in which is developed the form of collective and shared knowledge necessary to make the system work.

As Hausmann and Hidalgo said in their Atlas:

> *“Economic complexity is expressed in the composition of a country’s productive output and reflects the structures that emerge to hold and combine knowledge”.*

f

The more complex a nation is, the greater the amount, variety and connection of its capabilities.

A strategy adopted to reveal the Economic Complexity of a nation is to start from the composition of its production: countries do not produce the goods they need to realize, but those that they are able to achieve (Hausmann, Hidalgo, 2009).

1.6.2 How Economic Complexity is measured?

A country expresses its amount of knowledge through the number of different products it produces. If a nation has a wide range of knowledge, it can also produce numerous different types of assets. In addition to this, it can be deducted that products that require many notions and skills to be realized can only be implemented in those few countries where all those capabilities are available simultaneously. This allows the definition of two concepts:

- *Ubiquity*: the number of countries that make a product.
- *Diversity*: the number of products made by a nation.

Hausmann and Hidalgo to make the concept clearer use an analogy with the game of scrabble. In this game participants have to compose words using tiles with single letters. In the analogy, each word corresponds to a different product, while each letter represents a *capability*.

Measuring Economic Complexity is like trying to estimate both what fraction of the alphabet a player has, knowing how many words he can compose and how many other players are able to make those same words.

Obviously, the participants who have a greater number of letters will be able to compose more words: this shows that the diversity of the products of a country is strongly connected to the number of capabilities that it possesses. In addition, long words are rarer in the game. This also finds a match in reality: more complex goods are less ubiquitous.

Not all states possess the vast type of knowledge that these goods require for their realization. The number of players who manage to create a word tells us a lot about the variety of letters needed to build it, in fact a less ubiquitous product usually requires a great variety of capabilities.

Starting from the production mix, it is possible to see diversity as an approximation of the variety of capabilities available in each country, while ubiquity estimates how many capabilities are required for the production of a product.

Another factor that influences the dynamics of the game is the existence of rare letters, such as the X or the Q. Those who own them are able to compose words that few other players are able to create. Similarly, those who control particular natural resources that are not very

common because there are only in few places or are formed in exceptional environmental conditions, possess a distinct advantage over all others.
The scarce ubiquity of a product can therefore be caused both by the high number of capabilities that its production requires or by the scarcity of resources, and often it is not easy to determine which of the two is the real reason.
In the scrabble game, it is easy to understand looking at how many other words, different from the rare one, the player can build.
If the words created by the player with a rare letter are few, it is reasonable that the scarce ubiquity is due to the rarity of some letters, so the player is just lucky. If instead he manages to compose many other words besides the one containing the rare letter, this can be a sign of the great availability of letters of the player, which allowed him to compose even the longest and most complex ones.
Taking into account the case of natural resources such as diamonds: they can be found only in few countries, so the product is characterized by a low ubiquity. It is difficult to believe that is linked to the complexity and the large amount of knowledge needed to extract diamonds.

Diversity and Ubiquity are two separate measure but reciprocally one can be used to correct information carried by the other.
This process can be repeated infinite times using mathematics; correcting diversity with a ubiquity's measure that has already been adjusted by diversity and the other way round.
After some iterations the value converges, and it represents the *Economic Complexity* quantitative measures.

First time that Hidalgo and Hausmann in 2009 apply the theory, they develop the Method of Reflections and apply it to data of trade in order to show how it is possible to extract information about the presence of capabilities in a nation.
They rely on international trade data sources such as SITC, COMTRADE and NAICS.
They elaborate these data as bipartite networks in which nations are linked to products they export.
This network can be represented with the adjacency matrix M_{cp} that is equal to 1 if nation c is a significant exporter of product p, and to 0 otherwise.

In order to see if a nation is a significant exporter of an asset, they use the concept of Revealed Comparative Advantage (Hidalgo and Hausmann et al.,2007):

$$RCA_{cp} = \frac{\frac{X_{cp}}{\sum_c X_{cp}}}{\frac{\sum_p X_{cp}}{\sum_{c,p} X_{cp}}}$$

Equation VIII – RCA Formula

“It measures if a country c exports more of product p, as a share of its total, than the average country”.

They consider a country to be a significant exporter of a product if its RCA is greater or equal to 1.
Due to the fact that the matrix M_{cp} is symmetric, the Method of Reflections gives a symmetric cluster of variables for both countries and products.

“Method of Reflections consists of iteratively calculating the average value of the previous-level properties of a node’s neighbors and is defined as the set of observables:”

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} * k_{p,N-1}$$

Equation IX – Method of Reflections Formula

$$k_{p,N} = \frac{1}{k_{p,0}} \sum_c M_{cp} * k_{c,N-1}$$

Equation X – Method of Reflections Formula

When N = 0, it is given the country's diversification and the ubiquity of a product:

$$Diversity = k_{c,0} = \sum_{p} M_{cp}$$

Equation XI – Diversity of a Nation Formula

$$Ubiquity = k_{p,0} = \sum_{c} M_{cp}$$

Equation XII – Ubiquity of a Product Formula

Taking into account country, even variables (such as $k_{c,0}$ $k_{c,2}$ $k_{c,4}$…) represents generalized measure of diversity, while odd variables ($k_{c,1}$ $k_{c,3}$…) gives a measure of products' ubiquity. In terms of network analysis, $k_{c,1}$ and $k_{p,1}$ can be seen as the average nearest neighbor degree.

1.6.3 Why is Economic Complexity Important?

Once the level of Economic complexity of a country (ECI) is defined through the Method of Reflections, it is possible to exploit these indexes.
Relating the ECI to the GDP of the country shows the existence of a positive relationship: the Economic complexity is linked to the level of prosperity of a country.
Countries with an ECI higher than expected, given their GDP, have a faster growth compared to those that are too rich compared to their level of Economic Complexity: complexity seems to drive and stimulate the wealth of countries.
Complexity can be seen as a driver of future economic growth.
The ECI is able to explain the differences in the income of different nations.
Moreover, the ability of the ECI to predict future economic growth suggests that countries tend to arrive at an income level that reflect their overall level of internal know-how; if this does not happen, the income evolution is corrected through more or less accelerated growth.
The key to predicting the future growth of a country is therefore to know the difference between the level of income and its complexity.
Good levels of Economic Complexity are often difficult to reach; however, the more complex countries are, the greater the rewards in terms of well-being that they could afford is.

1.6.4 How is Possible to Develop Complexity?

The complexity of a country's economy reflects the amount of productive know-how it has. Societies increase the amount of their productive knowledge by moving towards products that make use of the capabilities that are already available.

These capabilities are available, however, because they are used to make other products.

Developing complexity is not always easy.

The capabilities, which are the foundation of a society's knowledge, are difficult to accumulate; on the one hand, a country cannot create products that require capabilities that it does not have.

Moreover, there are few incentives to develop new capabilities if there are not yet industries are able to use them.

The circularity of this problem slows down the process of developing complexity.

In the product space, products that are closely related, share most of the capabilities they need to be made.

The simplest way that countries can take to increase their complexity is to move towards goods closer to those they already produce.

Most probably for the realization of these products there are needed capabilities already present in the country and others that are to be developed.

It is possible to learn about the productive structure of the various States, their ability to develop and increase their Economic Complexity by observing the evolution of their positions within the product space.

To continue with the forest analogy, one could say that the development process, which involves increasing diversity and complexity of production can be seen like monkeys that colonize the forest, occupying more trees and moving mainly towards the more complex ones, the trees with more fruits.

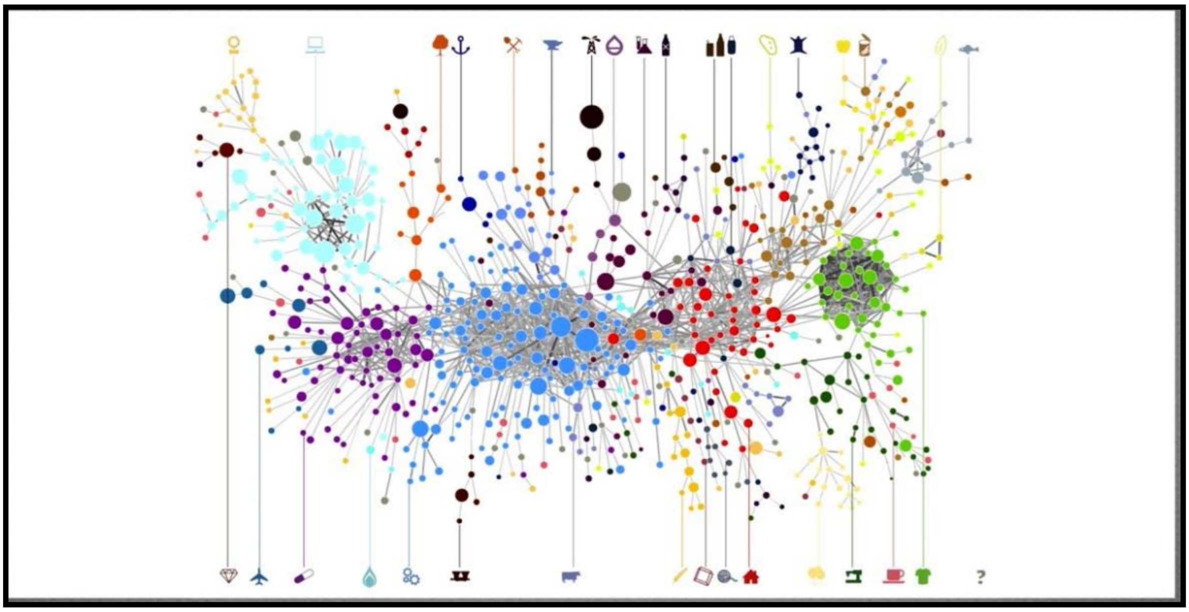


Figure VIII – Product Space Revisited with Node Sizes Proportional to the Product Complexity Index (PCI)

Have a deep knowledge of the characteristics of the product space allows people to fully exploit its potential.

Starting from a slightly different representation than the standard one, where the dimensions of the nodes are not proportional to the quantity of that good exchanged in the global trade, but they are proportional to the complexity of the products that indicate, it is possible to highlight some finding.

This representation with PCI shows that goods' communities tend to have similar levels of complexity, indeed nodes of the same color are similar even in size.

Visually it seems that the complexity of the products is greater in the center than in the periphery and that it grows progressively from right to left.

To produce the goods in the right area, few and "traditional" capabilities will be needed, while the products on the left require a greater number of capabilities.

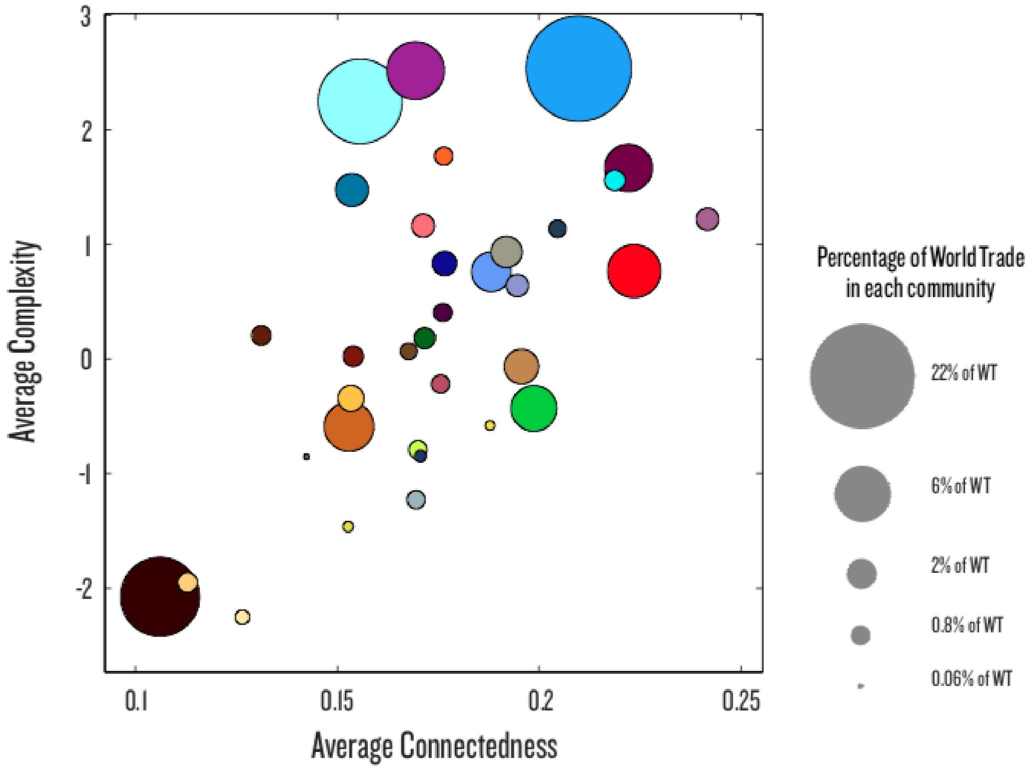


Figure IX – Average Complexity of the Products in each Community as a Function of its Connectedness. Size of the Bubble is Proportional to Community's Presence in World Trade

To further analyze the peculiarities of the product families it is necessary to introduce a new measure: the *Connectedness*. The connectedness is indicative of how a community is centrally located in the product space and is calculated as the average of the proximities of the products of that family compared to all other products. In the above figure this measure is related to the average complexity of products within the community (average PCI).

This comparison confirms the existence of a positive relationship between how the communities in the product space are centered and how complex the products that compose them are. Poorly connected communities such as oil (dark brown), cotton, rice and soybeans, that are situated at lower left corner tend to have low complexity.

On the other hand, machinery community (light blue) is very complex and highly connected. Sectors such as clothing (light green), textiles (dark green) and processed food products are instead in an intermediate position, being rather connected, but not very sophisticated.

Electronics (light blue) and chemical and pharmaceutical products (purple) are more complex than almost all communities, but not as connected as machinery community. Their poor connection suggests that they use specific capabilities, relevant within their community, but not outside it.

Once the structure of the product space is known, it is then possible to assess the global position of a country within it.

A new concept needs to be introduced: the *opportunity value*, which calculates how far a country is from products that it does not export and how complex these goods are.

It is the value of the option to move towards a greater number of products, or towards more complex goods.

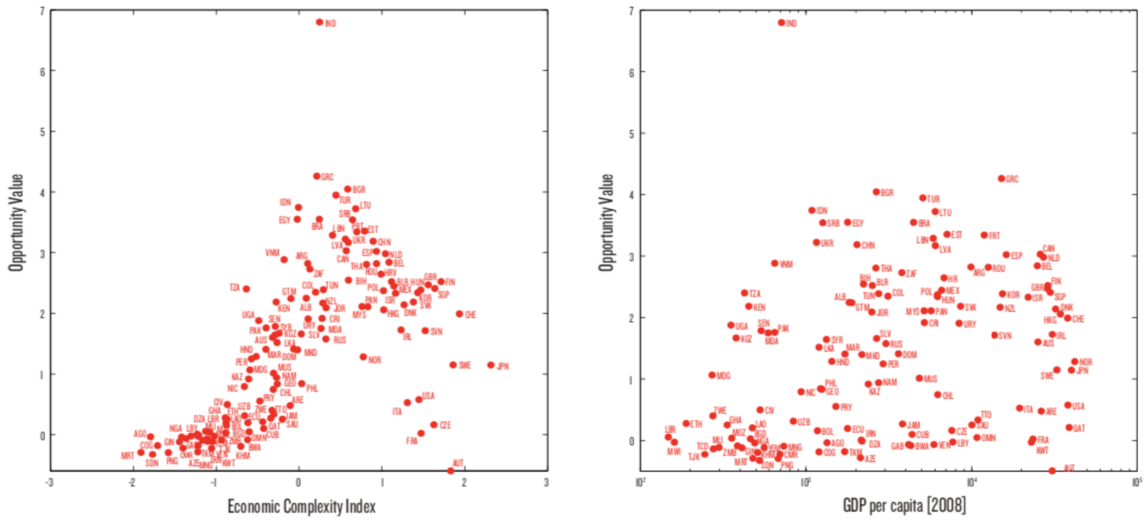


Figure X – Opportunity Value as a Function of the Economic Complexity Index and GDP per capita

The distribution of countries based on their opportunity value and ECI (figure above, on the left) shows that countries with low levels of complexity tend to have fewer opportunities available.

This is because the goods they produce tend to be peripheral in the product space.

Even complex economies tend to have fewer remaining opportunities, but because they already occupy a large fraction of the best part of the product space.

While in countries with an intermediate level of complexity, there is a remarkable variance in their opportunity value.

This difference can be seen in nations like Jamaica, Chile, that are located in areas of the product space where there are few opportunities, while others like India, Greece and Turkey are closer to the core, where there are many more.

The comparison of the opportunity value with the national GDP (figure above on the right), however, denies the existence of any relationship between these two indicators:
Countries with similar GDP, have completely different opportunities and richer ones, are not necessarily those who have greater residual opportunities.

2 Scope Definition and Research Problem Description

2.1 Introduction

Starting from the existent literature regarding ICOs and importance of the quality of network, the objective of this work is to apply the principle of Economic Complexity on the ICOs data, in order to understand if this economic field is able to correctly analyze ICOs campaigns. Furthermore this thesis has the aim of study the correlation between economic complexities measures referred to ICOs' members and the success of their campaign.

ICO projects are characterized by a strong information asymmetry, because of the absence of a screening and selection phase, that lead companies to face important inefficiencies (Stein, 2003).

This situation forces investors to based their decisions upon market signals to not catch "lemons" (Akerlof, 1970).

One signal can be the quality of the team (Javakhadze, 2016) or the enrichment of the network of a company (Ravasi and Marchisio, 2003); these explain the increase in literature of Social Network Analysis in order to achieve more information.

The next step is to analyze the interconnection of relationship through a new framework.

This work is aimed at covering the lack in the literature about Economic Complexity applied in ICOs, in order to further analyze this systems and extract as much as possible information on the crypto-funding world.

2.2 Objectives

In the last years, after that ICO phenomenon has started to be analyzed (Adhami et al., 2018; Fisch, 2019; Venegas, 2017; Zheng et al., 2017) also Social Network Analysis started to be applied to this world (Feng, 2019; Fideli, 2019). We contribute to this research, analyzing this phenomenon with a new framework: the Economic Complexity.

The aim is to see how the level of complexity related to a member of the campaign affects the performance of the funds.

Before analyzing the correlation of these measures, this work has the objective of controlling if the toolbox of Economic Complexity correctly analyzes the economic system.

This technique is able to extract information on the relationship between individuals and ICOs and to highlight the configuration of the systems.

Start-up need a high level of funding in order to scale up, however, differently from other type of companies, they are characterized by a lack of clear and reliable information. This is due to the fact that there are no historical records and no financial data about them.

When the phenomenon of ICOs became more relevant, thanks to the diffusion of the blockchain and cryptocurrencies, the information asymmetries started to enlarge.

Indeed the world linked to ICOs seems misleading, tricky and not regulated.

It has been shown that more than one ICO is a fraud, where for example team members with fictitious names are invented (Shifflet & Jones, 2018) or team disappeared after the end of the campaign (Zetzsche et al., 2017).

However, the lack of a straight control from authorities that starts to demand required prospectus too late in the year, the previous types of scams and the opacity of information can not stop the ongoing development.

This new disruptive innovation can not be seen only as something to be afraid of, indeed thanks to blockchain technology, ICO members can drastically decrease operational costs both through the use of alternative ways of financing and through the crypto-communities present on the net.

That is why is very important for us to prove the reliability of this fin-tech and we are going to do it through assessment of the level of complexity of the ICO team that is one of the signals that we can derive from the structure of the network.

It is a measure that through the quality of interconnection can explain the differences in the total amount of fundraised of several campaigns; moreover, it can be used to assess the quality of people’s work because a sound network and a respectable position inside it, is a signal for the investors for the reliability of the fundraising.

Strong relationships can lead to future advantages in the evolution of the project and in the funding campaign.

2.3 Research hypothesis

Starting from the current literature about social network analysis applied to the finance world (Xiong and Bharadwaj, 2011; Bajo et al., 2016) and, more in particular, to the crypto-world (Fideli and Giudici, 2019) and from the work of Hidalgo and Hausmann, dated 2009, on the Economic Complexity framework we these approaches to the ICO world.

Economic complexity sees a system as a bipartite network in which the level of diversification and ubiquity of the nodes explains the configuration of an economic system. The original economic-complexity index (ECI) proposed by Hidalgo and Hausmann (2009) can predict the future economic growth and success of a country.

With this work we are going to test if this approach can be applied to ICOs, and more in details to their team members.

2.3.1 Bipartite Network

A bipartite network represents the structure of the economic system and it is the basis of all the subsequent calculations.

Hidalgo and Hausmann linked together countries and products, elaborating data of nations' exports as a bipartite networks in which nations are linked to products they export and obtaining a network that can be represented with the adjacency matrix M_{cp} that is equal to 1 if nation *c* is a significant exporter of product *p*, and equal to 0 otherwise.

This representation has started to be used also in for financial systems with the aim of find useful information on risk and performance of agents (Caccioli et al., 2014; Di Gangi et al., 2018)

Our work has the intention of representing the cryptocurrencies system, through a bipartite network in which ICOs are linked together with members of the team that joined its campaign.

2.3.2 Diversity and Ubiquity

Hidalgo and Hausmann observed that a country expresses the amount of knowledge it has, through the number of different products that it produces. If a nation has a wide range of knowledge, then it can also produce a large number of different type of assets. In addition to this, it can be deducted that products, that require many notions and skills to be realized, can only be implemented in those few countries where all those capabilities are available simultaneously. Translated into two concepts, it is possible to define:

- *Ubiquity*: as the number of countries that make a product
- *Diversity*: as the number of products made by a nation

As Hausmann and Hidalgo did, to clarify this concept it is possible to use an analogy with the game of scrabble, a game where participants have to compose words using tiles containing single letters.
In this analogy, each word corresponds to a different product, while each letter represents a *capability*.
Measuring Economic Complexity is like estimating which fraction of the alphabet a player has, knowing how many words he can compose and how many other players are able to make those same words.

To justify and support the decision to use the Economic Complexity framework, it is necessary to analyze the valued obtained and verify if there is a clear pattern among them.
Only if this is the case, it will be possible to apply the Method of Reflections.

H1: Applying Economic Complexity measure to the bipartite network of ICO and member gives a clear pattern among measures.

2.3.3 Method of Reflections

Diversity and Ubiquity are two separate measure but reciprocally one can be used to correct information provided by the other.
“Method of Reflections consists of iteratively calculating the average value of the previous-level properties of a node’s neighbors and is defined as the set of observables:” (Hidalgo and Hausmann, 2009).
Working on the bipartite networks and applying Method of Reflections, after some iteration, the value of each node converges to its level of complexity.

2.3.4 Centrality Measure

Employing a wide variety of traditional centrality measures that are related with different aspects of the subject it is possible to achieve different type of information.
Usually the four centrality measures considered are: the degree centrality, the eigenvector centrality, the betweenness centrality and the closeness centrality; the latter, it is discarded in our analysis because the network we considered is not completely connected.
For this reason, it will be replaced with the nodal efficiency, developed by Latora and Marchiori (2001).
The preceding measures are applied on an adjacency matrix, connecting the members of the network.
The matrix is characterized by 1 if the two different members work together on at least one ICO and 0 otherwise.
The matrix is binary and symmetric, with 0 along the diagonal, generated from a network where the links are un-weighted and un-directed.

Here below, we list the centrality measures, already described in the paragraph 1.3.3, that will be used in our analysis.

The Degree Centrality

The degree centrality Deg_{cen} is a simple measure that counts how many links a node has. Defined as:

"A node is important if it has many neighbors, or, in the directed case, if there are many other nodes that link to it, or if it links to many other nodes."

The Eigenvector Centrality

The eigenvector centrality Eig_{cen} is a natural extension of degree centrality.
Defined as:

"A node is important if it is linked to by other important nodes."

The main difference with the in-degree centrality is that a node which receives many links does not means that has necessarily a high eigenvector centrality.

The Betweenness Centrality

The betweenness centrality Bet_{cen} analyzes the relations between vertices: vertices with high betweenness centrality may have a particular influence and importance within the network, thanks to their control over information passing between others.
This type of centrality differs from the other measure: a vertex can have quite low degree and could be connected with other low degree vertices, but still have high betweenness. it represents a "bridge" between two different groups in a network.

After calculating all these values, a comparison is needed between the level of centrality given by traditional measures and the values obtained with the Method of Reflections at different levels of iteration.

Plotting the level of centrality against the different level of iteration, it should highlight that, going on with iterations, values obtained gives a higher quality of information.

H2.a: Measures obtained with Method of Reflections have superior explanatory power in respect to traditional centrality measures.

This can also lead to the possibility that increasing the level of iteration, Method of Reflections have a higher predictive power.

H2.b: higher level of iteration of the Method of Reflections have superior explanatory power.

2.3.5 USD Raised

Economic Complexity Index (ECI) is able to predict the ongoing of an economic system. Hidalgo and Hausmann relates the ECI of countries to their GDP, showing the existence of a positive relationship: the Economic Complexity is linked to the level of prosperity of a country.
Countries that have an ECI larger than what might be expected, given their GDP, have faster growth than those that are richer compared to their level of Economic Complexity: complexity seems to drive and stimulate the wealth of countries.
Complexity can be seen as a driver of future economic growth.
Applying this on the ICOs world, the level of complexity of a member can be a driver of the future ongoing of the fundraising.

H3: Team members characterized by a high level of complexity are able to raise more funds

2.4 Methodologies

The fast expansion of blockchain technology has an impact on the diffusion of alternative ways of fundraising.

Initial Coin Offering is one of them, it can be considered one of the most innovative solutions that has been able to disrupt the finance world.

ICOs world reach such an important dimension that companies, thank to this innovative alternative, raised more than $22 billion in 2017 and 2018.

However, the regulatory process reacted slowly to this innovation and it is still ongoing, making this phenomenon unclear and misleading.

The Economic Complexity, with its capability of analysis, appears to be a useful conceptual framework to better understand the ICO system and better evaluate the quality of the team composition of a campaign.

Due to these reasons, we combine these two concepts to obtained a less blurred picture of the situation.

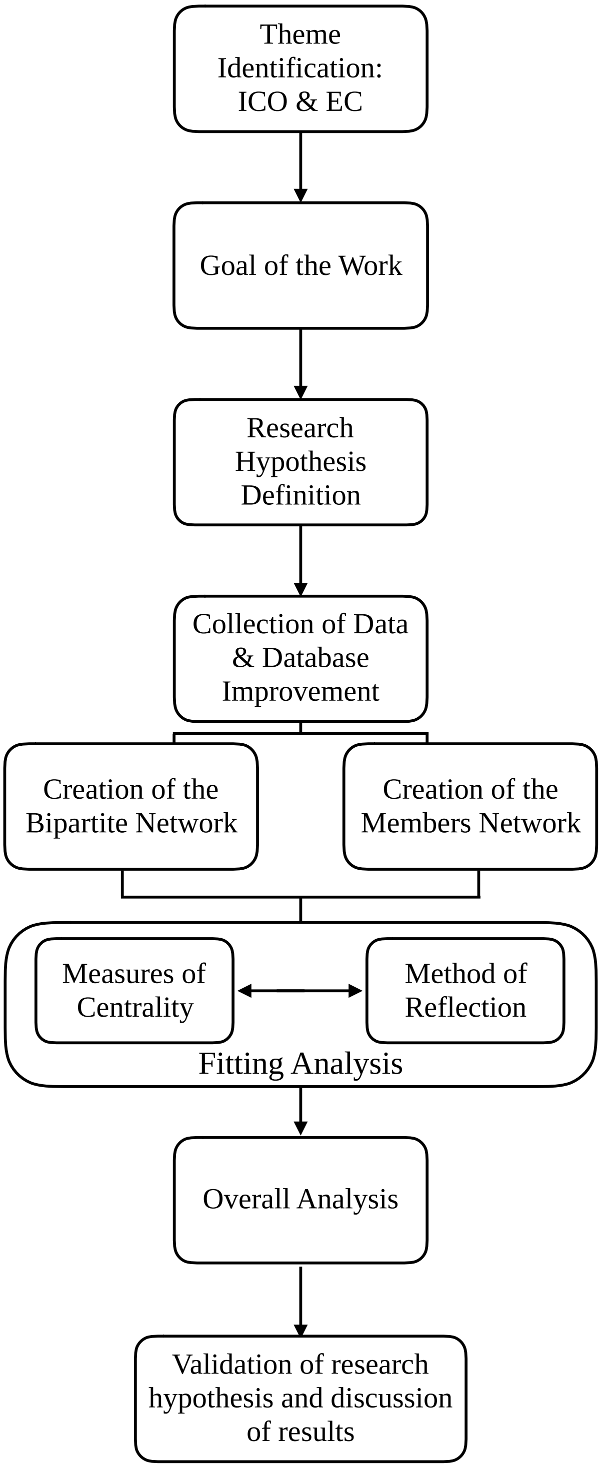


Figure XI – Conceptual Steps of the Thesis

The work we performed started with the collection of data about past and present ICOs, improving the already existent database populated by past colleagues.

The output of all this teamwork is a database of about 933 ICO and 10297 team members.

The next step was the learning of Economic Complexity framework and everything that is associated with it, to have a complete view of the theme and to be able to apply its toolbox.

To validate the assumption that the Economic Complexity framework is able to correctly analyze the ICOs world, we conducted a comparison with centrality measures.
To have a sound methodology, for the first part of the analysis we follow the Hidalgo and Hausmann work of 2009: "The building blocks of Economic Complexity".
In parallel, we performed an analysis of the members' network following the literature of the Social Network Analysis to derive the main centrality measures.
The purpose of using the Social Network Analysis, is to have a check on the fact that Economic Complexity indexes have better fitting in the ICO system in respect to centrality measures; measures obtained with Method of Reflections have superior explanatory power in respect to traditional centrality measures.

After this step, an analysis of the bipartite network was conducted to create a model able to explain the correlation between complexity level of a team member and the success of its ICO.

3 Empirical Analysis

3.1 Data Source

The robustness of the work is based on the database developed by colleagues and integrated by us since the appearance of the first ICO, in the late 2014. The research group, guided by Professor Giancarlo Giudici, updated the database during these years to improve its quality and to better describe ICO's trends.
Even if, the begin of the ICO phenomenon is on 2014, the majority of data refers come from 2017 to mid 2018. Whereas the trend has an exponential growth in 2017 (Adhami et al., 2018).

When populating the database, the main problem faced was the availability and the reliability of the information available on the net.
Even if, concept like cryptocurrencies and ICO are well-known nowadays, the phenomenon of ICO is still in its infancy and this generates high level of information asymmetries.
While it is easy to find on the net certain information on the actual price of shares and the data are the same even, if they come from different sources, it is not the same for ICOs.
The lack of regulatory schemes creates a hole as far as information disclosure is concerned and it is frequent that information differs from different sources.
That is why the research group decided to rely on several sites and comparing data collected to have a clearer view of each case to increase the reliability of the database.
A structured approach was adopted to standardize, as much as possible, the data collection process.

First, the group assigns a rating, from 1 to 5, for every utilized website to create a classification of the sources adopted. The rating depends on:

- (A) *Data's availability*
- (B) *Number of ICOs available*
- (C) *Whitepaper's availability*
- (D) *Reliability of data provided compering them with ones founded from other sources*

Source of Data	***A***	***B***	***C***	***D***	***Score***
IcoBench	*4*	*4*	*3*	*5*	*4.00*
IcoDrops	*5*	*1*	*5*	*5*	*4.00*
CoinMarketCap	*4*	*2*	*4*	*5*	*3.75*
IcoMarks	*5*	*4*	*2*	*4*	*3.75*
IcoRating	*3*	*4*	*5*	*2*	*3.5*
IcoBazar	*4*	*1*	*3*	*5*	*3.25*
FindICO	*4*	*1*	*4*	*4*	*3.25*
IcoHolder	*2*	*5*	*1*	*4*	*3.00*
TrackICO	*2*	*2*	*3*	*3*	*2.5*
IcoData	*2*	*3*	*1*	*3*	*2.25*

Table I – Reliability of Data Sources

Scores are given in relation to the entire set of sources, and even if more websites have been identified, due to their unreliability they are not considered.

The table above shows that the main websites for the research are *IcoBench* and *IcoDrops*. These two sites are the best in terms of reliability and amount of data for what concerns ICOs (Bitcointalk, 2018).

The two sites were for the research group the first sources to look at for the compilation of the database; if data of an ICO were available and aligned they were reported on the database, otherwise other sources were taken into account following the list of the table above.

Following this procedure, data have been collected, to create a first database where all the possible ICO variables are reported and a second one on teams' composition, where it is possible to find names and role of each person that took part of the campaign.

ICO Database

Formed by 926 ICO and composed by variables that describe the several aspects of fundraising, hereafter tables present and clarify the characteristic and information collected for each one.

Variable	***Description***
ICO Name	The name assigned to the ICO project.
Token Ticker	The unique code of the ICO. Usually, it is given by the first three consonants of there ICO Name.
Core Team	The number of members taking part at the ICO project; composed principally by the founder, Chief Officers and other managers.
Advisors	The number of external members who participated into the ICO project. Usually, they are experts of Blockchain and Digital Technology.
Country	It refers to the main nationality of the Core Team, sometimes not attributed due to a decentralized governance mechanism through an online cooperation from multiple locations.
Country Jurisdiction	It refers to the jurisdiction of the country of the ICO project.
Product	It is a description of the product/service that the ICO wants to offer to customers.
Industry Sector	It refers to the application field which the product/service is involved.
Blockchain	It is the underlining Blockchain where the ICO project is developed. In most of the cases is ETH, other are WAVES, BITCOIN and NEO.
White Paper	It is a dummy variable that assumes 1 if the white paper has been published, 0 otherwise.
Code Aviability	It is a dummy variable that assumes 1 if the code has been published completely or partially on Github.com, 0 otherwise.
Italian Team	It is a dummy variable that assumes 1 if the team is Italian, 0 otherwise.
Italian Team Member	It is a dummy variable that assumes 1 if there is at least an Italian team member, 0 otherwise.
Italian Advisors	It is a dummy variable that assumes 1 if there is at least an Italian advisor, 0 otherwise.

Table II – Fundraising Information

Variable	Description
Soft Cap	It is the minimum capital to be raised to have a successful ICO and to have the possibility to continue the project after the investment round. It is expressed in our database in USD.
Hard Cap	It is the maximum possible capital to be raised; when the collection is achieved, the ICO ends.
Starting Date ICO	It is the initial date of the ICO offer.
Ending Date ICO	It is the closing date of the ICO offer. It can be before the finished date if the Hard Cap is achieved.
ICO Duration	It is the number of the days between Starting and Ending Date of the ICO offering.
Token Supply	It is the number of tokens available for the ICO. It can be split: - Tokens Distributed Community: % of tokens allocated to the community - Tokens Distributed Management: % of tokens allocated to the team - Tokens Distributed Bounties: % of tokens allocated to people who help the projects in some way - Tokens Distributed Crowdsale: % of tokens available for external investors.
Token in ICO	Number of token available for external investors = % Tokens Distributed Crowdsale * Token Supply.
Token Price	It is the price of a single token during the offering, expressed in USD. If not, converted according to the exchange rate.
Presale	It is a dummy variable that assumes 1 if the ICO had a presale, 0 otherwise.
Bonus	It refers to a presence or not of some kinds of bonuses. It can be "early stage" if at the beginning of the ICO the price is lower; "major contributor" if the higher the number of tokens purchased, the lower is the price of them.
Raised	It is the most important data of the ICO since it traces the capital raised during the ICO process.
Status	It is a dummy variable that assumes 1 if the ICO process is successful, 0 otherwise.
Token Role	Five different binary variables: - Token Currency - Token Service Payments & Access - Token Governance & Voting Rights - Token Profit Sharing - Token Contribution Rights It is 1 if the token has that type of role, 0 otherwise.
Investment Round	It can be "first" round if never before there was a collection of funds, "second" if already one collection was done, and so on.

Table III – Token Characteristics

Variable	*Description*
SW Development	% of the funds raised during the ICO which is allocated by the team to the research and development of the platform and technology needed to improve the project.
Operations	% of funds raised allocated to all the operating activities needed to run the project.
Markting	% of funds raised allocated to the marketing and advertising campaigns to make the project more popular and know among possible customers.
Reserves	% of funds collected allocated for future activities.
Legal	% of funds collected allocated to legal services, needed to comply with the regulations in the different markets.

Table IV – Funds Distribution

Variable	*Description*
First Day Trading	It is a set of data referring to the trading phase after the end of the ICO: - First Day Trading Date: it is the first day in which the token is traded on an apposite crypto exchange. It is usually on the day or the Monday after the end of the ICO. - First Day Trading Open: it is the initial trading price of the token in its first day on the crypto exchange. - First Day Trading High: it is the highest value that the token achieves in its first trading day. - First Day Trading Low: it is the lowest value that the token achieves in its first trading day. - First Day Trading Close: it is the token price at the end of the first trading day. - First Day Trading Volume: it is the turnover of the first trading day. The price used for this evaluation is the First Day Trading Close. - First Day Trading Volume Token: it is the number of tokens that have been traded on the first day. It is equal to the First Day Trading Volume divided by the First Day Trading Close.
Underpricing	It is the result of a fraction: at the numerator there is the difference between the First Day Trading Close and the Token Price; at the denominator the Token Price.
Exchange Rate	It is a set of data concerning the exchange rate of the two biggest cryptocurrencies (Bitcoin and Ethereum) with the USD: - BTC CF: it is the average USD per BTC during the ICO period. - ETH CF: it is the average USD per ETH during the ICO period. - BTC CF End: it is the USD per BTC of the first day after the end of the ICO. - ETH CF End: it is the USD per ETH of the first day after the end of the ICO.
Avg. Log Return	- 30DRET: it is the average log return of the underlying blockchain (if not ”own” blockchain) return vs the USD in the 30 trading days preceding the ICO. - 7DRET: it is the average log return of the underlying blockchain return vs the USD in the 7 trading days preceding the ICO. - 30DVOL: it is the volatility log return of the underlying blockchain return vs the USD in the 30 trading days preceding the ICO. - 7DVOL: it is the volatility log return of the underlying blockchain return vs the USD in the 7 trading days preceding the ICO.

Table V – Trading Information

Team Database

The second databased populated is on the composition of the team that organized the ICOs. Due to problems of opacity of information and lack of data in some less reliable campaigns, not for all the fundraising it was possible to collect data about the team.

This has led to a set of information regarding 856 ICOs for a total of 9362 people where for each one it is highlighted the name, the role inside the team, so if she/he is a member or an advisor, and the number of campaigns performed.

Variable	***Description***
Name	It is the proper name of the member of an ICO; sometimes it could be a fictitious name due to the presence of possible frauds.
Role	It is the mansion referred to a member; he can be a "team member" with the aim of running the business or an "advisor" with the aim of support the principle activities of the project.
ICO	It is the name of the ICO where a member has taken part.
N. of Participations	It is referred at the number of different ICOs that a member has completed.

Table VI – Members Information

3.2 Sample Analysis

Before starting with the analysis of the variables we analyzed our samples in order to provide a general statistic of the two databases used.
As mentioned in the previous paragraph 3.1, we collected two different types of sample: in the first database we have general information about the ICOs campaigns, while in the second a more specific information regarding the team member.

First, we analyzed our sample of 926 ICOs; we focused on the information on main characteristics, success rate and the geographical area of reference.

Success Rate

Starting from the sample of the collected ICOs, shown in the Table VII, it is possible to derive the overall success rate.
Considering this part of the sample, 10,69% has no evidence of amount raised due to the lack of data, the remaining set of data was divided into successful ICOs and failed ones.

	Number	***%***
Completed	630	68,03%
Failed	134	14,47%
No Evidence	162	17,49%
Total	926	100%

Table VII – ICOs' Success

Success Rate in different Industries

To get a better overview on the ICOs' world, it is key to identify clusters considering the type of industries where ICOs are present.

All the ICOs without any information regarding the USD Amount Raised were removed from the data set to have a significant value on the average total USD raised for each industry.

The analysis performed showed that there are for this type of fund collection 17 clusters, as shown in the table below.

Industrial Sector	***Observations***	***Tot Raised (M $)***	***Avg. Raised (M $)***
Media, Entertainment & Advertising	207	2.790,8	13,5
Financial Services	169	2.513,2	14,9
Miscellaneous	97	999,7	10,3
HighTech Services	87	962,7	11,1
Cryptocurrencies & Payments	51	648,2	12,7
Blockchain Services	44	521,6	11,9
Gaming	29	334,4	11,5
Industry and Logistics	22	185,9	8,5
Gambling & Adult Industry	21	1.058,2	50,4
Data Mining & Cloud Services	11	86,6	7,9
Charity	9	83,4	9,3
Healthcare	4	118,8	29,7
Energy & Utilities	4	45,4	11,4
Others	2	1,8	0,9
Education	3	38,2	12,7
Real Estate	3	6,1	2,0
Hotel & Home Sharing	1	12,2	12,2
Total	764	10.407,2	13,6

Table VIII – ICOs' Industrial Sector vs. Amount Raised (M$)

At a first glance it possible to identify the investment trends related to the sectors and the most interesting industries for the investors.

Great relevance is in Media, Entertainment & Advertising and Financial Services in terms of observations, quite the half of our sample.

Thanks to these data, it is possible to state that 50% of the total ICO during last years were in these two clusters.

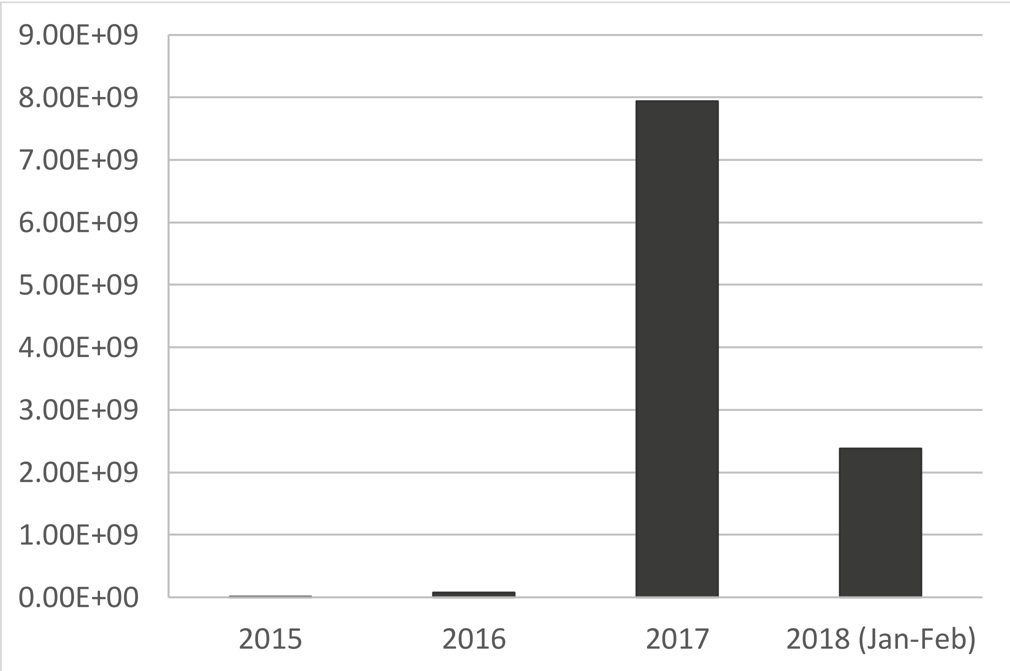
For the total amount raised, we found that the half of total is related, as expected, to the two clusters cited above.

A particular interest is also around the cluster of Gambling & Adult Industries that with a low number of ICOs, only 2,75% of the total, got the highest average raised, approximately 50,4 M$, +270,59% respect to the total average.

Total Raised Amount

Another insight on the USD raised can be obtained comparing the total raised per year: it is clearly evident that from 2016 to 2017 there is the explosion and the total diffusion of this new method of rising funds, passing from a paltry amount more or less about 79 M$ to a consistent amount near to 8 B$.

In term of percentage it represents an increment of +9900% in terms of fund raised and +2711% in terms of number of ICOs campaigns, passing from 26 in 2016 to 731 in 2017.



Graph I – Total Amount Raised per Year

Platform used

One of the first and most important step of an ICO campaign is the selection of the underlying blockchain. It could be based on different platform, the most known are Ethereum and Bitcoin.

As in the table below, the team most of the time (82,72%) chose the ERC20 standard token, due to the simplicity of the creation of new cryptocurrency in terms of tokens generation and distribution.

However almost the 8% of the teams decided to run their campaign by developing their own underlying platform to base their collection of funds, even if this way it is consuming and costly in terms of time, effort and money.
Although the Bitcoin is the most known cryptocurrency, due to a wide spread of information around the world, being the first important cryptocurrency appeared on the market, it is not chosen by the teams due to the lack of scalability, in terms of development of a decentralized application.

	Number	**%**
Ethereum	766	82,72%
Own (Private)	73	7,88%
Waves	34	3,67%
Other	33	3,56%
Bitcoin	11	1,19%
Neo	9	0,97%
Total	926	100%

Table IX – Underlining Blockchain

<u>*White Paper & Code*</u>

It is also important to be able to consider some observable characteristics which can assess the underlying quality of the project, such as the White Paper the document containing the main information of the campaign and the Code on which the fundraising puts its roots.
These elements are proxy of quality and they are able to reduce the information asymmetry that is one of the features of an ICO (Fisch et. al., 2019).
This evidence is confirmed in the analysis of our sample as shown in the table below: three-quarters of ICO that make available White Paper and the Code reach their Soft Cap.

Information Available	***Observation***	***%***	***Success***
White Paper	878	94,82%	75,17%
Code	607	65,55%	75,45%
White Paper + Code	586	63,28%	75,43%

Table X – ICOs' Success and Relative Signals: White Paper and Code

Team & Members

Team & Members are our second sample: it is composed by information on team members of the different ICOs.
This database is composed by 856 ICOs with relative teams, for a total of 9362 different members.

To have an overview on the dimension of these teams we performed a mean average with its respective standard deviation, shown in table below.
The dimension is very variable; this can be explained in relation with the complexity of the project and the required human capital.
If the competences required are several, there is the necessity of a higher number of members in the team respect to correspond to the industry standard.

Team	*Max Size*	*Min Size*	*Mean Size*	*Std. Dev.*
Value	65	1	12,03	7,84

Table XI – ICOs' Team Size

Looking at the participation of members it is important to highlight that on 9362 people only 547 participated in more than one ICO; this leads to very low average number of participations.
As from the low value of the standard deviation, it is rare to find a person that have joined more than two ICOs, in fact they are only 165.

Member	*Max*	*Min*	*Mean*	*Std. Dev.*
Value	25	1	1,10	0,57

Table XII – Members' Participation

Looking at the number of the ICOs that a person has participated, could be useful for a better understand the nature of these campaigns.
The table XIII shows the top ten members which took part in ICO most of the time.

This analysis highlights that the higher the number of ICO joined by a member, the higher is the probability of its success.

Looking at the average raised, it is possible to find a correlation between the probability of success, higher at higher level of participation of different ICO by a team member, and the funds collected.

When the probability of success is higher than 70% there is a strong increase in the ability of collecting money; that increase could be explained by the experience and knowledge acquired during the previous fundraising campaigns.

From the table below it is also possible to see that David Drake is to be considered an exception, due to the high presence in different ICOs when comparing him with the other top nine members showed here below.

This exception did not influence the success ratio, that it is capped over a certain value of ICOs participation.

Name	***Number of ICO***	***% Success***	***Avg. raised (M $)***	***Tot Raised (M $)***
David Drake	25	80%	14,7	367,4
Michael Terpi	14	86%	14,6	204,8
Moe Levin	12	83%	17,7	212,3
Antony Di Iorio	12	67%	14,8	177,6
Richard Titus	10	70%	8,1	81.4
Bo Shen	9	67%	5,3	47,5
Richard Kastelein	8	63%	7,2	57.9
Bok Khoo	8	63%	2,6	20,9
Tomoaki Sato	8	50%	5,1	40,7
Ian Scarffe	8	50%	3,8	30,6

Table XIII – Top Ten Participation

3.3 Variables univariate statistic

After performing an overall analysis of the two samples highlighting the main results we performed an univariate statistic analysis of the variables defined and presented in the previous paragraph.

These variables were used for the formulation of a multivariate model.

3.3.1 Bipartite Network

Frist we built the bipartite matrix $M_{m,i}$ that represents the ICO network relating the members *m* with the ICOs *i*. We have a correlation when one member *m* is part of ICO *i*; if there is a correlation between a member and an ICO, the link is defined by the value as 1, and is put as 0 otherwise.
The matrix $M_{m,i}$ obtained with our data counts 9362 unique members and 856 unique ICOs, generating a total of 10296 nodes.

Method of Reflections

Applying Method of Reflections on the Bipartite network (856 ; 9362) we assessed the complexity level of each member, starting from diversity and ubiquity, two separate measure, but one can be used to correct information carried by the other.
Each level of iteration represent a higher order of analysis of the system that improves the previous level; we expected that going through higher level of $k_{m,N}$ we get more reliable and accurate measures of the structure of the system.
This means that Method of Reflections is able to find a stronger level of correlation, through an iterative pattern, between members of the team and ICOs.
Theoretically this method converges to a final value that represent the Economic Complexity Index of a member.

The higher the final level of $k_{m,N}$, the higher the quality of interconnection that a member has developed.

To start we performed an analysis of first level of Method of Reflection; it consists of an iteration of the average value of the previous level, considering the nearest nodes properties, and it generates a symmetric set of variables for both type of nodes: member *m* and ICO *i*. Following the respective formula of the model and applying it on our metrics we obtain:

$$k_{m,N} = \frac{1}{k_{m,0}} \sum_{i} M_{m,i} * k_{i,N-1}$$

$$k_{i,N} = \frac{1}{k_{i,0}} \sum_{m} M_{m,i} * k_{m,N-1}$$

for $N \geq 1$; starting from an initial condition characterized by the degree or number of links of members and ICOs.

$$k_{m,0} = \sum_{i} M_{m,i}$$

$$k_{i,0} = \sum_{m} M_{m,i}$$

Where $k_{m,0}$ represents the level of diversification of a member *m*: how many ICOs the member *m* has done; while, $k_{i,0}$ is the level of ubiquity of an ICO *i*: how many members are present into the team of the ICO *i*.

We can define our two nodes through the vector $\overrightarrow{k_m} = (k_{m,0}, k_{m,1}, \dots, k_{m,\mathrm{N}})$ for each member and $\overrightarrow{k_i} = (k_{i,0}, k_{i,1}, \dots, k_{i,\mathrm{N}})$ for each ICO.

It is important to highlight that for a member even variables $(k_{m,0}, k_{m,2}, k_{m,4}, \dots)$ represent general measures of diversification, while odd variables $(k_{m,1}, k_{m,3}, k_{m,5}, \dots)$ define general measures of ubiquity of ICO in which she or he is involved.

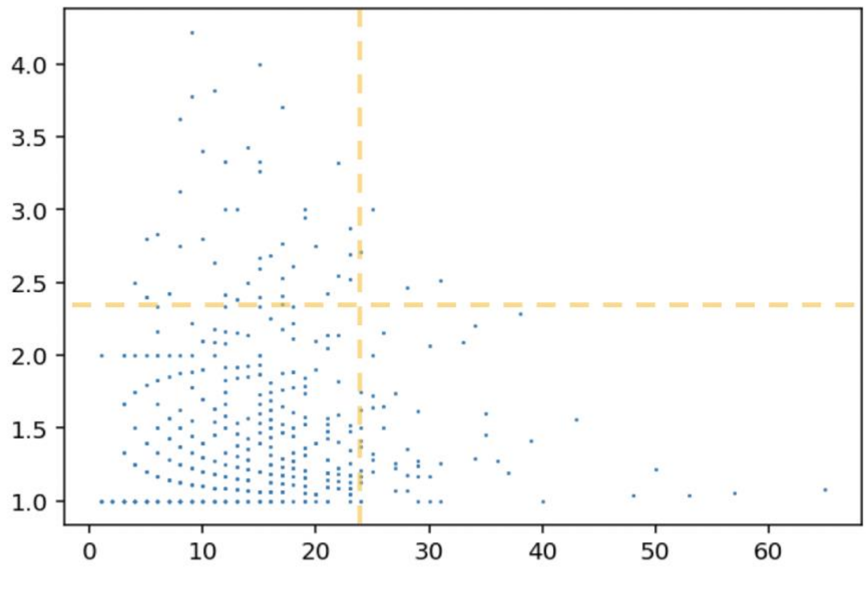
In particular:

- $k_{m,1}$ represents the mean ubiquity of the ICOs that have member m in their team.

- $k_{i,1}$ represents the average diversification of team members in ICO i.

For $N > 1$ as by Hidalgo and Hausmann (2009) "higher order variables, …, can be interpreted as a linear combination of the properties of all of the nodes in the network with coefficients given by the probability that a random walker that started at a given node ends up at another node after N steps.".

Following the fathers of Economic Complexity in their work "building block of Economic Complexity", as a first step, we applied the first two levels of measures of the Method of Reflection: $k_{i,0}$ $k_{i,1}$, in order to have a first look on the characteristics of the ICOs.



Graph II – $k_{i,0}$ $k_{i,1}$

Plotting results as shown in the graph above, it is possible to derive some information from the picture captured by the Method of Reflections.

To analyze the data, we have divided the area into four quadrants: we decide to split the graph using the 94° percentile of the members, considering that 94% of them have participated to only one ICO and only the residual part more than one. Through this type of calculation, we have taken for the x-axis a value of $k_{i,0} = 24$ and for y-axis a value of $k_{i,1} = 2{,}35$.

Not diversified ICO High members ubiquity 2	Diversified ICO High member ubiquity 1
Not diversified ICO Low members ubiquity 3	Diversified ICO Low members ubiquity 4

Table XIV – General Characteristics of $k_{i,0}$ and $k_{i,1}$ Quadrants

The characteristics of the ICOs can be described in relation to their positioning:

- The majority part of ICOs is placed in the third quadrant (3) meaning that, usually, the ICOs with a team composed by a low number of members, have also members that on average joined to a low number of ICOs.

- In the second quadrant (2), there are exceptions where ICOs characterized by a small team have members that joined in several campaigns.

- An important evidence is captured in the fourth quadrant (4) every ICOs composed by a team higher than the average have always members who participated on average to few campaigns.

- The first quadrant (1) shows that not even an ICO with a larger team respect to the average has members with high ubiquity.

After performing a first analysis of the ICO scenarios in order to recreate what Hidalgo and Hausmann have proposed in their work, we looked at the univariate statistic related to the different levels of iteration, divided in even and odd, because, as already said, they reciprocally refer to Members and ICOs characteristic, table below.

Variable	*Observations*	*Mean*	*Std. Dev.*	*Median*	1^{st} *Quartile*	3^{rd} *Quartile*
$k_{m,0}$	9362	1,098	0,569	1,0	1,0	1,0
$k_{m,2}$	9362	1,349	0,482	1,174	1,0	1,490
$k_{m,4}$	9362	1,353	0,446	1,192	1,0	1,519
$k_{m,6}$	9362	1,356	0,422	1,209	1,0	1,538
$k_{m,8}$	9362	1,358	0,403	1,226	1,0	1,554
$k_{m,10}$	9362	1,360	0,389	1,240	1,0	1,569
$k_{m,12}$	9362	1,362	0,377	1,255	1,0	1,582
$k_{m,14}$	9362	1,363	0,367	1,272	1,0	1,592
$k_{m,16}$	9362	1,364	0,359	1,282	1,0	1,598
$k_{m,18}$	9362	1,365	0,352	1,292	1,0	1,607

Table XV – Even Value of Method of Reflections Main Statistics

Variable	*Observations*	*Mean*	*Std. Dev.*	*Median*	1^{st} *Quartile*	3^{rd} *Quartile*
$k_{m,1}$	9362	17,056	10,056	15,0	10,0	21,0
$k_{m,3}$	9362	17,036	9,616	15,719	11,0	21,0
$k_{m,5}$	9362	17,020	9,271	15,879	11,0	20,814
$k_{m,7}$	9362	17,009	8,991	16,0	11,50	20,826
$k_{m,9}$	9362	17,0	8,757	16,0	11,922	20,663
$k_{m,11}$	9362	16,992	8,557	16,212	12,0	20,564
$k_{m,13}$	9362	16,986	8,384	16,357	12,0	20,434
$k_{m,15}$	9362	16,980	8,231	16,593	12,0	20,320
$k_{m,17}$	9362	16,976	8,095	16,714	12,174	20,165
$k_{m,19}$	9362	16,972	7,973	16,851	12,531	20,079

Table XVI – Odd Value of Method of Reflections Main Statistics

It is possible to notice that at each level of iteration the value of the Mean, in both even and odd values, tends to converge to a stable value, as expected.

The Method of Reflectionsconverges to a final value that represent the final level of complexity of a node.

3.3.2 Members Network

After analyzing the bipartite network with the Economic Complexity framework and appling the Method of Reflections, we introduced a new matrix in order to perform the Social Network Analysis.
In this matrix, a new configuration of the network was performed.
Starting from the initial bipartite network, only members were taken into account, obtaining a matrix where people are connected if they have participated at least at one ICO together. This passage has led to a matrix with dimension of 9362 members x 9362 members. Rhis is a step needed to apply Social Network Analysis.

Degree Centrality

In this part of our work the degree centrality is linked with the members of the teams of the ICOs, considering the in-degree centrality, in this case, the measure is: a person is important if he has links with many people. The higher the number is the more popular the individual is inside the network.
The formula for the degree centrality for a node *i* is:

$$Deg_{cen(i)} = \sum_{j} a_{ij} \quad \forall j \neq i$$

Equation XIII – Degree Centrality Formula

Eigenvector Centrality

We appied this approach to understand if a member has a high number of links and at the same time if these links are important or not.
The formula for eigenvector centrality, considering λ the largest eigenvalue, is:

$$Eig_{cen(i)} = \frac{1}{\lambda}\sum_{j} a_{ij} * Eig_{cen(j)} \quad \forall j \neq i$$

Equation XIV – Eigenvector Centrality Formula

Betweenness Centrality

Applying this approach to our sample of members, it is possible to asses the position of a person inside the network, taking into account the ability that she/he has to connect to two or more nucleus of people.
The betweenness centrality formula is:

$$Bet_{cen(i)} = \sum_{s \neq v \neq j} \frac{\sigma_{s,t}(i)}{\sigma_{s,t}}$$

Equation XV – Betweenness Centrality Formula

betweenness centrality represents the sum of the ratios between the number of shortest paths $\sigma_{s,t}$ connecting every pair of nodes *(s, t)* in the network and the number of those that transit through an edge linked to node *i*. The role of this measure can also been seen such as the figure of a "broker", that connects the nodes in the network between others.

Summarizing, the values of centrality in Table XVII show some important outcomes:

Variables	*Observations*	*Mean*	*Std. Dev.*	*Median*	1^{st} *Quartile*	3^{rd} *Quartile*
Degree Centrality	9362	0,0021	0,0015	0,0018	0,0013	0,0026
Eigenvector Centrality	9362	0,0009	0,0103	1,41e-8	4,90e-25	3,50e-7
Betweenness Centrality	9362	0,0002	0,0016	0,0	0,0	0,0

Table XVII – Centrality Measures Main Statistics

Measures of centrality, especially betweenness and eigenvector centrality, are not able to measures properly the network of members.

Looking at the values, it is possible to see too many low values that cannot highlight the quality of the position of a person inside the network.

A first explanation could be that inside the graph, there is a high number of people with just one participation in an ICO, which is represented by a sample of 8815 peoples on 9362.

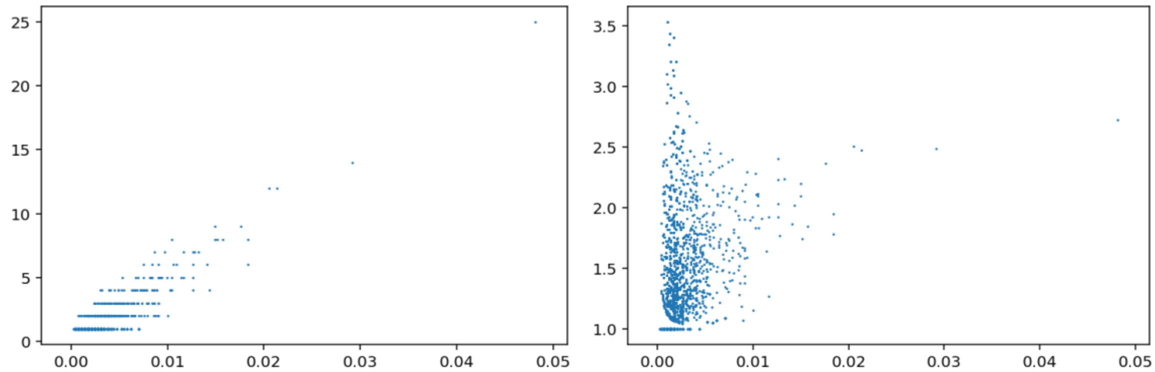
Due to this reason, we considered the possibility that further analysis should focus only on a new downsized network composed of 547 peoples. Those are the members who participated in more than one ICO.

3.3.3 Complexity vs Centrality

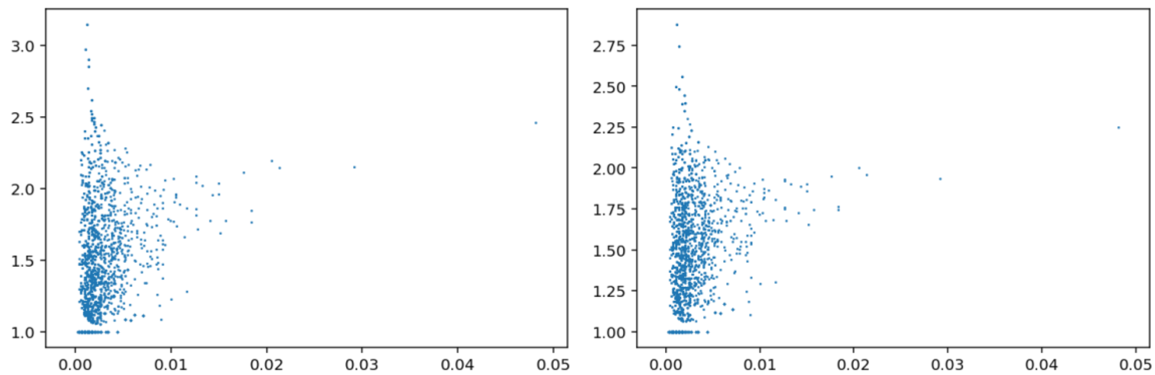
In this paragraph, we continued the analysis of the measures of complexity and centrality, still considering the complete sample in order to have a clearer idea of the quality of the measures.

To retrace the path of analysis of Hidalgo & Hausmann, we performed a comparison between complexity and centrality in order to test if higher levels of iteration of the Method of Reflections generate higher fitting and give more information about the dynamic of the fundraising campaigns.

<u>Degree Centrality x-axis and even k y-axis</u>



Graph III – $k_{m,0} - k_{m,4}$



Graph IV – $k_{m,10} - k_{m,18}$

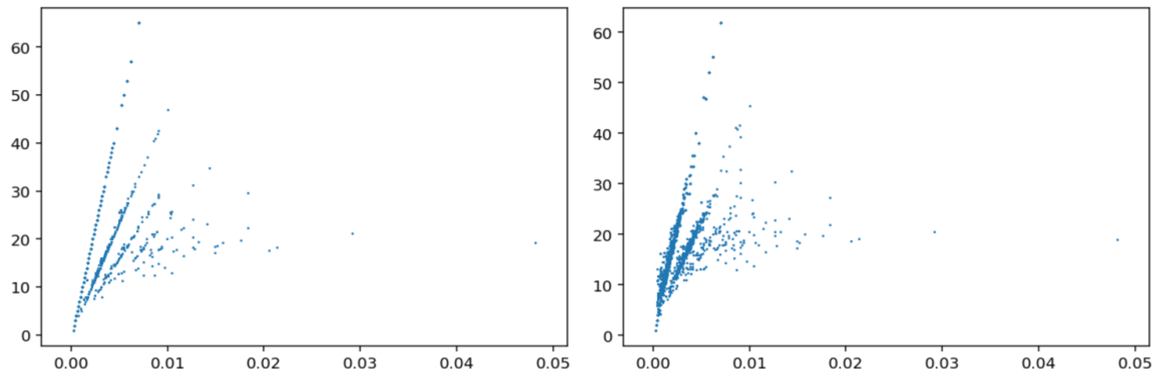
The Graphs III and IV above show the correlation between level of degree centrality of a member and his level of diversification at level zero and consider also the other relationships with the other nodes at higher levels.

It is possible to observe that there is an evolution of the correlation between the data.

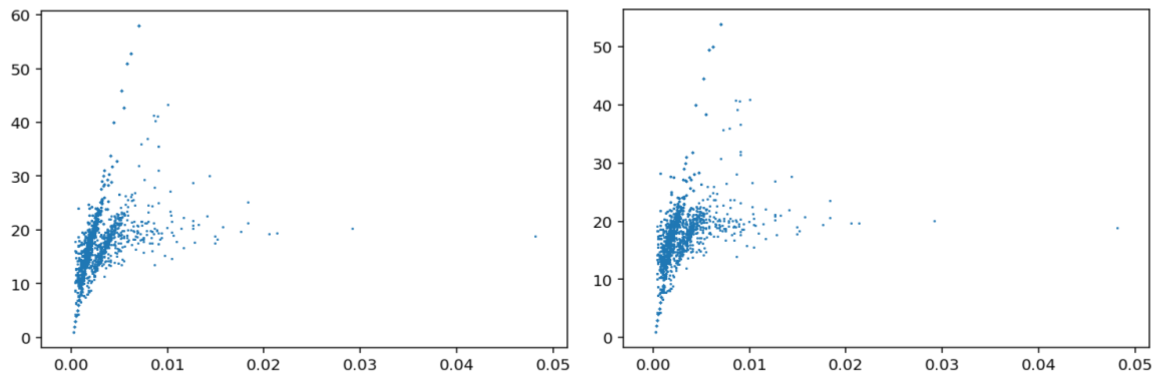
There is a constant positive correlation between the diversification of the members and degree centrality, if a member is characterized by a high level of complexity, he should have a high level of degree centrality.

It possible to observe that the positive correlation persists in each level of iteration, moreover it is necessary highlighting the improvement of the correlation at low levels of iteration, stabilized from $k_{m,6}$ and going on with higher levels of iteration.

Degree Centrality x-axis and odd k y-axis



Graph V– $k_{m,1} - k_{m,5}$



Graph VI – $k_{m,11} - k_{m,19}$

Odd variables are analyzed separately because they represent, differently from the even ones, at the first level, the average ubiquity of the ICOs that have member *m* in their team.

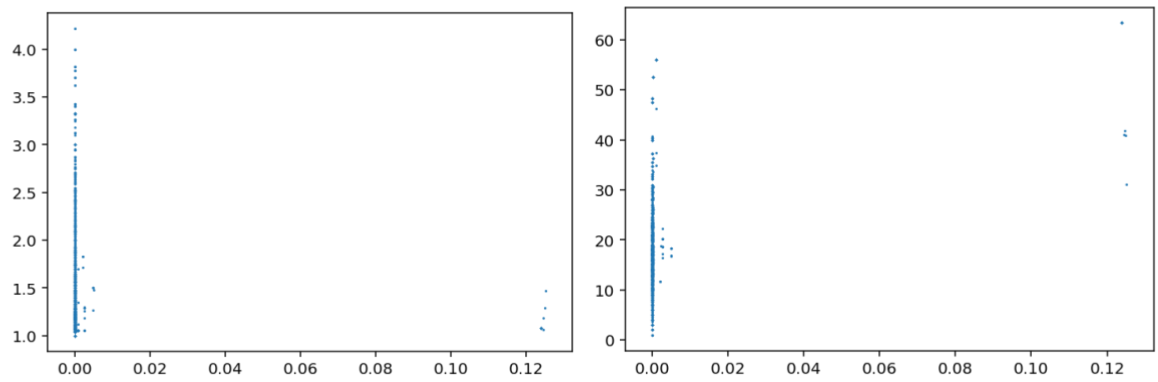
At a higher level of N, the values take into account also the characteristic of all the N neighbor nodes in the network.

In this case, there is a positive and stronger correlation, respect to the previous case, between variables.

The higher the value of ubiquity of the ICOs related a member, the higher her/his level of importance inside the network given by the level of degree centrality.

Eigenvector Centrality x-axis and k y-axis

Passing to a more complex analysis of centrality the correlation with complexity indicators starts to have no more reasonable dependence.



Graph VII – $k_{m,2} - k_{m,3}$

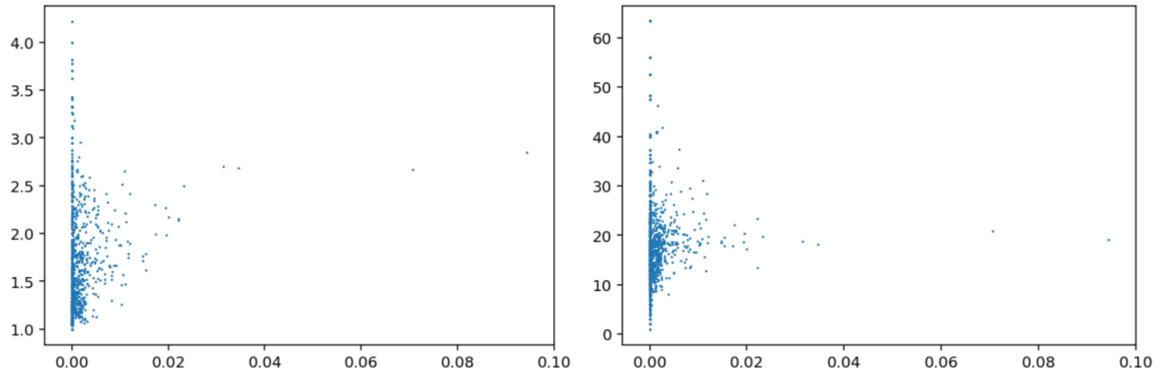
As highlighted in the Graph VII, the correlation between different levels of $k_{m,N}$ and the eigenvector centrality is null, in fact it is evident that majority of the observations have no significant value of centrality despite an increasing value of complexity.

Moreover, for higher level of iterations the fitting does not improve, loosing completely the relevance of the model.

Betweenness Centrality x-axis and k y-axis

The betweenness centrality shows some correlation with the complexity near to a null value. This correlation is better respect to eigenvector centrality, but still not significant.

As shown below, the observations are not spread on the scatterplot and they do not follow any type of deductible pattern.



Graph VIII – $k_{m,2} - k_{m,3}$

At the end, this evidence reconfirms our thesis to have the possibility to resize the sample, due to the inability of the last two measures of centrality to estimate a good and significant value of the quality of the connections.

it is useful to recall that our sample is composed by 94% of member which have participated to only one ICO fundraising campaign, leading to a huge number of nodes, but with a lower mean in terms of links.

3.3.4 Downsized network

Going on with the analysis, it was evident the need to cut the sample down and perform new calculations to find a better fit between centrality and complexity.
Reducing the sample from 9362 to 547 members, only those members who have taken part at more than one ICO campaign more significant results were obtained.
However, even if the sample is strongly reduced it should be more representative for the purpose of finding a correlation due to the increased number of links, that permits to have a higher relevance in the measures of centrality.

Performing again the univariate statistic, both even and odd, new results were derived, as shown in the tables below.

Variable	***Observations***	***Mean***	***Std. Dev.***	***Median***	1^{st} ***Quartile***	3^{rd} ***Quartile***
$k_{m,0}$	547	2,682	1,695	2,0	2,0	3,0
$k_{m,2}$	547	3,330	1,188	3,083	2,40	3,929
$k_{m,4}$	547	3,497	1,007	3,369	2,817	4,091
$k_{m,6}$	547	3,570	0,879	3,535	3,028	4,125
$k_{m,8}$	547	3,612	0,789	3,616	3,155	4,115
$k_{m,10}$	547	3,636	0,723	3,690	3,247	4,106
$k_{m,12}$	547	3,653	0,673	3,751	3,317	4,106
$k_{m,14}$	547	3,664	0,635	3,798	3,391	4,087
$k_{m,16}$	547	3,673	0,604	3,819	3,449	4,068
$k_{m,18}$	547	3,680	0,579	3,835	3,483	4,048

Table XVIII – Even Value of Method of Reflections Main Statistics

Variable	***Observations***	***Mean***	***Std. Dev.***	***Median***	1^{st} ***Quartile***	3^{rd} ***Quartile***
$k_{m,1}$	547	4,441	2,002	4,0	3,0	5,50
$k_{m,3}$	547	4,433	1,479	4,332	3,409	5,419
$k_{m,5}$	547	4,445	1,249	4,438	3,621	5,280
$k_{m,7}$	547	4,457	1,106	4,498	3,849	5,169
$k_{m,9}$	547	4,466	1,006	4,550	3,999	5,125
$k_{m,11}$	547	4,474	0,932	4,590	4,027	5,086
$k_{m,13}$	547	4,480	0,875	4,613	4,433	5,048
$k_{m,15}$	547	4,485	0,831	4,641	4,490	5,003
$k_{m,17}$	547	4,490	0,80	4,667	4,234	4,967
$k_{m,19}$	547	4,494	0,767	4,690	4,280	4,938

Table XIX – Odd Value of Method of Reflections Main Statistics

Variables	*Observations*	*Mean*	*Std. Dev.*	*Median*	1^{st} *Quartile*	3^{rd} *Quartile*
Degree Centrality	547	0,0194	0,0143	0,0165	0,0110	0,0238
Eigenvector Centrality	547	0,0241	0,0353	0,0105	0,0023	0,0291
Betweenness Centrality	547	0,0041	0,0110	0,0010	0,0001	0,0037

Table XX – Centrality Measures Main Statistics

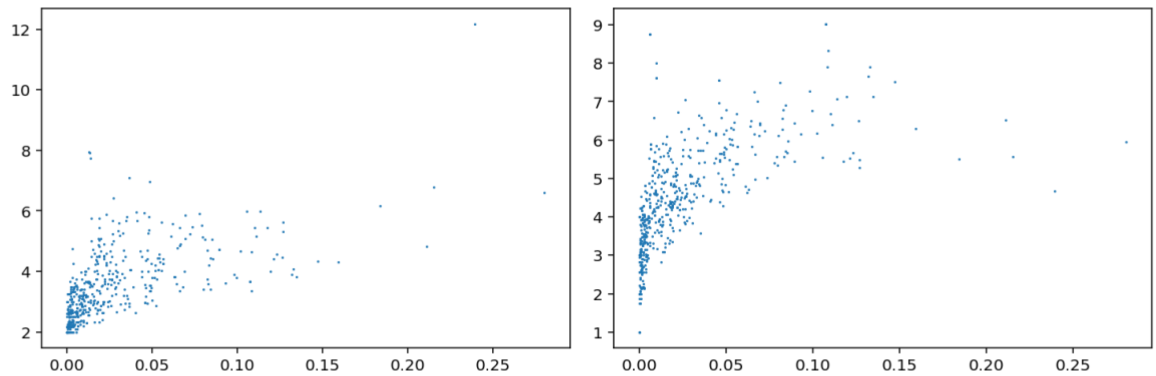
Regarding the simplest measure of centrality, degree centrality, it is possible to confirm, as expected, an increasing on the fitting of the observations, having already, in the previous sample, a discrete correlation.

The actual improvement of the downsized sample is with eigenvector and betweenness centrality as shown in the Graphs IX and X.

Eigenvector Centrality x-axis and *k* y-axis

Comparing the eigenvector centrality, a new scenario was obtained: it was possible to observe a correlation both in diversification of the members and ubiquity of the ICOs starting from low level of complexity.

This new fit is possible thanks to the reduction of dispersion of the data and the correlation can be seen at scatterplots level; at higher level of $k_{m,N}$ corresponds higher values of eigenvector centrality.

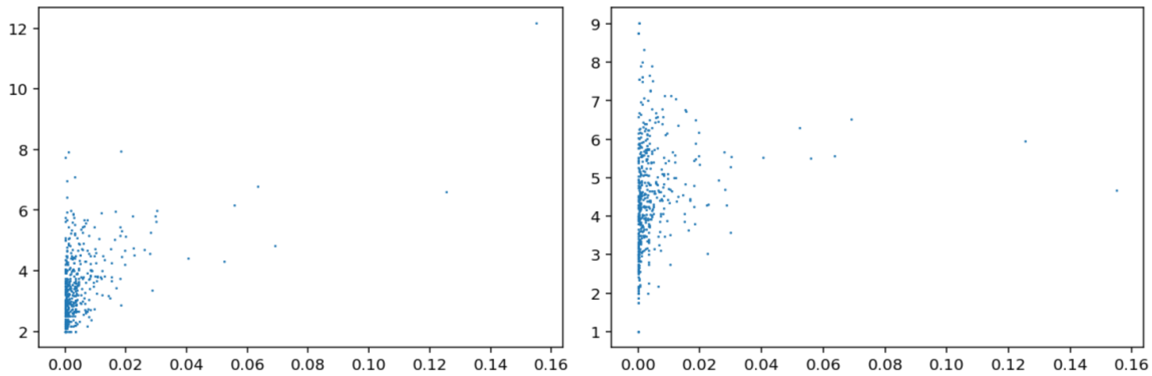


Graph IX – $k_{m,2} - k_{m,3}$

Betweenness Centrality x-axis and k y-axis

Regarding betweenness centrality, we have found an improvement, but correlation still remains near to a value of zero.

This behavior could be explained by the high distance between the different members, due to their rareness to find themselves in the same ICO. It is rare to find couple, trio or groups of more people which work together in more than one ICO.



Graph X – $k_{m,2} - k_{m,3}$

3.3.5 Remarks on Univariate Statistics

The value of $k_{m,N}$ is confirmed by the positive correlation with the measures of centrality, in particular a strong evidence is underlined by the degree centrality.

For what concern eigenvector centrality, it is necessary to make a distinction between the two different samples analyzed:

- The first sample, the one that is made of all the members of our database (9362), does not present a possible correlation due to the intrinsic characteristics of the measure: in fact the low presence of links among a high number of nodes makes difficult the valuation of the quality and importance of the edges.

- The second sample, the downsized one (547), thanks to a reduction of the entropy of our database, is characterized by a significant number of links that can give a better importance and a better value of a member centrality in the network.

Regarding the last measure of centrality, betweenness centrality, is interesting to see that for both the samples there is no correlation.

It is clearly evident that it is complex to find a correlation due to the lack of multiple connection between the different groups of different ICOs; this means that the number of couple or group of members that perform more than one ICO together has a very low frequency.

Finally, in order to use attenable sample and its relative variables, it is possible to say that the values obtained with the Method of Reflectionshave a statistical relevance in both samples.

For what concern the centrality measures, obtained with the Social Network Analysis, they are more relevant in the resized sample.

This first part of our work was useful to have a better vision and evidence of the sample and its characteristics.
Moreover, it helps to confirm our hypothesis:

- H1: Applying Economic Complexity measure to the bipartite network of ICO and member gives a clear pattern among measure.

- H2.a: Measures obtained with Method of Reflections have superior explanatory power in respect to traditional centrality measures.

In fact, we assess that the Economic Complexity measures are better for the first network analyzed, the complete and the most dispersive one, through the analysis obtained in the univariate statistic.
Therefore, it is possible to say that Economic Complexity framework is able to correctly analyze an economic network even if this is really dispersive and characterized by a high number of entities with a single connection (94% of the totality).
The toolbox of the Economic Complexity can correctly extract information on the relationship between agents and fundraising campaigns with the aim of getting evidence of the configuration of the systems, validating H1.
While for what concerns the downsized network the measure of complexity can investigate the composition of the relationship in the same way as the centrality measures. This fact still validates H1.

Looking at the evolution of the graphs that are present along this paragraph, we noted that for both databases, the complete and the resized one, measures of Economic Complexity adjust the relationship with centrality measures going on with higher level of iterations. This happens with particular evidence with degree centrality, where a good correlation was found.

This ability of the Method of Reflections to increase the fitting on higher level of iteration, leads us to say that it is not just the centrality of a member inside the ICO, but the higher level of iteration of Method of Reflections that gives more information on the dynamics of an ICO, confirming the hypothesis H2.a

3.4 Multivariate Analysis

Arrived at this point of the work, after having performed the univariate analysis and studied our data samples, we set our multivariate regression models on the base of the variables before introduced.

We arrive at this final step after having computed the complexity values of each member of our cluster at different levels of iteration by adopting the Method of Reflection.
After that we assess the quality of the complexity level associated with each member, studying its correlation with centrality measures in order to find statistical evidence of the Method of Reflections measures.

Now the objective is to set a link between values obtained and data from the samples.
For this reason, we introduced a model to define and understand the correlation between independent variables of our interest, that have been already analyzed, and measures that are able to give a level of success of a member.
The model used for the regression is the Ordinary Least Square (OLS), where our explanatory variables are linked with the dependent variable of USD Raised through a linear function.
The parameters of this function are defined thanks to the principle of least squares: it approximates the solution calculating the sum of the square of the difference made in the results of every equation and minimizing it.
The USD Raised value has been regressed over values of Economic Complexity given by the Method of Reflections together with the use of suitable control variables that are referred to characteristics of members that organized an ICO.

The reliability of the model has been assessed through the use of adjusted R-squared, a modified version of R-squared, that take into account the fact that new terms can improve more than expected the model or not. It can be lower or equal to the R-squared, assuming also negative values.

For what concerns the goodness of independent variables in terms of statistical significance, we have considered the p-value and for evaluating the dispersion of observations, we have looked at the standard error as its proxies.

We have structured several models, first starting from a lower level of iteration, and then we progressively structured the model with a higher level of iteration. Moreover, we add in a sequential way also measures of centrality with the aim of improving the capabilities of capture the relevance of quality relations and the capabilities of networking of the members. To complete the model, we add every time control variables, to not skew the results.

3.4.1 Dependent Variable

As already mentioned, the dependent variable of our work is the USD Raised by each person. The starting value is the quantity of USD that a company has raised in the ICO; however, a member can perform more than one ICO, so in order to allocate a significant value, we consider two ways for allocating the final quantity at each member.

We sum all the USD that have been raised in each ICO *i* in which the person *m* is part of the team:

$$USD\_Raised_m = \sum_{i=1}^{I} USD\_Raised_i$$

Equation XVI – Sum of USD Raised

We sum the weighted quantity of USD that has been raised in each ICO *i* in which the person *m* is part of the team; where the weight is the number of people inside the team of the ICO *i*:

$$USD\_Raised_m = \sum_{i=1}^{I} \frac{USD\_Raised_i}{Team\ Size_i}$$

Equation XVII – Weighted Sum of USD Raised

After obtained these two sets of variables, analyzing them in respect of the sample in which we operate, we have decided to use the first equation.

In fact, the weighted sum does not lead to significant measures because of the presence of high variability of the size of the team: the minimum is 1 and the max size inside our dataset is 65.

Moreover, we have seen in paragraph 3.3.1 that ICOs with a big team are formed with member that make no other fundraising campaign.

Variable	***Description***
USD Raised	It represents the sum of the amount collected by the member m, considering the ICOs where he has patecipated.

Table XXI – Dependent Variable Description

3.4.2 Independent Variables

After having defined the dependent variable, we introduced the set of variables that are going to predict the trend.

The set of independent variables we decide to use, can be clustered as Social Capitalvariables. These qualities represented by the variables have been already chosen in numerously past studies.

After the work of Hidalgo and Hausmann (2009) that introduced the concept of Economic Complexity, new literature on economic networks has grown (Kali et al., 2013 and Morrison et al., 2017) arriving also to analyze the financial world.

The work of Caccioli et al., (2014), for example, is based on the bipartite network of agents and instruments to asses the systemic risk level associated with the linkages between financial market and assets.

While measures of Social Network Analysis where used in several works, for example to assess how the position of an underwriter inside the investment banks' network can affect IPO (Bajo et al., 2016). Or looking at that Georgieva et al. (2016), who analyzed the effect of a CEO position inside the network of worldwide executives, through the degree and eigenvector centrality, on the IPOs performances.

We considered firstly the measures obtained with the Method of Reflection:

- $k_{m,0,2,4....,20}$: represent the generalized measure of diversification of members.
- $k_{m,1,3,5....,21}$: represent the generalized measure of the ubiquity of ICOs.

As already said in paragraph 3.3.1 the nature of the measures, changes if the level of iteration is odd or even.
That is why in order to have a better representation of the quality of the social capital related to a member, the levels of $k_{m,N}$ are always taken in couple.

In order to enrich the level of analysis regarding the social capital value of a person inside the network, we add a measure of the social network analysis.
Among the measure of Social Network Analysis already shown in the previous paragraphs, we have seen that there is no correlation between $k_{m,N}$ and betweenness centrality, so this variable will be used.

Variable	***Description***
$k_{m,N}$	It represents the Economic Complexity value; in particular: $k_{m,0}$ represents the level of diversification of a member m: how many ICOs the member m has done; while, $k_{m,1}$ represents the mean ubiquity of the ICOs that have member m in their team. Higher order variables can be interpreted as a linear combination of the properties of all of the nodes in the network with coefficients given by the probability that a random walker that started at a given node ends up at another node after N steps.
Betwennes Centrality	It represents the relations between vertices; vertices with high betweenness centrality may have a particular influence and importance within the network, thanks to their control over information passing between others.

Table XXII – Independent Variable Description

3.4.3 Control Variables

In addition to the independent variables, we took into account a set of control variables. They are all dummy variables related to people characteristic inside the ICO group. We define them following the current literature on the ICOs.

As already stated in Ante et al. (2018) Chen (2019) it is important to differentiate between team members and advisors.
Based on the works of Adhami et al. (2018) and Fisch (2019), we add variables that take into account the industrial sector in which a person is used to work and variables that indicates the willingness of a person to appear honest, clear and precise to the market.
This was defined through the presence or not of white paper and code in the ICOs in which the member worked.

A problem that we had to face is that a person can have joined more than one ICO and their characteristic could be different.
So, in order to activate a dummy variable, we have seen if the characteristic is present in at least fifty percent of the cases.
For example, if a person *m* has worked on ICOs that are in the Financial Services sector for 4 times and in total he has worked in 6 ICOs, we have considered him an expert on financial services.
In the following table XXIII, each control variables are explained.

Control Variable	Description
Advisor	It is a dummy variable that assumes 1 if the member is an "advisor" at least in the 5(of the ICOs where he has participated, 0 otherwise.
Code	It is a dummy variable that assumes 1 if the member has published the code, complet or partially, on GitHub.com at least in the 50% of the ICOs where he has participatec 0 otherwise.
ETH	It is a dummy variable that assumes 1 if the member has partecipated into an ICO Ethereum based, at least in the 50% of the ICOs where he has participated, 0 otherwi
WP	It is a dummy variable that assumes 1 if the member has published the whitepaper at least in the 50% of the ICOs where he has participated, 0 otherwise.
Blockchain	It is a dummy variable that assumes 1 if the member is an expert of the Blockchain Services sector. He is considered an expert if he at least in the 50% of the ICOs, wher has participated, are in that specific sector, 0 otherwise.
Cryptocurrencies	It is a dummy variable that assumes 1 if the member is an expert of the Crytpocurrer & Payments sector. He is considered an expert if he at least in the 50% of the ICOs, where has participated, are in that specific sector, 0 otherwise.
Financial	It is a dummy variable that assumes 1 if the member is an expert of the Financial Services sector. He is considered an expert if he at least in the 50% of the ICOs, wher has participated, are in that specific sector, 0 otherwise.
HighTech	It is a dummy variable that assumes 1 if the member is an expert of the HighTech Services sector. He is considered an expert if he at least in the 50% of the ICOs, wher has participated, are in that specific sector, 0 otherwise.
Media	It is a dummy variable that assumes 1 if the member is an expert of the Media, Entertainment & Advertising sector. He is considered an expert if he at least in the 50% of the ICOs, where has participated, are in that specific sector, 0 otherwise.

Table XXIII – Control Variables Description

3.4.1 Results

In this section, we will present the results of our regressions, as it is possible to see in the tables below, in order to answer to the research hypothesis.

It is possible to notice that first, we start from a model composed of the simplest measures of complexity and then we progressively increase the level of iteration of the $k_{m,\mathrm{n}}$ in order to see if higher levels of iteration are able to better analyze the economic network of the ICOs' world.

The observations are not constant along the work; this is related to the opacity and lack of information that leads to an impossibility of collecting data about all the ICOs.

Regarding the p-value, a measure of the probability of obtaining the predicted results considering the null hypothesis test correct, is used to catch the smallest possible level of significance at the level of rejection of the null hypothesis.

We define some symbols to describe the levels of the p-value, remembering that the smaller is the value, the higher is the evidence and the confidence level of the data.

Symbols are: "***" referred to the p-value when it is under 0.01, "**" under 0.05, and "*" under 0.1.

Before starting our analysis, we have made a statistical test, test of Durbin – Watson, to analyze the possible existent correlation between our variables.

This test analyzes the possible autocorrelation between the residuals of a regression model; this value is between 0 and 4 with the following statistical results: 2 if there are any type of autocorrelation between the data, smaller values mean that the successive residuals, on average, are close each other, or positively correlated, while higher values mean that successive residuals are very different between each other or negatively correlated.

As it is possible to observe from the Table XXIV and XXV the values of the test are close to 2, especially in the complete sample, this can lead us to state that the residuals of our models are not correlated, so we have the possibility to run a correct analysis of the database.

MODEL I

Starting from the results of this first Model it possible to notice that they are relevant; in fact, looking at the p-values related to $k_{m,0}$ and $k_{m,1}$ we can understand that these variables are significant: both have a level of significance at 99.9%. Moreover, they, are positively related to the independent variables.

According with the two above information obtained, we can verify our hypothesis H3, related with the ability of a member to raise funds.

The results obtained in this model are related to the simplest level of complexity, given by the first level of iteration of the Method of Reflection: $k_{m,0}$ is the average diversification of team member m and $k_{m,1}$ is the mean ubiquity of the ICOs that have member m in their team.

Finally, it is possible to state that team members characterized by a higher level of complexity are able to raise more funds.

MODEL II

Looking at the results of the analysis, also in the model II the p-values of the complexity measures are still relevant characterized by a confidence level at 99,9%.

Through this model, we can assess that increasing the level of iteration the predictive power of the measures is not lost.

MODEL III & IV

The objective of the setting of these two models is the verification of the hypothesis H2.b, related to the predictive power of the level of complexity.

We have progressively increased the level of iteration and we obtained as results always a significant level of confidence. In both models, the pairs of independent variables are statistically significant at 99,9% confidence level.

The most important evidence, in this case, is the value of adjusted R-squared. In fact, as shown in the table below, the adjusted R-squared increases among the first four models with the increase of the level of iteration, or at least remain stable, giving to the models a higher power of predictions thanks to the higher iterations that adjust and increase the quality of the samples.

Thanks to this evidence, hypothesis H2.b is verified, so it is possible to say that a higher level of iteration of the Method of Reflectionshas higher explanatory power.

	Dependent variable: Log USD Raised			
	OLS	***OLS***	***OLS***	***OLS***
	(I)	***(II)***	***(III)***	***(IV)***
$k_{m,0}$	0,579*** (0,038)			
$k_{m,1}$	0,074*** (0,002)			
$k_{m,2}$		0,800*** (0,046)		
$k_{m,3}$		0,0760*** (0,002)		
$k_{m,6}$			0,915*** (0,051)	
$k_{m,7}$			0,079*** (0,003)	
$k_{m,10}$				0,999*** (0,056)
$k_{m,11}$				0,082*** (0,003)
Advisors	0,213*** (0,056)	0,256*** (0,055)	0,254*** (0,055)	0,252*** (0,055)
Code	0,172 (0,271)	0,140 (0,270)	0,192 (0,269)	0,2302 (0,269)
ETH	0,172 (0,271)	0,140 (0,270)	0,192 (0,269)	0,2302 (0,269)
WP	0,460*** (0,114)	0,516*** (0,113)	0,475*** (0,113)	0,449*** (0,113)
Blockchain	-0,101 (0,095)	0,001 (0,095)	0,0188 (0,095)	0,022 (0,095)
Cryptocurrencies	0,406*** (0,104)	0,358** (0,104)	0,347** (0,104)	0,340** (0,104)
Financial	0,511*** (0,068)	0,518*** (0,067)	0,502*** (0,067)	0,486*** (0,067)
HighTech	0,362*** (0,075)	0,394*** (0,075)	0,404*** (0,075)	0,406*** (0,075)
Media	-0,120* (0,065)	-0,108* (0,064)	-0,103 (0,064)	-0,101 (0,064)
Constant	12,414*** (0,532)	12,876*** (0,079)	11,592*** (0,532)	11,376*** (0,534)
Observations	7494	7494	7494	7494
Adj. R^2	0,160	0,170	0,172	0,172
Durbin - Watson	1,951	1,953	1,955	1,956

Table XXIV – Models with 7494 Observations

In the following two last models we used the resized sample described in the paragraph 3.4. This decision is related to the fact that we wanted to assess the reliability of the Economic Complexity framework also with members with higher number of links, having a network with higher level of density.

MODEL V

The model V has been thought to assess the explanatory power of the independent variable even on the downsized network.

It is interesting to analyze $k_{m,18}$ and $k_{m,19}$ separately in this smaller network.

Noting that: the first measure is related to the level of diversification of member *m*, defined by the linear combination of the properties of all the nodes in the network that could be reached through a random walk of 18 steps, starting from the node *m*; the second is related to the level of ubiquity of ICO *i* where the member *m* has participated, defined by the linear combination of the properties of all the nodes in the network that could be reached through a random walk of 19 steps, starting from the node *m*.

It is possible to observe that $k_{m,18}$ holds a still significant level of confidence at 95%, while $k_{m,19}$ loses part of it, having now a p-value higher than 0,1.

However, the adjusted R-squared remains stable, so the predictive power of the model remain constant, even if the network has been changed.

MODEL VI

In the last model, we introduced a more complete structure in terms of analysis of the position of a person inside the network. The aim of this part of our work is to find a pattern between the Social Capital assessment, his capability to build relationships of quality, and the success of his work.

For this purpose, we add to the level of $k_{m,18}$ and $k_{m,19}$ the measures of betweenness centrality, to enrich the set of independent variables with a measure that can assess the ability of a broker (the person who work between important group of people and get them in touch).

The Betweenness Centrality has a confidence level of 99,9% and we have already tested, in the paragraph 3.4, that there is no correlation between Method of Reflections and Betweenness Centrality. In accordance with this key result we have the possibility to use this measure such as another independent variable improving the model.
Looking at the value of adjusted R-squared, thanks to this integration, the reliability of the model improves impressively.
This model has to be tested on the downsized network due to the fact that centrality measures, as explained in paragraph 3.3, cannot assume significant value when they are used in the complete network, due to its inability to estimate the quality of the links.

Dependent Variable: Log USD Raised		
Variable	***OLS (V)***	***OLS (VI)***
$k_{m,18}$	0,315** (0,138)	0,267** (0,133)
$k_{m,19}$	0,169 (0,108)	0,159 (0,104)
Bet_Centrality		34,086*** (5,542)
Advisor	0,536*** (0,125)	0,446*** (0,122)
Code	0,598*** (0,155)	0,571*** (0,150)
ETH (constant)	13,177*** (0,693)	13,285*** (0,670)
WP	1,169* (0,626)	1,078* (0,616)
Blockchain	-0,036 (0,210)	0,070 (0,204)
Cryptocurrencies	-0,985*** (0,219)	-0,082*** (0,214)
Financial	-0,011 (0,144)	0,115 (0,140)
HighTech	-0,114 (0,148)	0,019 (0,145)
Media	-0,468*** (0,130)	-0,340*** (0,128)
Observations	540	540
Adj. R^2	0,173	0,227
Durbin - Watson	1,389	1,425

Table XXV – Models with 540 Observations

4 Conclusion

The birth of the Blockchain has changed the structure of informatics and information technologies.
Before its appearance all forms of data collection were centralized; now, thanks to this disruptive innovation, decentralization can take place.
Blockchain is an open database of records of all transactions, that make users free from the role of intermediaries in a secure and transparent way. This is possible thanks to a sustainable technology that relies on the multitude of participants to preserve the information.
Blockchain had an impact on many different fields, but one of the most affected one was the financial industry.
In 2017 blockchain and cryptocurrencies re-shaped the world of finance with the Initial Coin Offering (ICO), raising more than $25 billion between 2017 and 2018.

An ICO is an innovative fundraising campaign that can be used by firms, usually start-up, to finance their growth, in 2017 it reached its peak of popularity.
The success that ICO had in last years can be explained mainly by two main reasons: first, the traditional financing industry was still paying the consequences of the recession and this opened the way to alternative finance to small entities such as start-up; Second, at the same time it started the trend of cryptocurrencies.
Nowadays, after a stop in 2018 when authorities started to regulate this processes, new forms of ICOs are developing and integrating its structures with new features, often appreciated also by the regulatory entities.
Today there are Security Token Offer (STO) that gives the right to the owner of getting profits or reward and Initial Exchange Offer (IEO), where campaigns are not conducted by the team of the company, but on a fundraising platform.
Nevertheless, even if names change, the aim is still the same: fundraising through blockchain technology.

ICO, unfortunately, has also been associated with numerous types of scams and sometimes it has been characterized by the opacity of information. These negative aspects do not stop the ongoing development.

Today, thanks to blockchain technology, companies can drastically decrease operational costs thanks to the use of alternative ways of financing and the presence of crypto-communities on the net.

Our work fits in the trend of the disruptive alternative financial tools and investigates how transparency, with specific regard to the team member of a start-up, can increase the success of an ICO. We aim at proving that it is possible to find what Akerlof named "peaches" in to give alternative investors the opportunity to better spot good projects to sustain their development.

We investigated this aspect by developing a model capable to analyze one of the few signals that we can derive from the data publicly available on ICOs, the quality of the social capital. We wanted to assess how the quality of the relationship that a person has affects a crypto-fundraising campaign.

Our aim is also to show the high importance of the human side in a world that becomes every day more and more virtual.

4.1 Comments on the finding

The relevance of the ICOs phenomenon has led to the production of several papers such as the ones by Adhami et al. (2018), Fisch (2019), Venegas (2017), Zheng et al. (2017).

Most of them focused on the factors that impact on the success of ICOs, starting from the presence of the white paper and the code, passing from the ability of the team to generate innovative products and services arriving to the human capital analysis and the related level of education of the member of the teams that participate to the ICOs fundraising campaign.

After these first works, studies started to base their attention on the Social Network Analysis, applied to this world by Feng (2019) and Fideli (2019).

These papers put in evidence how much the social capital is important for a success of an ICO. The authors highlight the relevance of good relationship among different actors of the networks and its impact on the probability of the goodness of the ICO.

To perform the Social Network Analysis several measures have ben introduced and applied to assess the quality of the connection inside the network.

The results led to state that the higher the level of social capital linked to the group of an ICO, the higher the probability of success.

With our work we contributed to this research, analyzing the impact of social capital using a new approach: the Economic Complexity.

Economic Complexity was introduced by Hidalgo and Hausmann to analyze the structure of a nation.

They observed that a country expresses the amount of knowledge it has, through the number of different products that it manufactures; in relation with this concept, they developed two different variables: *Ubiquity*, that represents the number of countries that make a product; and *Diversity*, that represents the number of products made by a nation.

Diversity and Ubiquity are two separate measure but reciprocally connected since one can be used to correct information carried by the other. Moreover they are utilized in the Method of Reflections, consisting in a iterative calculation of the "average value of the previous-level properties of a node's neighbors and is defined as the set of observables:" (Hidalgo and Hausman, 2009).

Following this conceptual framework by Hidalgo and Hausmann, we applied these definitions, creating a new bipartite network, composed by *m* team members and *i* ICOs. We then redefined the concept of diversification and ubiquity, respectively how many ICOs the member *m* has done and how many members are present into the team of the ICO *i*.

After applying the Method of Reflections to our two samples, a complete and a resized one, we assigned to each actor of the network, the *m* members of the different team of different ICOs i, their respective value of complexity $k_{m,\mathrm{N}}$.

The values of complexity for each actor, represent the quality of the social capital of each member, assessing the importance and the relevance of a person in the ICOs' world.

After completing this first step analysis, we linked the different values of complexity with our most relevant variable of the sample, the USD Raised, to assess if there is or not a correlation.
We observed this correlation developing six different OLS models, that allowed us to proof the acceptance of our initial hypothesis.

The final results of our work show that:

- Team members characterized by a higher level of complexity are able to raise more funds.

- Increasing the level of iteration, the predictive power of the measures is not lost.

- Higher level of iteration of the Method of Reflection has higher explanatory power.

In the alternative finance industry, characterized by a strong information asymmetry, our model is able to improve the decision making process providing a tool to better asses the quality of an ICO before its first collecting round, giving the possibility to investors to have an evidence on the potential for success in advance.
With our model we contribute to a better information analyzing the social capital referred to each actor and assessing their position and their relevance inside the network.

4.2 Limitation of the Work

The main limitation of our work comes from the reliability of the data. The collection of the data, that populate our database, was done without any type of technological support, going directly on the different website, judged according to the procedures of our team and classified with a scale of reliability going from 1 to 5 points. Due to the very opacity of the data and the discordance we observed among different sources, we were forced to apply our own model not on the totality of the existent ICOs, but on a reduced number of them. This lack of reliable data and the presence of a strong evidence of information asymmetry, especially in the ICOs' world, lead to some potential lack of reliability of our results, with

possible discrepancies with the actual process and the development of each fundraising campaign.
Starting from this evidence, it will be necessary for future studies to find and assess reliable sources of data to increase the confidence on the results and leave no room for doubt.
Moreover, the process of populating the database, conducted completely in a manual way, may have incorporated some human error; in future analysis, it will be useful to use a semi-automatic process to increase reliability of the data input.
Furthermore, as far as ICOs' environment is concerned, we observed how it is in continuous development with an increasing number of in process regulations and restrictions. For this reason, the future spread of the Initial Coin Offering fundraising is still uncertain.
The ongoing development of similar financing method, such as STO and IEO, still based on cryptocurrencies, bypassing intermediaries and utilizing the blockchain technology, permits to maintain a positive outlook on this innovative filed of technology applied to the finance world, the so-called Fintech industry.

Finally, the literature analyzed in our thesis and the underlining research work will continue in the next future with the possibility of applying the model developed and tested with this thesis in future studies to better understand the role of social capital in relation with the ongoing cryptocurrencies' world.

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