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Managerial connections among investee companies in the Italian equity crowdfunding market

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APPENDIX

CHAPTER 1
INTRODUCTION

1.1 Structure of the work

In this dissertation is going to be investigated the phenomenon of crowdfunding related to new ventures, more in particular the effects that social capital, seriality of Founders and presence of commonality of stakeholders with other startups that raised funds through crowdfunding, may have on the company.

The attention will be focused only on the Equity Crowdfunding campaigns, where the subscriber of the offering obtains ownership in the company. Other kind of crowdfunding venues i.e. minibonds, reward-based CF, donation-based CF, P2P lending are out of the scope of this study. Additionally, the analysis is strictly on Innovative Startups, therefore companies born in the last five years, with yearly revenues below €5 millions and with high technological content. PMIs are not considered in our work nor Real Estate projects.

In this first introductory part, the phenomenon of Crowdfunding will be discussed from its origins to its current state, with a brief analysis of the Italian landscape. Finally, the concept of Social Capital will be presented.

The second chapter is a deep dive in the concept of Social Capital. The literature about this topic will be presented and discussed in order to explain why it is extremely relevant for this type of work. The third chapter revolves around the initial goal of this dissertation, which is the investigation about the phenomenon of Serial Entrepreneurship in the Italian Equity Crowdfunding space. Firstly, all the steps for the gathering of data will be presented, then the econometric studies and results will be discussed.

In the fourth chapter the scope was broadened not only to focus on the figure of the Founder in a startup, but the whole Human Capital of a new venture, mainly his team and his initial investors. It will also be presented and explained how the first ever network of interconnected startups that participated in the Equity Crowdfunding space in Italy has been created, with emphasis on its evolution through the years.

In the following chapter, all the possible connections will be investigated, therefore no more focussing exclusively on the Founder-Founder typology. This is done using econometrics variables that take into account the seriality volume, the positioning and other parameters for the startups about the network's effect. The results will be discussed and related to the concepts of Social Capital and Human Capital presented in the second chapter. Finally, the dissertation will be concluded with the closing remarks and what further studies can be done on the matter.

1.2 The crowdfunding phenomenon

The phenomenon of crowdfunding was originated in the 90s during the boom of the internet, and it was initially relegated only to donations. People on the internet had for the first time the possibility to interact with each other in a totally revolutionary way. For example, artists and musicians sought this opportunity to raise funds from their fans.
Only in the new millennium thanks to multiple platforms which has spawned in the US in the late 2000s, the phenomenon started to be taken more seriously and to be used to fund projects and different kinds of endeavors. Initially, it was exclusively donation-based or at maximum reward-based, therefore it was still a form of financing but not as complex and developed as traditional finance, i.e. Debt instruments or issuance of Equity.

In the early 2010s, in both the United States and United Kingdom, the first platforms for Equity crowdfunding (ECF) started to appear and in detail they were ProFounder (US) and Seedrs (UK). This was a new innovative way to raise funds and scale companies without relying on angel investors, early VCs or other actors that could be involved in the seeding phase. The strength of ECF relies on its simplicity because a pitch of the company, the business plan, historical financials data and past KPIs are the only requirements to be listed on a portal. If the idea and vision of the company is embraced by the crowd, funds will be raised with relative ease and without much friction in the process. On the other side, it opens up and it democratises the possibility of investing in the early stages of a company to virtually anyone interested, thus sharing the risk but also the upside potential. This opportunity was essentially impossible for the average investing people prior to ECF, as only having direct connection with the founder or investing in VC Funds would have given the possibility to participate in seed rounds. The reasons behind this not democratic condition are financial, but they are bypassed thanks to crowdfunding as campaigns are accessible to anyone as they use to have a minus ticket size of €250-500.

In Italy, Equity Crowdfunding was regulated and started in 2013 with the first platform StarsUp which is still active today. From that year on, multiple portals started to appear up to the 42 authorised platforms of today. The overall volume of deals went from €1.3m in 2014 to €65.18m in 2019 (CAGR of 119%) and cumulatively in these years a total of €120.5m has been raised through this alternative financing source in Italy. The biggest platform for cumulative volume is MamaCrowd, with €34m raised, followed by CrowdFundMe at €29m and Walliance (specialised in Real Estate business) at €22m. A total of 595 campaigns were launched to raise capital through equity crowdfunding and of these 402 (68%) were successful as of September 2020.

Below is shown the number of deals throughout the years as of 2019 and the amount of capital raised in the Equity Crowdfunding (Fig.1.2.1). The trend shows a clear and incessant growth for the space, with 2019 as the biggest year for both deals and money raising. This trend is expected to continue also in the coming years.

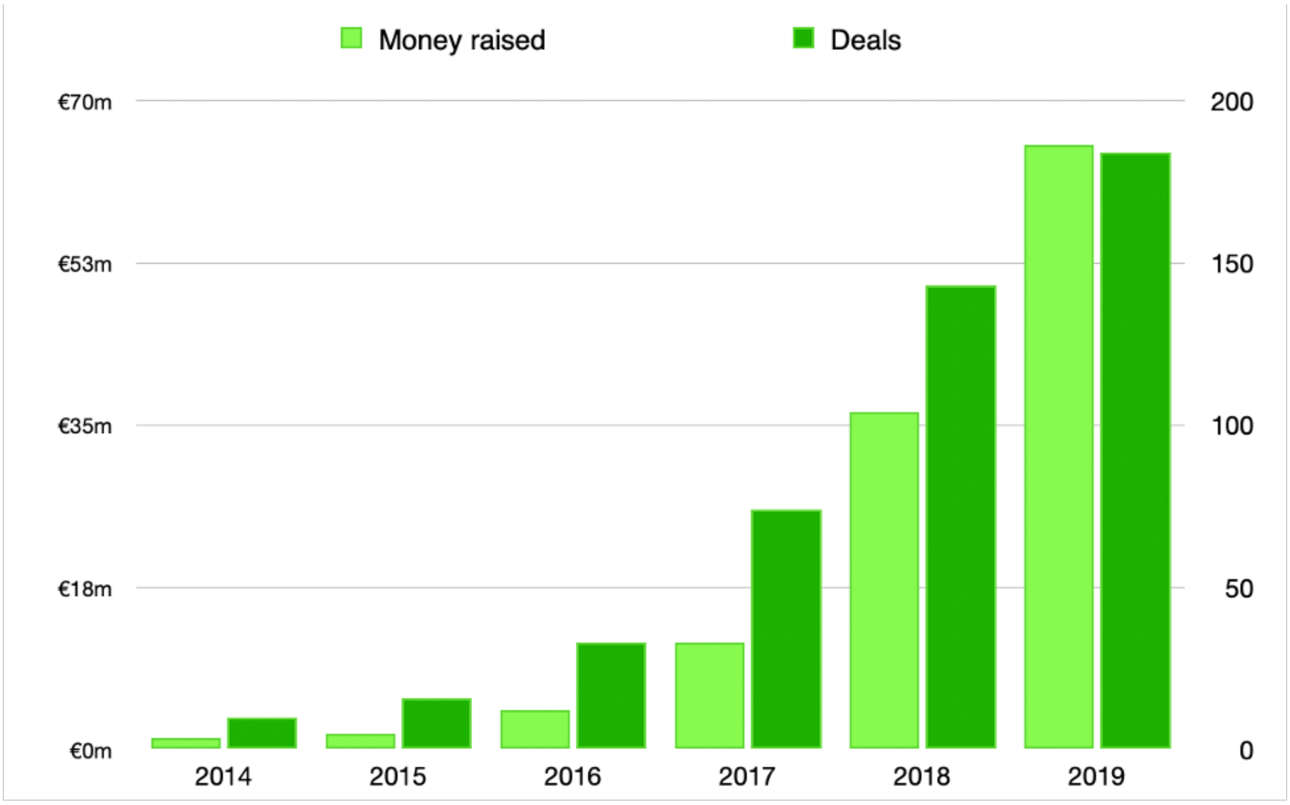

Fig.1.2.1 Growth of the Italian EC through the years

1.3 Social capital

Despite the crowdfunding is a relatively new phenomenon in Italy with less than 10 years of history, it's already possible to find interconnections and overlaps between stakeholders of the different companies that participated in a crowdfunding campaign, considering connections which are at founder level, team level, or shareholders in common. Therefore, with that information a network of inter winded startups can be created.

This open up the possibility to study and to investigate the potential effects of the phenomenon known as Social Capital (Woolcock 1998) in the context of the Italian ECF space, which encompass the physical, personal or psychosocial resources to which individuals and groups have access through their social networks. What is going to be investigated in this work are the benefits that may derive from that, more in particular by information and skill-sharing brought to the companies by individuals present in multiple ones, so individuals belonging to a network of people that in return link and connect different startups. The concepts of knowhow, learning process, learning from doing and learning from failure in case of entrepreneurial seriality are fundamental in this study, because these are concepts related to founders who after having raised funds with a startup through crowdfunding go on to repeat the same thing with a new venture. Said in other terms, the focus of the work is not aimed at studying the Social Capital that is already present inside a company, but tries to observe how external social capital, that has been previously created in other startups, and Intellectual Capital, bundle of knowledge and competencies acquired through time, are going to impact the performance of a crowdfunding campaign. This means that the underlying idea is to investigate the impact of external capital once it has already been "incorporated" inside the company and merged with the internal one that's already present and the potential positive externalities and spill-over effects of competencies from one startup to the next that may occur.

The starting point of the analysis was the understanding of the effects of serial entrepreneurship in the landscape of Italian Equity crowdfunding, therefore what may be the benefit of having a founder who created multiple companies. Subsequently, the scope was broadened to any type of connection and link between startups in the ecosystem, focussing not only on commonality of founders but of stakeholders as a whole, thus studying the potential impact of social capital in his complete sense. Three categories of stakeholders have been defined as links between the different startups: 'founder', 'team member' and 'shareholder'. If two or multiple startup have one in common, then a connection has been created. More details and the complete description of the methodology used will be presented in the following chapters. The total number of startup that have approached ECF to raise funds since its inception in Italy in 2014 to December 2020 are 641 and in this number are considered also PMIs and real estate projects, with an overall number of campaigns of 709. Considering that successful startups may have done multiple raises and that also initial failure case tried a second campaign on a different platform, it is possible to observe that multiple campaigns by the same company are 68. Considering only innovative Startups, the number of startups is 442 for a total of 481 campaigns and this represents the total sample on which the work is based. The startups that present connections among them and thus join the final network, as of December 2020, are 141 and they represent the nodes of the studied network. Below in Fig.1.3.1, it is shown a timetable that illustrates in the years from 2014 to 2020 each startup that will end up forming the network raised funds for the first time. This gives an idea of the evolution and of the populating process of the network. The year with the biggest volume of joining companies inside the network was 2018, followed closely by 2019 and 2017 which is the year in which Equity Crowdfunding in Italy really took-off. It is important to note that even if a startup appears in a specific year in the network, it may take time before building a connection, so remaining as an isolated node for some time. This concept will be deepened in the following chapters.

Timetable of campaigns

2014	2015	2016	2017	2018		2019	2020
Diaman Tech	Inoxsail	Xnext	Melixa	Sfrecciando	JustMary	Growishpay	Apping
Fannabee	Insono	CleanBNB	yakkyo	Inpolitix	Green Idea	Gardenstuff	Ener2Crowd
	Cartina	P2R	TAEBioenergy	Olzemusic	Seed Money	Wonderstore	ByciSolarStreet
	OpenTail	Forever Bambu	FindMyLost	Live Based Value	Revotree	Interweb	The Hundred
		Nexapp	Bloovery	Karaoke One	Wiralex	Vidoser	Retail Efficiency Venezia
		Linfa Crowd	YouDroop	Maid Service	Soisy	Recrowd	DesignItaly
		Sharewood	Raft	Everyware	Eattiamo	Green Energy Sharing	Prestito Super
		Parterre	TaskHunters	Prestofood	You are my guide	Livesonar	Deliveristo
		Nano	Graphene XT	Criptomining	Fol the best	Start&Partners	Novatek
		Perfrutto	SoundOfThings	Userbot	Racine Caree	Vintag	AvvocatoFlash
		Luche	Green Energy Storage	Sthimaty	InkDome	My Secret Case	Coffinardi e Delpanno Industries
		InfinityHUB	Take Off	Marshmallows	WindEnergyEfficiency	Social Academy	Affitto Certificato
			Verso Technologies	BioInvestments	Domoki	Axieme	Irides
			GlassToPower	Biovecblok	Japal	Welfare Efficienct Piemonte	MeetMyPet
			Qaplà	Eggup	Sportit	Quomi	Eutronica
			Babaiola	Edgar	Locare	Sportclubby	Olivone
			Classup	InReception	My Credit Service	Nuova Industria Torinese	Smart Mobility
			WeBeers	Verum	TiAssisto24	Salva Assistance	Elsilab
			Sustainable Mobility	Sintesi Forma	Autentico	GoGOBus	Flowdron
			Nettowork	Bikee Bike		SEO tester	WEY Dolce ER
			Bermat	AR Market		Leark	Alterego
			Coco	Eligo		Noixa	Sterify
			LeoNardi Milano	EYS BA		Fremslife	110Efficiency
			Socopet	ShapeMe		PickMeApp	MPD SME Capital
			Sync	Biogenera		OIP start	
			Scloby	Traction Management		Repup	
				My Lab Nutrition		Rentapp	

Fig.1.3.1 Timetable of the population in the network

An extract of the network of startup that has been created as part of this work is presented below in Fig.1.3.2. Every node represents a startup and a connection is present if there's a stakeholder in common between the two. Bigger arrows mean that there are multiple people connecting the two startups. The direction of the arrows gives an idea of the temporality of network, meaning which is the startup that comes later and "anchors" itself to another one. All about the methodology and the creation of the network itself will be presented and discussed in full details in the following chapters.

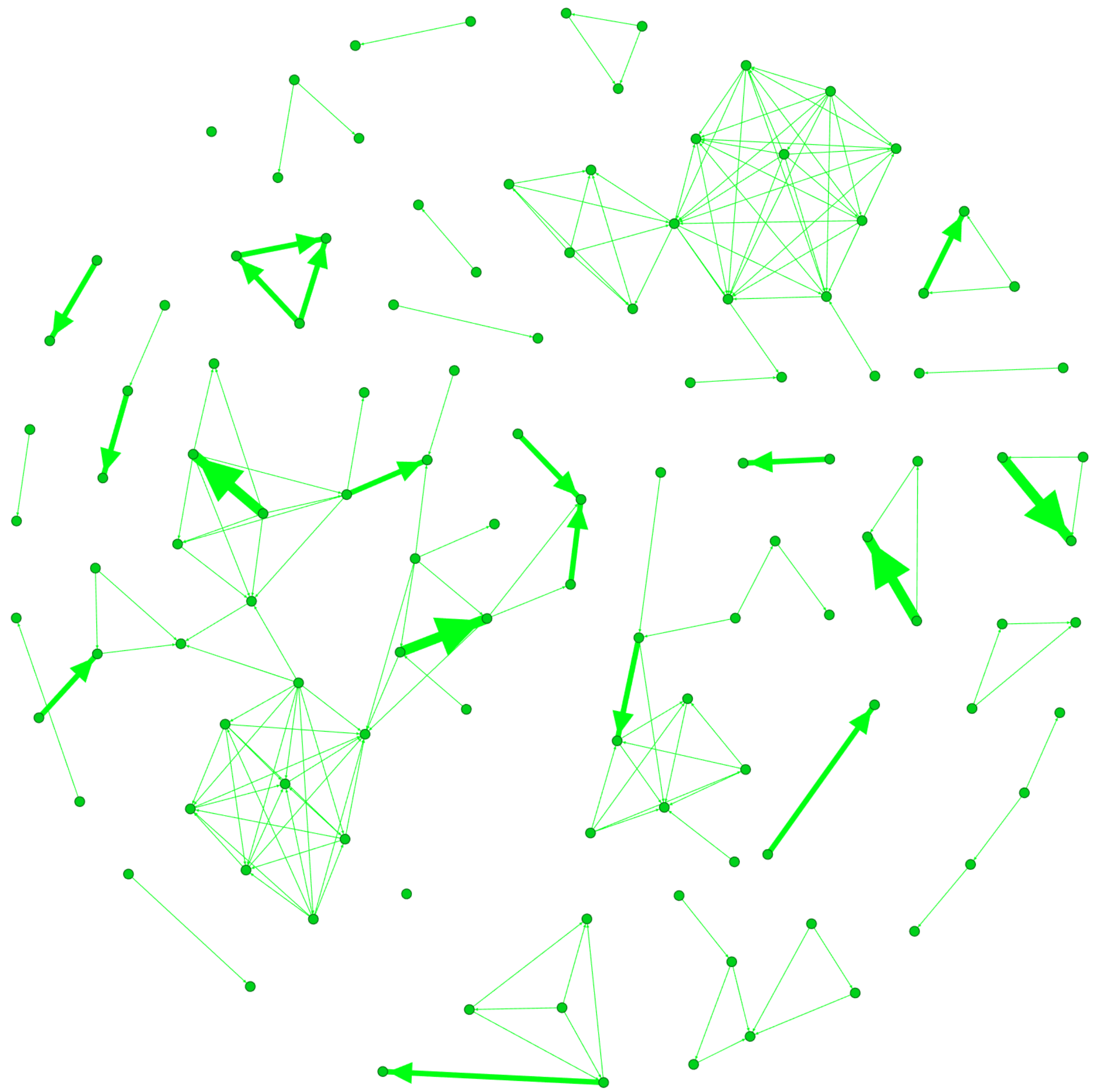

Fig.1.3.2 Network of inter-connected startups at the end of 2019

CHAPTER 2
SOCIAL AND INTELLECTUAL CAPITAL

2.1 Introduction to capitals

Social and *Intellectual capital* are two fundamental components on which the analysis work is based. The *Social capital* is defined as the resource produced thanks to the overall amount of relationships that a single individual has inside his personal social network (Mary Dunne, 2020). In particular in this study the observed entity is the single startup that works and lives inside the overall Italian equity crowdfunding network. It is possible to identify different types of relationships with different origins and different intensities. In accordance with the origin of the relation, the Social capital can be divided into 'external' and 'internal' capital (Cai, Polzin, Stam, 2020). The external one is based on relationship with the external environment outside the startup, in other words with the rest of the social network. A concrete example could be the relation between two startups in the same platform thanks to the presence of a common team member. On the other hand, the internal one is built on internal relationships inside the startup and a clear example is a possible link between two founders of the same startup.

The essence of Social capital is to give the opportunity of connection between people, considering already close people but also someone who would never be in touch.

This capital can be divided in three sub-categories (Nahapiet and Ghosal, 1998), each of them is focused on different aspects of this macro topic and plays a very important strategic role in the definition of Social capital. Of course, each category can be studied looking both the external and internal dimension.

The first category is the 'Structural part' and it represents the relational infrastructure that allows the different nodes to come into contact with each other. It is something measurable and it can be studied looking the number and the complexity of the relationships which link one point with the rest of the network. This subcategory is important for the study of how the startup influences others and how itself is influenced by the network. In particular, this information can be studied looking the direct and indirect relationships that link the startup with the rest of the network, so as observing the ways through which the information spread through that startup.

The second category is the 'Relation part' and it is associated with the interpersonal relationships between people in the network such as friendship, trust and behavioral norms. The relational subcategory includes an important concept that is the 'duty', so the idea of being obliged to behave in a way just because someone has previously behaved in the same way (Troise, Tani, Jones, 2020). For example, an individual may feel obligated to spread information only because he has received info from that same counterpart before.

This concept is important if introduced in a context of seriality and connection between different startups, as it tends to further expand the spread of information among nodes (Coleman, 1990).

Another important concept to include in this category is 'trust' (Troise, Tani, Jones, 2020). By trust it is meant a strong relationship that influences a great deal the effectiveness and the performance of the social capital, especially in the case of the equity crowdfunding business, as it is based on people's money and on online transactions without real and physical contact with people and knowledge of them. Thus, an increase in trust involves a possible increase in social relations since people feel more in safe without fear to jump.

The third and last category is the 'Cognitive part' and it is linked to the idea of sharing a common meaning, language and direction to the members of the group. The main purpose is to align people with the same objective and the same direction creating a sort of common group identity.

The Social capital can be additionally studied looking two macro-categories: Bridging and Bonding social capital (Mary Dunne, 2020).

These are defined as:

- Bridging Social capital: case with loose structure with weak relationships. The presence of weak relationships is not always seen as a disadvantage, as it allows a free and easier flow of information without typical problems of closed working group. In particular, the presence of a poorly connected environment contributes to increase the efficiency of the network's components as they are left alone without a strong influence among each others. This condition pushes them to work in the best possible way and independently from each other.
- Bonding Social capital: solid structure with strong and well structured relationships. This strong closeness is good for building social personal relationships but it can raise issues such as group thinking (i.e. to regard something as true just because it is said by someone with a certain authority in the group/community), fear of prejudice and scarcity of efficiency. As far as the network perspective is concerned, the strong and close relations can cause a bad quality spread of information and knowledge, as it tends to remain inside the group, increasing just the human and social capital of group members only. On the other way

around, the existence of close relationships is good for the elaboration of a strong sense of collectivity.

Understanding the boundaries between these types of Social capital gives the opportunity to understand how information flows within the network, as it is possible to understand where the information passes and where it is blocked.

The *Intellectual capital* is an intangible capital associated to knowledge, capabilities and skills of people. Similarly to the Social one, it is composed by three sub-categories which are: 'Human capital' (skills, knowledge and talent previously acquired thanks to personal background), 'Structural capital' (relational infrastructure) and 'Relation capital' (relational and emotional side) (Mary Dunne, 2020). This dimension is associated to the general and natural talent and skills of people as well as with their working and educative backgrounds. The idea is that the previous working and study experiences increase the Intellectual capital and it positively impacts the performances of the startup and of the fundraising campaign.
The concept of Human capital has been taken up several times in the course of economic and sociological studies. One of the first study in which were introduced Human capital concepts is 'Wealth of Nations', (Smith, 1776). This study aimed to highlight how the skills, the capabilities and the knowledge of the employees are fundamental factors to have positive impact on the performance of the production process and on the quality of the outputs. This document emphasizes also the importance of investing in Human capital by companies, ensuring a high level of education for better performing the internal activities. The concept was furtherly developed during the 20th century. For the first time the concept of Human capital was grouped within the company's total capital, considering it together with the material and financial capitals (Fisher, 1906). The underlying idea is that these different types of capital should be grouped together because they all create a return for the company. Therefore, the capitals that should be considered are not only the material ones but also the immaterial. Other studies have strengthened the concept of Human capital, defining it as a multiplying factor of skills and capabilities of people (Ulrich, 1998) but also emphasizing how this capital is fundamental for companies' competitive advantage (Barney, 1991). According to the latter, companies base a large portion of their competitive advantage on the rarity, difficulty of replication and difficulty of replacement of their assets. Being the Human capital something intangible and highly personal with poor replicative capacity, then this greatly increases the potentiality of this asset. For this reason, companies must invest in this for increasing their status above the other companies, highlighting what was initially

discussed by Smith. Not only companies have to invest in their employees' Human capital but also people have to invest in themselves for improving their levels of capital for increasing their productive capacities (Schultz, 1960). An incentive to bring individuals to invest for this improvement could be the use of wages based on productivity and on education and knowledge levels.

Obviously, this investment represents a cost for the single individual, therefore the investor must take into account the trade-off among costs and benefits arising from the investment. Depending on the level of already existing capital, the marginal return is not constant at the same cost. For example, if a newly graduated student and an expert company manager undertake the same study course, the impact created on the level of human capital of the manager is lower than the one generated on the newly graduated student who has a very low level. At the same time the capital increase is not infinite, so a continuous increase in costs does not lead to an infinite increase in capital. In particular, a rational investor tends to increase its investment volume until the marginal return equals the marginal cost.

The impact of Human capital on profits can be describes in the Fig.2.1.1 (Schultz, 1960).

$$E = B + R - K$$

Fig.2.1.1 Equation which shows the impact of human capital on investor's net real earnings

'E' represents the Net Real Earnings from the investment, 'B' indicates the level of basic earnings, 'R' is the gross return from the human capital investment and 'K' is the investment cost.

To provide a further set of information, it is possible to take into account a specific cataloging of Human capital, observing different categories according to the origin of the capital (Blaug, 1976). These categories are formal schooling, on-the-job training, job search, information retrieval, migration and improvement in health. An important fact to be defined is the not substitutive capacity of the various categories. Therefore, there is not complementarity that guarantees to use Human Capital from one category for covering the lack in another.

At the same time, it is possible to identify an additional dimension of Human Capital which doesn't result from the above described six categories. It wants to communicate the existence of a distinction between general and specific Human capital (Becker, 1964).

The first type increases the overall productivity of the individual, while the second increases the productivity only in specific contexts, as in case of a specific work to be carried out within a production process.For this reason, the existence of general Human capital and specific one that can be developed case by case can be both identified in each individual.

Considering that the accumulation of capital in individual generates a positive impact on the productivity of this, it is possible to define a mathematical function that describes at theoretical level how capital affects productivity (Erikson, Nerdrum, 2015). This function considers as Y variable the marginal productivity MP of the individual and three parameters as explanatory variables X. These parameters are L (labor quantity usually expressed in working hours), H (human capital) and C (additional capabilities and skills as motivation, endurance, physical condition and others similar). The basic idea is to show the positive impact of these three explanatory parameters on marginal productivity, but also to study that parameter C has a positive influence on H and vice versa. For example, the psychophysical and motivational state influence learning activity, causing an increase of H. At the same time, the H and C parameters also have an influence on L, since the total working hours of an employee are dependent by the level of knowledge and experience and by his/her general motivational and psychophysical condition. The existence of this series of influencing effects generates a circular relationship that leads to an increase in productivity. Within the function is interesting to assess the existence of the dual nature of Human capital, thus considering the general Human Capital, GH, and the specific Human Capital, SH (Becker,1964).

The theoretical function can be easily explained in Fig.2.1.2.

$$MP \ = f(L+; C+; (GH + SH)+)$$

$$MP = \ \beta 1\ L \ + \ \beta 2\ (L\ x\ GC) \ + \ \beta 3\ (L\ x\ SC) + \ \beta 4\ (L\ x\ C) + \ \beta 5\ (L\ x\ H\ x\ C)$$

Fig.2.1.2 Theoretical function that generally describes the influence of labor, human capital and additional physical and mental factors on the marginal productivity (Erikson, Nerdrum, 2015)

This topic of intellectual capital is based on a different perspective than the Social one. The latter is more focused on 'who that individual knows', whereas the Intellectual capital is based one 'what that individual knows'. These are different concepts but they have a cooperating role that is fundamental in our analysis.

2.2 Information asymmetry phenomenon

The phenomenon of *Information Asymmetry* is one of the main theoretical causes of market failures. This problematic condition arises when there is a situation in which two or more counterparts of the transaction do not have the same level of information. Therefore, one faction is more informed than another causing a not balanced information level which sequently increases the level of inefficiency of the transaction. This phenomenon can be divided into two macro categories, depending on the time orientation in which the information asymmetry affects the transaction. These categories are ‘Adverse Selection’ and ‘Moral Hazard’.

It is possible to talk about ‘Adverse Selection’ when the informative not equilibrium involves a situation when a counterpart lacks information about relevant aspects of the transaction before that transaction occurs. This situation results in a hidden information problem because the asymmetric condition involves information about the transaction, for this reason it is also defined as information deficiency. In particular due to its time orientation, it is defined as ‘Ex-Ante information asymmetry’. A classic example of this problematic situation is the asymmetric condition that could occur when the seller of a product is more informed than the buyer, thus creating a negative condition for the customer.

The problem of Adverse Selection was studied in the seminal paper ‘The market for lemons’ (Akerlof, 1970), which focused on the study of the phenomenon but in particular on the effect that ex-ante information asymmetry generates on the market and on its players. The conclusion elaborated by Akerlof is that the existence of information asymmetry generates an overall inability of distinction between good quality and bad quality players, forcing good quality ones to exit the market due to unfavourable conditions. Their exit generates a subsequent general qualitative decrease of the market as only low quality players tend to remain within the market. If this concept is applied to the equity crowdfunding business, it is possible to imagine a situation of inefficiency in which startups with a better idea and a more efficient team collect the same amount of capital of those with a lower quality level. Due to the higher costs of team and project development, this capital could not be enough for good startups, causing their exit and their approach to other financing sources.

Therefore, it is important to try to limit this effect and one solution is the ‘Signaling’. Signals are observable attributes and actions that provide information about unobservable actions and attributes, therefore these are tools useful for showing the good quality and the good willingness of the counterpart. In the case of startups on CF platforms, one way to achieve signaling is to show information about past and potential future performances, data about team composition, and information about the project for which they ask capital and the relative plan for its concrete implementation. A further signal can be generated by the share of information about team members' past experiences and track records. The inclusion of qualified personnel in the team allows to highlight what said by Spence in his seminal paper 'Job Market Signaling' (Spence, 1970). According to this, the education is a credible signal that improves the efficiency of the transaction. Therefore, it is possible to emphasize that the intellectual capital portfolio that a startup owns can be seen as a decreasing factor of information asymmetry problems. Looking at this theoretical model, it is possible to observe as the good quality condition is a key component for a startup but also for companies in general. This happens because these entities pay money to show and to increase their quality levels, in particular the cost is inversely proportional to the level of quality because a company is required to spend less for showing and for increasing its good quality if the already existing quality level is high. At the same time, if the quality level is not high enough, the company is required to spend more money. This means that the two companies are able to earn different profits in front of the same investment return because the good quality ones can achieve a better profitable condition thanks to the not existence of extra expenses related to the increase and the show of quality level. In this way, it is possible to understand the importance of having an internal good quality because it is an improver of the transaction efficiency.

In order to protect investors, even platforms have an important role for the improvement of the condition of information asymmetry issues as these try to select the hosted campaigns, choosing only those with a good quality level. This is important for creating a good reputation of the platform, useful to attract both investors and startups in the future.

The other category related to information asymmetry problems is the 'Moral Hazard'. This category includes situations where a counterpart of the transaction lacks information on the actions of the other party. It is the result of a hidden action problem, which causes an 'Ex-Post information asymmetry' issue. Applying the concept to the CF environment, a clear example is the absence of knowledge about how the startup will really use the raised funds after the end of the round. A possible remedy to the Moral Hazard problems is the use of 'Incentives contracts', that induce both counterpart to not have opportunistic behaviours. An example could be the use of contracts with pecuniary clauses in case of not achievement of a specific result.

Looking the equity crowdfunding dimension, both types of information asymmetry problems are present. Before the campaign investors can be held back during the investment due to lack of information, that would be useful to allow to have a correct and detailed picture of the situation reducing any doubts and the investment uncertainty. On the other hand, also moral hazard issues

exist. In fact, the investor gets in touch with the ideas of raised capital's future use through published business plans, but until the end he/she doesn't know if these promises will be respected or not.
In order to optimize the fundraising process and thus improve round's performance, it is important to eliminate both categories of information asymmetry as this would reduce the overall level of uncertainty of investors.

2.3 Capitals during fundraise

During the fundraising period, the Social and the Intellectual capitals cover two fundamental roles. What is important to understand is that they are both important for the general performances as they work in a sort of cooperative way.
The main idea is that the Social capital serves as link between different network's nodes but what it is important to know is its capacity of working as a diffuser of the Intellectual capital, because the knowledge, the talent and the ideas can be diffused inside the network only thanks to relationships among people (Brown, Mawson, Rowe, 2018). This means that the Social capital offers the opportunity of increasing the Intellectual capital inside a startup, causing a good and positive impact on the startup's fundraising and general performances. From a metaphorical perspective, it is possible to identify the social capital as a library (Mary Dunne, 2020) where people get in touch and discuss about the books' content. This information can be shared only thanks to interpersonal relationships and communications because if readers don't speak among each others creating a series of interpersonal interactions, they will not share information.
Therefore, the main idea is to use the Social capital as a series of bridges among startups that are useful for spreading the knowledge and skills of people. For this reason, these capitals are connected among each other and they both work as key players in the studied network.
In this way, the startups can be linked among each others and the knowledge and skills that are developed in one can be transferred to another one. This happens thanks to existence of an individual who has worked in a startup and subsequently has worked in a second one. In this way the learned skills and the experience can be shared in the second, generating good effects on the general management and fundraising performances. This means that thanks to the existence of social relation interactions, the internal intellectual capital developed in a startup can be moved to a second dimension.
The existence of these cooperating capitals and the presence of a concrete network allows startups to work on some issues. As previously mentioned, the spread of knowledge and capabilities

contributes to the creation of a good and positive impact on the general startup's performances. This happens because startups' management acquires information about how to behave, how to collect resources and how to bargain with investors thanks to previous experiences. Moreover, a very important impact from the cooperation is a possible reduction on information asymmetry problems that characterise the fundraising and the startup (Butticè, Orsenigo & Wright, 2017) (Barbi, Mattioli, 2019).

The presence of a good quality internal social and human capital, and so the presence of individuals that have been already involved in other startups and in other campaigns, reduces the general level of information asymmetry on the startup, including both ex-ante and ex-post problematic asymmetric condition. Therefore, investors recognise in the presence of already experienced and good track recorded individuals a good solution for signaling the quality of the project. It means that the good quality individuals are useful for ensuring investors about the quality of the project and at the same time about the correct use of the invested capital, solving both moral hazard and adverse selection issues. In this way, the building of external social capital is influenced by the existing internal social and intellectual capital (Butticè, Orsenigo & Wright, 2017) and (Cai, Polzin & Stam, 2019).

The project's backers see the 'components' of the startup as a sign of good quality and their presence strongly influence their willingness to invest in the project, especially when the startup operates in a new business characterised by high level of uncertainty and information opacity. This positive effect serves also to reduce a typical startup's issue that is the 'Liability of newness' (Brown, Mawson, Rowe, 2018), which is an information asymmetry problem due to the fact that the startup is introducing something new with a significant level of uncertainty.

This means that the experience and the track record are key for spreading information and for reducing information asymmetry. Of course, the beneficial effects of seriality (people that have already developed intellectual capital) are amplified if such experienced position cover key and active roles within the startup (Brown, Mawson, Rowe, 2018).

This dual effect (on general performances and on fundraising ones) can generate a sort of virtuous circle in which startups want to build relationships for solving information asymmetry issues and for personal improving performances, the financing supporters are attracted by the existence of good quality relationships, the startup benefits from these seriality cases and, therefore, it can decide to further increase relationships receiving again benefits and so on.

The objective of this thesis analysis is the understanding of how the human capital previously developed in crowdfunding campaigns influences the fundraising performances.

It is important to consider the idea that information asymmetry problems are not fully solved by people's Social and Intellectual capital. Indeed, the fundraise platforms have a strong interest in reducing these problems for personal economic and reputational interests. It is like the concept of 'Reputational network' (Lechner & Dowling, 2003). In order to do this, they initially screen the project, they select only reliable ones and, subsequently, they personally share information about startups to investors.

2.4 The role of the 'supporting crowd'

Having seriality in the equity crowdfunding environment allows not just the share of experience and knowledge, but also the creation of a backers community that trusts and follows the serial fundraiser in his/her different campaigns (Skirnevskiy, 2017). This group of supporters represents a case of external social capital because it is based on relationships that are built with individuals who are outside the company. In this way, the single serial individual works as mover of this crowd and as bridge between two or more different startups that go through equity crowdfunding at the same time. The existence of this community of followers is very important especially in the initial period of the fundraising, as the presence of a community of investors that decides to invest immediately is regarded as a positively passed quality test by potential hesitant investors, causing them to invest in the same project, which is now perceived as less risky and with a lower uncertainty level (Butticè, Orsenigo, Wright, 2018). This is a sort of combined effect provided by 'signaling' and 'information cascade' concepts because initial investors show the good quality (signaling effect) and the second investors group decides to invest only after someone has previously done that (information cascade) (Cai, Polzin, Stam, 2020) and (Butticè, Orsenigo, Wright, 2018). The concept of 'signaling' has been already introduced in paragraph 2.2, while it is useful to give a brief explanation of the concept of 'information cascade' in order to better understand how the crowd influences the investment decision of the other supporters. 'Information cascade' refers to a phenomenon described in behavioral economics and network theories in which a certain number of people take a particular decision in a sequential way according to what is decided by people before. The process can be summarily defined in five components: creation of a situation in which a decision has to be taken, the decision provides a limited choice (i.e., accept/reject decision), the crowd makes a specific decision while the other part of crowd continues to observes what the crowd does, persons who have not made yet the decision receive and analyse information from the environment and finally the crowd influences the remaining part that follows the crowd's behavior. This is a strong tool that can be used to move and to attract people towards certain behaviours, but the issue is that the single individual can be led to not behave rationally. Therefore, the single person can take decision that are in the opposite direction than what he/she really considers as the optimal choice. The idea is that the individual is too much affected by the strong social pressure from the crowd. The same 'flow mode' of information is found within social network (Dotey, 2011). The analysis of the information movement allows to identify who are the most influential elements within the network, thus understanding how it is possible to maximise the effectiveness of the communication influence.

This effect is amplified if within the supporting crowd there are professional investors because they are seen as additional carriers of experience and so as additional symptom of quality by the investors of the campaign thanks to their further experience (Barbi & Mattioli, 2019).

At the same time, this social community has another beneficial aspect which is its capacity to work as loudspeaker of the campaign's information, which can be nowadays further fostered by social networks and media. It is a clear example of how the 'Word of Mouth' can be efficient for this business.

However, an identified problem related to this crowd is that although there may be a relationship between the serial individual and the following crowd that lasts over time, it is possible to observe the presence of weak relationships between this crowd and the projects of the serial. For this reason, in order to not loose trust and interest of this population, it is important to urge it continuously (Butticè, Orsengi, Wright, 2018). This continuous stimulus should be given through several sharing of information through social media and through the implementation of multiple fundraising campaigns in order to stimulate the sense of investment-challenge in the supporter.

2.5 Evolution of the network in time

Thanks to its nature, the equity crowdfunding business fosters the creation of a network and of interactions between startups and investors (Brown, Mawson, Rowe, 2018). In fact, in some cases startups tend to decide to enter in this business to solve the problem of not presence in a network from which they can draw financing sources and from which they can receive information and knowledge (Brown, Mawson, Rowe, 2018). This doesn't mean that startups create a network around them only through crowdfunding business, as they actually create a personal network of knowledge and financing since their first moments of life.

An interesting aspect is to understand how the relationships between startups and other members change during time, causing an evolution of Social capital. At the beginning, a startup tends to build strong and lasting relationships with first backers (as family, friends and Business Angels) and the first management team which drives the startup in the early stage of life. BA are influential and competent individuals who provide financial, social and especially intellectual capital to the startup. In exchange they receive an ownership share, then entering directly and personally within the startup. They hold a sort of intermediate position between FF and VC because differently than FF they usually provide a larger volume of capital and above all a greater amount of managerial knowledge, while differently than VC they provide a lower amount of financing resource. Thanks to these early stage investors, the startup is able to receive funding, motivated and competent individuals but also a series of potential relationships with other companies linked to BA thanks to which the startup can better develop.

Therefore, the aim of these relationships is to optimise the internal organisation and to run the startup in the most optimal way inside its competence business during the first phase of life. This initially created personal network can be seen as a sort of 'hidden social network' because it is not created during the fundraising phase but, at the same time, it is beneficial for the achievement of the fundraising target in the crowdfunding phase (Brown, Mawson, Rowe, 2018) and (Butticè, Orsengi, Wright, 2018). Therefore, during the phase of fundraising, the hidden network is already seen as internal capital. The creation of this hidden capital is related to the first period of life and it is the 'Seed capital' phase. This is metaphorically associated with the name of 'Valley of Death' because the capital provided by family, friends and angels is mainly used for the first essential expenses, rarely causing the achievement of a profitable condition. Due to this unprofitable condition, it is said that at this stage the money is 'burned', as it is used just for the initial sustenance and development of the startup. For this reason, it is necessary to have strong social relations that bind startup with these external people, because if there were no strong relationships and no trust, they would not finance the startup and they would not decide to enter in the management of this as they see their investment and their effort in grave danger. The relation is strong because there is not a simple financial interest, but also a strong personal and emotional involvement that results in a relational strengthening. In particular, it is possible to notice an increase in all the Social capital's components as relational due to the increase of the emotional side as trust, structural due to the increase of the volume of relationships and cognitive due to the alignment of all the characters towards a common cause of startup's successful development. The thesis work has shown that the presence of seriality cases and, therefore, of a certain level of Intellectual capital inside the startup already before the round can generate a positive impact on the crowdfunding fundraise.

During the fundraising phase, the startup establishes relationships with investors and platforms. In particular, the latter works as means for creating as many interactions as possible among startups and backers. Obviously, the main interests of the platform are personal economic and reputational benefits. For this reason, these external oriented relationships are less strong than those created in the pre-fundraise crowdfunding phase. This means that there is creation of external social capital at this stage but less powerful than the one created before the fundraising. With the investors, the startup creates relationships that are less intense than those created with the first supporters. These are social interactions that do not involve the direct involvement of the investor within the startup, but only the provision of financial support. Obviously, the investor has a financial interest, as he/she doesn't want to waste personal money but in most cases he/she has not a significant personal involvement as in the case of early supporters.

Thus, looking at how and with whom startups connect, it is possible to study the evolution of the Social capital during the collection period. Obviously, there is a creation of capital identifiable thanks to new social interactions that cause an enlargement of the structural component. As previously stated, these relationships include investors-startups, startups-platforms and startups-serial individuals who play a certain role in another startup always in this network. The latter case generates an important relationship which is very useful for the share of good information and knowledge level. In this work, the bonds that the different startups establish with the platform on which they launch their campaign and the potential benefits and consequences of those connections won't be explore. It may be a subject for further studies on the effects of social capital in the crowdfunding space.

The infrastructure generates also new relational capital, for example trust that investors and platform have in the startup, and this relational side tends to be increased thanks to the feeling of 'startup ownership' transmitted to investors. This factor is important for increasing the emotional and participation level of investors in the process (Butticè, Orsengi, Wright, 2018).
At the cognitive level, there is an alignment of the target perceived by the startup and the investors. If this were not present, the investors would have no interest in the startup, and they would avoid investments.

CHAPTER 3
SERIAL ENTREPRENEURSHIP IN EQUITY CF.

3.1 Introduction of serial entrepreneurship

In its initial development phase, the work's objective was the investigation of the Serial Entrepreneurship phenomenon in the Equity Crowdfunding space in Italy. A serial entrepreneur is defined as an individual who founds, builds, and scales multiple ventures. He/she can do it in a successive manner, thus funding a new business after exiting the previous one, or he/she can decide to run multiple entrepreneurial activities in different companies at the same time, representing a case defined as Portfolio Entrepreneur.

In Europe the contribution of serial entrepreneurs on the total entrepreneurial activity is very relevant and it is around the 18–30%, while in the US is more marginal 12,5% (Plehn-Dujowich, 2010). Going into more details for the EU zone, in the UK 19–25% of entrepreneurs are serial (Westhead et al. 2005; Westhead and Wright 1998). In Germany, their contribution is 18% (Wagner 2003), and in Finland the seriality level is almost 30% (Hyytinen and Ilmakunnas 2007).

In our case, we identified as serial entrepreneur not only someone who has experienced as founder in multiple startups but at the same time that has conducted in a serial manner equity crowdfunding campaigns to finance his own business. What has been found across previous multiple studies (Butticè, Orsenigo & Wright, 2017), (Westhead-Ucbasaran-Wright-Binks 2005), (Holmes and Schmitz 1996; Headd 2003) is that startups which are ran by serial entrepreneurs are more likely to survive, to have better financial performances, to have access to bigger financial resources and to reach better profitability metrics. (Butticè, Orsenigo & Wright, 2017)

The motivations behind this phenomenon are disparate. They could be innate managerial capacities or superior ability in selecting the team, but in reality the most noteworthy element is that entrepreneurship is a learned activity. This means that it is not just innate talent that determines futures success because previous business experiences play a very crucial and important role, as the general skills are the pillars in entrepreneurship and some of them can be learned with experiences. (Lafontaine, Shaw 2014) (Lazear, 2005). This concept is widely known as "Learning by doing" and it stands to represent the accumulated experience that allows an individual to have better skills and resources after having handled challenges in the past. Some of these skills can be identified as managerial in nature or they can be negotiation skills, which can be very useful in the interaction with financial institutions.

As discussed in the previous thesis part, the biggest advantage of serial entrepreneurs in the context of funding the venture is about the reduction in the problem of information asymmetries between them and potential investors. This can be done thanks to the exhibitions of their track records and their past experiences, through which they immediately and effortlessly signal their higher quality to the market, thus attracting more capital (Zhang, 2007). At the same time, the effect of seriality contributes also to the creation of the supporter crowd which follows the serial individual and supports the fundraising.

The positive effect of the seriality increases if serial case affects relevant and active position inside the company such as Founder or team member.

3.2 The investigation

To study this phenomenon in the Italian Equity Crowdfunding landscape, the work had to start from ground zero since there was not an existing database about the individuals in every startups that have raised funds through equity crowdfunding campaigns. Since the scope was restricted to innovative startups, the PMIs and Real Estate projects were not considered in the analysis. Everything started by creating a database which contains all the known stakeholders for each startup using information from the public domain as the resources available for each campaign in the different crowdfunding portals. These used information sources are mainly the pitch, the business plan, the Chamber of Commerce registration and the "Team" section that most sites have for each campaign. In this way, it has been possible to create a comprehensive database of the Human Capital structure for each startup. In some cases, we also verified and reinforced the database by cross-checking using LinkedIn. It is important to note that in rare occasions companies may be characterised by commonalities between the stakeholders of startups, therefore for this reason they can generate connections across startups and have been taken into account in this work because it's still a form of Social Capital and vector of know-how, skills and competencies. The study has been done for the period 2014-2020, and in particular after December 2020 the database has not been updated, then it misses any campaign and startup that may have raised funds after that date. As said in the introductory part, the complete database encompass a total of 442 startups which raised funds across 25 different platforms. Since some of them have performed multiple rounds, the overall total of campaigns is larger than the overall number of startups and it is equal to 481. This is the basis for all the analysis and work that follows. All the econometric and network studies rely on this key information collection. During the stakeholder analysis, the startups have been subdivided by platform through which they have raised capital, in particular if they have raised multiple rounds on different portals the first one they have used was considered. Additionally, the stakeholders were subdivided in three main categories: Founders, Team members and Investors. Identified investors are the ones that are already present before the crowdfunding campaign and with an equity stake above the 0.5%. It was also annotated if the campaign was successful and of how much it went in over-funding if so. To preserve the privacy of people, it will never be mentioned any name in the whole dissertation. Below in Fig.3.2.1, there is a fragment of our database, in this case it is considered the platform 200Crowd. Since was done at the beginning of the work there's also a fourth column called "Amministrazione", that has been later merged with the team section or the founder section depending on the type of role carried out in the company.

200Crowd			
SOCIETA'	Alfonsino	Axieme	Biogenera
SUCCESS	✅	✅	✅
AMMINISTRAZIONE	Giuseppe Palmiero	Edoardo Monaco	Valentina Bertuccioli
FOUNDER & CO-FOUNDER			Roberto Tonelli, Andrea Pession
TEAM	Carmine Iodice Antonella Ragozzino Armando Cipriani DomenicoPascarellaPasquale Madonna Davide Barbiero Claudio Cirpiani Francesco delle femmine Dario Ribattezzato	Marco Pollara, Matteo Gallo, Clea la rosa, Stefania Civatti	Valentina Bertuccioli, Pablo Rodriguez
SOCIO	RAGOZZINO ANTONELLA (30%), IODICE CARMINE (30%), PALMIERO GIUSEPPE (20%), CIPRIANI ARMANDO (20%)	MONACO EDOARDO (52%), GALLO MATTEO (14,25%), POLLARA MARCO (11,85%), DIGITAL MAGICS S.P.A. (6,37%), KINETICA S.R.L. (6%), CIVATTI GIAMPAOLO (1,38%), ANTONICIELLO GIULIANO (1,77%), CHIODA PAOLO (1,35%), ROCCIA PAOLO (0,92%), DZERTA HOME - SOCIETA' SEMPLICE, CAMPISE OMAR, BERTINELLI GIANFRANCO, BETTA GIORGIO,BETTA MARCO CRISTIAN,MANGIA ROBERTO,ANTONINI FRANCO	CHAN YUET LON, BARBUTO LUCIANO, SHAWO SERGIO, FIORENTINI MARCO, ZALAMBANI GIANPAOLO, ZOCCA ALESSANDRO,RUSSO GAGLIARDO FABIO, LANZA CAMILLO, GHERARDI ROSA, GIUSTI ALBERTO MARIA, FLABOREA MICHELA, ZANASI LUCA,PESARESI PIA,AVRAAM LICIA, ZUNINO DE PIGNIER MARIA ALESSAND, GALLUCCI FRANCESCO, PINNA MARCO, TCHEN WEI KIEN MASSIMO, FRANCIA JADER, DE CESARE LUCA,CIUDINO PIERGIACOMO,DADO DANIELA,LAFFI DONATELLA ,T & T S.R.L. ,ANTOGNOLI LIVIO, PAPA FRANCESCA, MUCELI ANTONINO, FRACASSI MASSIMILIANO, ZALAMBANI FABIO, SFORZA NICOLA MARCO,BENINI NICOLA, QUARTARONE LUIGI , GOFFI SILVIA,CARLETTI DANIELE,RUINI SILVANO,MARANI MARINA,LACCHINI EMANUELA,GAGGINI FILIPPO (24,73%),D'ERRICO MAURO,BICOCCHI PICHI MARCO,GARGIUOLO ANDREA,PETRICCIUOLO VALENTINA,MASSARI AUGUSTO,MARCHI DARIO,MARINI DAVIDE,SANTORO MADDALENA,FIDUCIARIA GIARDINI S.P.A. (10,08%), GARGIUOLO ALESSANDRO,CASALE NICOLA,BERTINI ALESSIA,TONELLI ROBERTO,GIANOGLIO SIMONE,MANZATO CARLO,DETTI CLAUDIO,LOLINI MARUSCA,FRANCHINI ANNA,BARDOLET DAVID,BENEDETTI LUCIA,PINUCCI ISABELLA,AVRAAM GIAN ANESTIS, LIPPI ALESSANDRO,FARABINI ANDREA,GALLO GIANLUIGI,CIRROTTI DOMENICO,BELLORINI NICOLO',DELLACECCA DANIELA,CARRARA ELIO,PASCUCCI GIANLUCA,LI GENY REGINA,TONELLI GIOVANNI, BOSCOLO POMPEO,BOCCALETTI MIRIAM,GARGIUOLO RICCARDO,INNOVANDO SRL,FERRANTE STEFANO,CARLONI TERESA, PATELLA DANIELA,AVVANZO PIERLUIGI,HAN ZHIHUA (13,45%)

Fig.3.2.1. Example of the stakeholders subdivision used during the investigation which was done for each startups that have accessed Equity Crowdfunding in Italy

Then the process of finding overlaps and connection started. As said above, a connection between two startups is born if there's at least one entity in both of them that acts as a bridge between the two. In more rare occasion, also a company may have the role of bridge and in most of the cases this case is represented by an incubator, accelerator or a fund. This case is expected to be as an entity that it will show up as an investor in more than one startups that underwent a crowdfunding campaign. The most notable examples are LVenture Group Spa, MNS Capital and Digital Magics Spa. Since three macro categories were implemented to categorize Human Capital inside each startup, six different kinds of connections can be identified. These types of connections are listed below:

- Founder- Founder (FF)
- Founder-Team (FA)
- Founder-Investor (FS)
- Team-Team (AA)
- Team-Investor (SA)
- Investor-Investor (SS)

A little note about the remarks, AA stands for Amministrazione-Amministrazione (Team member) in Italian, likewise SS stands for Socio-Socio (Investor)

To have a more organized picture of all the connections and more importantly of the startups involved, a Matrix of connections has been created. In this spreadsheet all the startups that present a connection have been written. The columns and row of the matrix are the three main categories of the Human Capital (Founders, Team and Investor) and in the cells each row represents an entity linking two or more startups. The important concept to understand is that people are the bridges between startups, but since the work is focused on understanding the effects of Social Capital on startups and for anonymity reasons, the startups involved and linked have been directly written down, skipping the exact definition of the bonding entity.

Not considering the directionality of the connections allows to have a symmetric matrix. The diagonal elements are the most intuitive to understand because involve startups that have entities in them covering the same role (founder, team member or investor) and these are defined as 'pure' serial cases. A "-" between the name of companies has been introduce to indicate that a single entity links them. While in the extra-diagonal elements the link is generated by an entity that cover different roles in the involved startups. Here the signal "-" between the name of two companies has been introduce to separate the role in the different startups the part on the left of the dash refers to the role on the corresponding row, while the part on the right the role of the corresponding column. In some cases, a single entity covers the same role in different startups and at the same time another role in others. For this reason a "/" has been introduce to take it into account. Double counting has been avoided giving priority to extra-diagonal terms, if for example a person is a team member in two startups and investor in a third, the connections that he generates will all appear in the Team-Investor cell of the matrix only and won't appear again in the Team-

Team cell. For last, if two pairs of startups are written more than one time, it means that there are multiple individuals who has the same role in both of them. Entities that work in all three roles in different startups have not been found.

Additionally a “hierarchy” of roles has been considered, with founder the highest and investor the lowest. That’s because it’s almost certain that a Founder has also a stake in its business and not uncommon that also team members have some ownership of the startup. For this reason, if an individual has a founding role and also appears as shareholder, then he’ll be labelled as founder for that startups and the links that he will generate will involve him with that role in that specific startup. The same thing applies if an individual is member of the team and also appears as investor, he will be labelled as team member and will generate connections considering that position. This has been done to avoid chaotic labelling in the matrix and unnecessary over-complication of the network. Below is the complete matrix of all the connections present between startups that raised funds through Equity Crowdfunding in Italy, from 2014 to 2020 (Fig.3.2.2).

Overlaps Dec 2020

	Founder	Team	Investor
Founder	ByciSolarStreet Sardegna-InfinityHub Spa- 110 Efficiency Sustainable Mobility - EYS BA - WindEnergyEfficiency - Welfare Efficiency Piemonte - Retail Efficiency Venezia - WEY Dolce ER - 110 Efficiency Glasstopower-Green Energy storage JustMary-Criptomining JustMary-Criptomining Locare-Salva Assistance Locare-Salva Assistance Quomi-Leo Nardi Milano Revotree-Fol the best Olivone-Green Energy Sharing Olivone-Green Energy Sharing Petzolla-Petsempre Petzolla-Petsempre Start&Partners - BioInvestments Japal-Leo Nardi Milano Japal-Leo Nardi Milano Leark -Olzemusic AR Market -Findmylost NexApp -Elsilab Verso Technologies - Pickmeapp Sterify - Eutronica	Glasstopower/Green Energy Storage - Green Idea Technology Start&Partners -BioInvestments Green Energy Storage -SoundofThings SoundofThings -Green Energy Storage Japal - Classup Raft -P2R LinfaCrowd - Biovecblok MeetMyPet - Apping Inoxsail - Forever Bambu Fremslife - InSono Sharewood - Wiralex/GardenStuff Olzemusic - LiveSonar Leark/Olzemusic - LiveSonar Olzemusic - LiveSonar	CleanBNB/Seed Money - Repup Traction Management -Babaiola Nuova Industria Torinese - Sin Tesi Forma Start&Partners - BioInvestments Japal/Userbot - Prestofood /Novatek /Vidoser /SEO Tester Sustainable Mobility Umbria - ByciSolarStreet Sardegna Start&Partners- OIP Start Gogobus - Biogenera The Hundred - MySecretCase Take OFF - Verum
Team		Green Idea Technologies - Recrowd - TaskHunters - Quomi Bermat - Melixa Coco - Sportit Xnext - Diaman Tech Prestito Super - Everyware Perfrutto - Socopet - Graphene XT Verum - Nuova Industria Torinese Recrowd - Green Energy Sharing - Ener2Crowd Elsilab - Nexapp Elsilab - Nexapp	Open Tail - Shape Me Open Tail - Shape Me Verum - Nettowork DesignItaly - Deliveristo Infinity Hub - ByciSolarStreet Sardegna Infinity Hub - ByciSolarStreet Sardegna/WEY Dolce ER Eligo- MPD SME Capital Eligo- MPD SME Capital
Investor	Double name = Two people or more link the two companies In diagonal cells “-“ separate the different SU linked by the same entity In extra diagonal cells “-“ separates the row to the colum for the different roles		RentApp - Repup Green Idea Technologies - Recrowd Green Idea Technologies - Recrowd Racine Caree - Quomi InfinityHub - EYS BA InfinityHub - EYS BA Locare - TAEBioenergy - Coffinardi e Delpanno Industries - Interweb Fannabee - Eattiamo - InReception P2R - Apping Live Based Value - Xnext Luche - Autentico Luche - Autentico - Eligo Luche - Autentico Sfrecciando - Live Based Value TAEBioenergy - Prestofood - Axieme Qaplà - Edgar Qaplà - Sync Maid Service - Sin Tesi Forma Green Energy Storage - Glasstopower Verum - Nettowork Flowdron - Elsilab Noixa - Soisy Sportclubby - Pickmeapp Leo Nardi Milano - Vintag Biovecblok - Irides - Linfa Crowd Biovecblok - Irides Yakkyo - Inkdome - MyLab Nutrition - Babaiola - Social Academy - Tiassisto24 - Karaoke One - Bloovery - sync -AvvocatoFlash Bermat - Bikee Bike - Melixa P2R - Sthimaty - Ener2Crowd - Inpolitix - Nano - Nettowork You are my guide - Parterre - Sync - Scloby - YouDroop Sharewood - Wiralex - Gardenstuff CleanBNB - Marshmallows Game - MySecretCase Taskhunters - Affitto Certificato - Wonderstore - Axieme - Domoki - Eggup - Growishpay - WeBeers - MyCredit Service Axieme - Alterego SEO Tester - Vidoser - Cartina SEO Tester - Vidoser Smart Mobility - Vintag 110 Efficiency - Retail Efficiency Venezia 110 Efficiency - InfinityHub Spa Eligo- MPD SME Capital Eligo- MPD SME Capital P2R - Verum

Fig.3.2.2 Matrix representation of the Italian Equity Crowdfunding network

In this part of the thesis work, the attention will be focused exclusively on the analysis of Serial Entrepreneurship and therefore on the Founder-Founder type of connection that is the only point of interest. A totality of 21 Serial Founders, therefore people who have covered the role of Founders in more than one startup, who link an overall of 34 startups have been identified in Italian ECF space. The Founder-Founder portion of the matrix is highlighted below in Fig.3.2.3 and it is the Cell 1-1 of the whole seriality matrix.

	Founder
Founder	ByciSolarStreet Sardegna-InfinityHub Spa- 110 Efficiency Sustainable Mobility - EYS BA - WindEnergyEfficiency - Welfare Efficiency Piemonte - Retail Efficiency Venezia - WEY Dolce ER - 110 Efficiency Glasstopower-Green Energy storage JustMary-Criptomining JustMary-Criptomining Locare-Salva Assistance Locare-Salva Assistance Quomi-Leo Nardi Milano Revotree-Fol the best Olivone-Green Energy Sharing Olivone-Green Energy Sharing Petzolla-Petsempre Petzolla-Petsempre Start&Partners - BioInvestments Japal-Leo Nardi Milano Japal-Leo Nardi Milano Leark -Olzemusic AR Market -Findmylost NexApp -Elsilab Verso Technologies - Pickmeapp Sterify - Eutronica

Fig.3.2.3. Matrix frame of the Founder-Founder subdivision in the network

Below in Fig.3.2.4 there is a visual representation of the these connections and the network that is generated by them and it is what will be discussed and analysed in the following section. It's important to point out again that it is not the whole network of interconnected startups present in the Italian equity crowdfunding space, but only the one where the founders are the bridge/ the bonding entity among them. It is the web generated only by links of the FF type, meaning founder who after founding a company have the same founding position in a second one.
The methodology and the software used for the creation and visualisation of this kind of networks will be explained in details in Chapter 4.

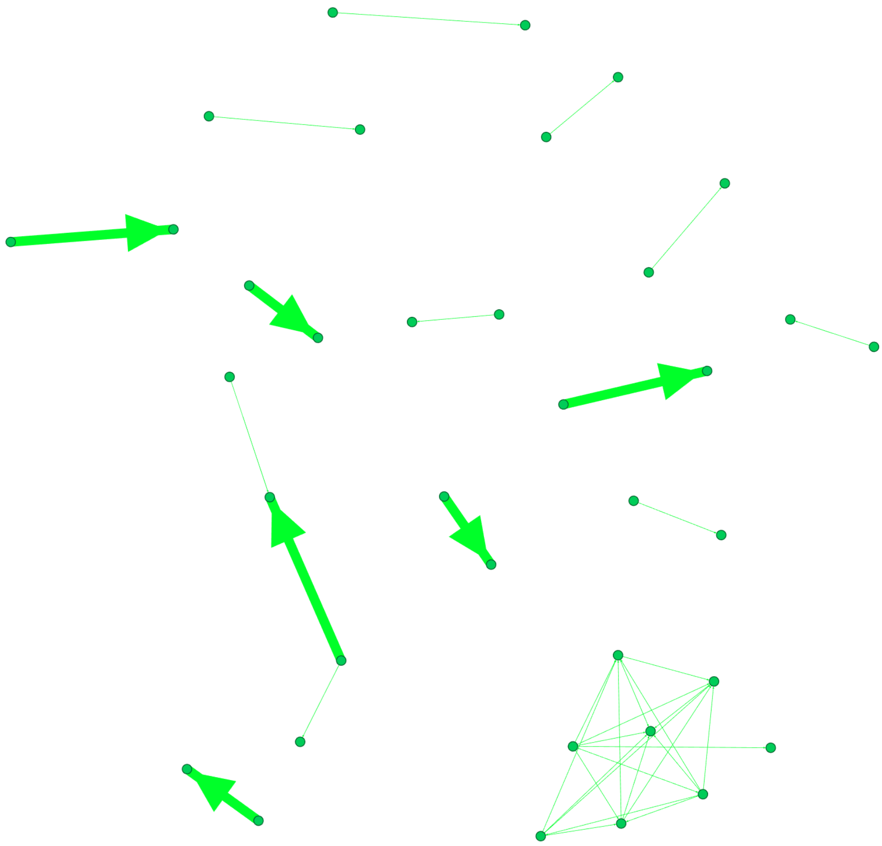

Fig.3.2.4 Network generated by FF connections

As can be seen it's very sparse and disconnecting, there isn't consistent seriality present and in all cases except one the founding entity just links two companies, the density of this network is 0,057, meaning that of all the possible potential connections only 5,7% are actually present, an exhaustive explanation of density will be present in the following chapter.

3.3 Analytical and numerical study of the Network

In order to study the network of equity crowdfunding serial entrepreneurship in Italy, it was important to rely on the discipline of the 'Social Network Analysis', SNA. It is a modern theoretical and practical methodology useful for analyzing, for measuring and for representing how different individuals, and groups of them, interact inside a social network. The aim is therefore to analyze the society which is created by all the founders of innovative startups who have accessed to equity crowdfunding financing source.

This discipline allows both a graphical representation of the society and its numerical interpretation in order to analyse case by case how the nodes (in this case founders) relate and how they are positioned within the studied society.
In this part of the thesis work, the network's nodes are all the founders of innovative startups that have crowdfunded in Italy from 2014 to 2020. They have been identified thanks to the previous data collection work through which all the innovative startups were investigated for searching in each of them the founding team, the administration team and the pool of members. This research has led to the identification of 898 founders.

The first step of the study was the creation of a graphic representation of the founders' society. This was done using a typical Social Network Analysis tool called 'Adjacency matrix' which is partially represented in Fig.3.3.1. This numerical tool provides a matrix representation of all the 898 founder nodes within the network and of the connections which bind them. The logic behind the creation of this squared 898x898 matrix is to associate the value 1 to the point of the matrix a(i,j) when the two founders i and j have a relationship, so they are in contact (Stawinoga, 2014). In this way, the value 1 works as numerical representation of an interconnection among them. Instead, when the two founders i and j have not a direct linking contact, the associated value to the matrix position a(i,j) is 0. In this way, it is possible to 'draw' through a numerical matrix representation the whole society and it is possible to understand how different players interact among each other. In this analysis the temporal dimension was not taken into account and for this reason the resulted adjacency matrix was symmetrical.
Only by looking the matrix, it is possible to get a general idea of the network. In our studied case, it is possible to observe how the entrepreneurs' network is strongly disconnected and this absence of social interconnections can lead us to say that there is not a real social network looking this category of individuals. The graphical representation shows how most nodes are not interconnected and that the few cases of seriality founders involve very few startups. There are very few cases of 'grouping' of startups linked to a single founder and in addition they are disconnected with the rest of the network. This means that one problem with them is their closure with the external society because these groups lack of external interactions. This compromises the presence of easy flow of information and knowledge through them because flows tend to stay inside the group and stop there. This is like the case of Bonding Social capital discussed in the theoretical section, as it is characterised by strong relationship inside the group increasing the sense of community but poor communication and interaction with the outside.

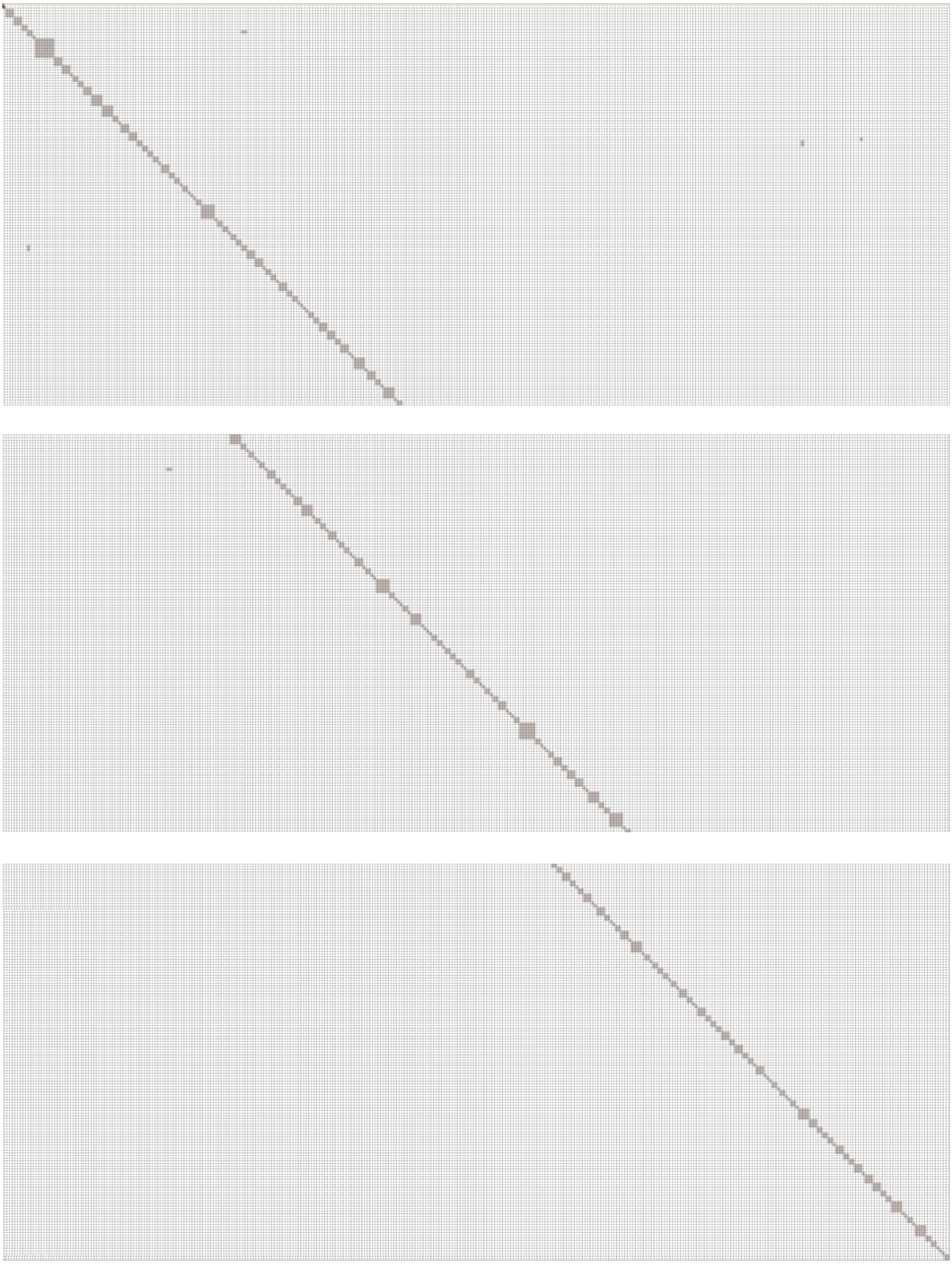

Fig.3.3.1. Frames of ‘Serial Entrepreneurial network’s adjacency matrix’

The network study was further developed introducing a quantitative analysis by the computation of a set of typical parameters from the Social Network Analysis per each single founder (Giudici, Moncayo & Martinazzi, 2020). This analysis has further demonstrated the presence of a non cohesive infrastructure of relations between the various nodes of the entrepreneurs' network.
The first studied parameter is 'n' and it shows the number of startups in which the founder is involved. Meaning it doesn't study the relationships but it only wants to quantify the volume of startups in which that individual 'i' participates in a founding position. Just by looking at this parameter, it is quite easy to understand how social disaggregation reigns supreme within the network. In fact, after measuring this indicator for each single individual founder, it is possible to see that the 97,88% has an associated value of n equal to 1, the 2,01% has a value of n equal to 2 and just the 0,11% has a value larger than 2. This means that the 97,88% of the 898 founders of innovative startups present in the Italian network have decided to access to equity crowdfunding financing source just once. As previously said, this lack of repetition leads to a sharp reduction in the funders' interactions, creating a disaggregated condition among nodes.
Focusing only on serial founders' group, the average value of n is 2,4. On this observed cluster, all the cases have an associated value of n equal to 2 and just one serial case has a value larger than this. This conclusion further demonstrates how this network is characterised by large relational holes.

Mean	*Median*	*Std dev.*	*Max*	*Min*
1,03	1,00	0,33	10,00	1,00

Table.3.3.1. Statistical results about the 'n' parameter observing the whole cluster of the 898 founders presented in the network

The second studied parameter is 'd'. it is called 'Degree' and it identifies the number of direct connections that the founder 'I' has with other founders inside the network. With the term 'direct connection', it means a founder-founder interaction without having to pass through another node, which would work as bridge between the two considered nodes. This means that direct connections can only be established between founders who are within the same startup. Showing the number of direct connections, gives the possibility to this indicator to communicate the ability of the studied founder to directly interact with and influence other founders, and at the same time to be influenced by them.
The computation of the Degree is carried out looking the 'Adjacency matrix'. Each founder i-th has an associated degree value equivalent to the sum of all the binary values (0;1) that can be found in

the row dedicated to that specific founder inside the general adjacency matrix. To this sum must be then removed the 1 of the main diagonal (analytically it is equivalent to say to not consider in the summation the point with j = i), otherwise this means to consider also the interaction with the founder itself. The used equation is defined as in Fig.3.3.2.

$$d(\mathrm{i}) = \sum_{j=1}^{g} \mathrm{a}(\mathrm{i},\mathrm{j}) \quad , \quad with\, j \neq i$$

Fig.3.3.2. Equation for the computation of the 'Degree' parameter

The parameter can take values from 0, in case of isolated node without connections, to (g-1), where g is the total number of nodes, in case of connections with all the other nodes in the network.

A negative aspect of the 'Degree' parameter is its incapacity to express the real effect that the studied node can have on the network. In fact, the simple count of direct links is not always enough to provide an analysis on the global network because this parameter doesn't take into account the conditions of the nodes that are linked with the studied one. For example, if a node has a lot of direct connections (high value of d) but these other nodes are not well connected with the rest of the network, the exercised power by the first observed node is quite limited on the overall network.

During our study, also the parameter 'd' was calculated for all the identified founders. It was possible to identify that the 15,5% of founders have an associated value of d equal to 0, the 34,8% a value equal to 1 and the remained 49,7% a value larger than 1. This could influence the reader to think that the number of connections is high, erroneously leading him to think that the network is featured by a good relational infrastructure.

The average value calculated over all the founders is 1,79 (max value 8) while it is 2,5 if computed considering just the serial cluster. These average values are useful to furtherly demonstrate how the number of interactions among founders is quite low.

Mean	*Median*	*Std dev.*	*Max*	*Min*
1,79	1,00	1,46	8,00	0,00

Table.3.3.2. Statistical results about the Degree parameter observing the whole cluster of the 898 founders presented in the network

To further deepen the study of the network, it was introduced for each single founder the calculation of an additional parameter called 'Eigenvector'. (Borgatti & Everett, 2016) and (Cheng, 2019).
Its numerical meaning is the study of the connections that a single individual has, considering also the weights that these have within the network. This is very important for better understanding the real influence that this specific node generates in the network. In this way, not only direct interactions are taken into account but also how they develop in the social network, thus limiting one of the main issue of the parameter 'd'.
The higher is the value of the parameter 'e', the greater is the overall influence that the node exerts in the network.
The computation of this parameter takes a long time. First of all, it has been calculated only for serial founders and for founders connected to them because calculating it in absence of connections makes it no sense since the meaning of the index is strongly based on connections and on their importance in the network. First, we need to calculate the parameter 'e' for each node since the calculation for the studied i-th node involves the index values of all the j-ths nodes that are connected to the studied one. Fundamental step for calculation is the identification of the maximum eigenvalue associated to the 'adjacency matrix' that is linked with that seriality case. Therefore, just considering the serial founder 'i' and the associated 'j' founders, we have found an associated adjacency matrix case by case and thanks to MATLAB scripts we have defined the relative eigenvector, the maximum eigenvalue and finally the value of the index 'e'. In this way, it was found an effective way for the calculation of 'e' index for all the studied serial founders.
The computation formula is defined as in Fig.3.3.3.

$$e(\mathrm{i}) = \left(\frac{1}{\lambda}\right) \times \sum_{j=1}^{m} [\mathrm{a}(\mathrm{i},\mathrm{j}) \times e(j)] \quad , \; with\; j \neq i$$

Fig.3.3.3. Equation for the computation of 'Eigenvector' parameter

Where λ is the maximum eigenvalue of the matrix of the seriality case, m is the number of founders associated to the i-th case and the e(j) is the eigenvalue of the associated founder.
As said before, the higher the value of 'e' the greater is the impact of that node and of the relative connections in the network. This means that if a node has connections, but these do not then go to branch in the network, the value of 'e' assumes very low value which in some cases is close to 0. In particular, the study shows that null value is assumed in case of very poorly connected nodes

because they have very few direct relations which, being in turn little connected, have 'small weight' within the overall network. This is what is empirically shown through our analysis.

This indicator is very detailed, in fact its value does not tend to increase only thanks to an increase in direct connections as this increase would generate an increase of the adjacency matrix and of the relative maximum eigenvalue. The problem is that the λ is the denominator, so a simple direct connection volume increase leads to a decrease of the index. This means that for having an increase in the computed 'e', it is fundamental to have an increase at numerator and therefore an increase of the 'e' values sum of the j nodes. It means that it is fundamental to have an increase in the relative weight that each single connected individual has in the network. So, for increasing the 'e' index is not important to increase the number of connections but it is important to increase the 'number of the connections of the previous connections'.

Considering the cluster of nodes of serial founders and of the ones related to the serial, it is possible to observe as only 5 cases on the identified 55 show an index value larger than the unit. These 5 cases are pure serial ones and this observation underlines how the serial founders tend to remain isolated, causing further isolation of the founders who are related to them. Then, this measurement further demonstrates that this network is characterised by a very low level of relationship diffusion.

The computed data set shows an average value equal to 0,24, value that can be easily compared to a case with very low volume and very weak weight of connection.

Mean	*Median*	*Std dev.*	*Max*	*Min*
0,24	0,00	0,46	1,83	0,00

Table.3.3.3. Statistical results about the Eigenvector index observing the whole cluster of the serial founders and those related to them presented in the network

Another important indicator that we have included in the thesis work is the 'Closeness', 'c' (Horton, 2012). Its objective is to understand how the studied node can spread information in the network through all the associated direct and indirect relationships. The important point of this indicator is the study of the physical placement of the node within the network. A node takes a central position when it is closer to other nodes, ensuring a fast interaction with them. For this reason, the associated parameter 'c' to a specific founder is inversely proportional to the distance of the geodesic patch between the studied founder and all the other ones that are related with the observed. For this reason, if the sum of the geodesic distance lengths increases, then the distance between the studied node and the associated ones increases causing a decrease of the parameter

value. This means that central nodes have a high value of c, while the not central nodes have lower values.
The measure of the geodesic path between founder i and founder j is equivalent to the sum of all the intermediate relationship steps between the two nodes, considering in the sum the shortest possible path which links the nodes (Bajo, 2016).
This means that in order to be less distant from the others, it means to have a low associated geodesic distance and so an access to others through few intermediary relationships.
The computation is done following the equation in Fig.3.3.4.

$$c(\mathrm{i}) = \frac{n}{\sum_{j=1}^{m} \mathrm{s}(\mathrm{i},\mathrm{j})}$$

Fig.3.3.4.Equation for the computation of 'Closeness' parameter

The parameter m stands for the number of directly and indirectly linked nodes associated to the studied node i, while s(i,j) represents the value of the geodesic path among i and j.
The issue of this parameter is the comparison difficulty of c values calculated for the different nodes. In fact, under the logic introduced by (Horton et al, 2012), Closeness is high when the nodes are closely connected among the others showing an easier possibility of information diffusion associated to that studied node. If you want to look at the network as a whole, this way of interpreting the index value can be applied in network situations with dense connections, where there are no major disparities in the number of connected startups and the only difference would be the way through which different nodes interconnect. In this way we would understand who has a more peripheral positioning and who instead has a more central positioning.
However in our analysed case, the disaggregation of the network does not allow us to understand well who is in a more central position or not just observing at the value of 'c'. Instead, this index could be more useful to understand the centrality of the node in the founder's personal network but not in the global one.
In our case the problem arises because considering the length of the geodesic path, the nodes that are connected with more founders have by default an associated value of c that is lower than other nodes that instead have a lower number of associated nodes. This happens because being the summation of the geodesic distance at denominator, if it increases the parameter subsequently decreases and so it happens regardless of the complexity of the relational infrastructure. Therefore, the difficulty of the parameter to not consider associated nodes but to only consider

geodesic path distance does not guarantee its proper functioning if this index would be introduced for an overall observation of the network.
As for other observed indicators, the computation of the parameter has been done for all the 898 identified founders. Focusing only on serials and those connected to them, the average value of this index is 311,88 and this result additionally confirms that there is little structural connection between nodes and how they use to behave in a very poor central condition. In fact, this value shows that on average there is a medium geodesic path with an average length of only 2,90. Being this value calculated as the sum of the 'distances' with all the nodes related to it, this underlines how the average link is composed by only 3 possible interaction steps.
The table below (Table.3.3.4) shows some statistical values associated to the cluster composed by serial founders and those associated to them. Even if they are computed in the analysis, no data for not serial founders have been reported, as they are not considered important due to their isolated behavior in the network which involves a not central positioning.

Mean	*Median*	*Std dev.*	*Max*	*Min*
311,88	179,60	268,68	895	74,83

Table.3.3.4. Statistical results about the Closeness index observing the whole cluster of the serial founders and those related to them that are presented in the network

The last numeric parameter typically used in the SNA discipline that has been used in this thesis work is the 'Betweenness', 'b'. This index measures the founder's ability to work as link between two founders, so to act as bridge among nodes. This positioning study is useful for observing how and how many flows of information and knowledge are diffused through the studied node.
Even for this index it is important to introduce the concept of geodesic path, but in this case the study doesn't care about the path's length but about the number of paths that involve the studied founder. In other words, considering the total number of nodes connected with the studied founder and identifying the shortest route between two generic associated nodes j and z, the higher is the number of shorter paths that pass through i, then the higher is the value of the b index relative for the founder i. This means that the higher is generally the flow through node i, the higher will be the value of b(i).
Thanks to this study, it is possible to study the flow through a specific node and also how is developed the relational infrastructure which characterises the network. In fact, if the network is featured by a general low level of b index, then it is seen as a symptom of relational holes and scarcity of bridging nodes.

The index was computed just for pure serial founders following the equation represented in Fig.3.3.5.

$$b(i) = \sum_{z} \sum_{j<z} \frac{\rho(ijz)}{\rho(jz)} \quad , \quad with\, j \neq i$$

Fig.3.3.5. Equation for the computation of Betweenness parameter

$\rho(ijz)$is the number of geodesic path between j and z which passes through i.

$\rho(jz)$ is the number of all the paths between j and z.

The computation has included only pure serial founders because just them can work as linking point among groups of founders. The results have shown again that groups of founders use to maintain isolated positions, so the flow of information involves just serial founders without exiting the relative group.

Mean	*Median*	*Std dev.*	*Max*	*Min*
2,76	0,00	5,53	22,00	0,00

Table.3.3.5. Statistical results about the Betweenness index observing the whole cluster of the serial founders presented in the network

Being the founder network disconnected and characterised by the presence of few groups which themselves tend to maintain an isolated position, the developed thesis work involves the introduction of a new parameter introduced by us which is based on strong assumptions of ideality. This index wants to study the diffusion and influence of interconnections among nodes in hypothetical and ideal conditions. This means to have situations with full and free communication and share of idea, and in which indirect connections still have an important sharing role. This latter features conveys the idea that even if a founder 'i' is connected with a founder 'j' of another startup, thanks to an indirect relationship, this founder i exerts an influence on j. Certainly, the intensity of the interaction is lower than in a direct interaction case (Granovetter, 1973) and therefore the impact of this indirect type on the measure of diffusion parameter 'g' must be considered in a different way.

This index is calculated with a very simple approach: first we associate the weight 1 to direct connections, 0,5 to the indirect connections and 0,25 to the indirect connections of second degree. Secondly, these weights are multiplied by the number of direct, indirect and second degree indirect connections that the node has within the network. In this way, it is possible to obtain an

approximation of the spreading and influencing capacity of the founder within the network. One important aspect to underline is that connections are not evaluated by looking at the people interactions but observing the relationships that the single founder has with other startups.
This index was computed for all the founders. Of course, the majority has an associated value equal to 1 being them involved in just one single startup. Only 55 on 898 founders have an index value larger than one, with a maximum value of 10. Considering the whole amount of founders, the average value of 'g' is 1,074, umpteenth symptom of a very low level of serial entrepreneurial activity.
Considering the 'pure' serial founders pool, the mean value is equal to 2,4. This value is equivalent to saying that on average a serial founder is in direct contact with two startups (foundation of two startups) and in indirect contact of first degree with only one. This shows not only the low seriality level but also the low level of relationship diffusion within the network because in addition to be founders of few startups (low factors multiplied by 1) these are not even able to establish relationships with other nodes in the network.

Mean	*Median*	*Std Dev.*	*Max*	*Min*
1,074	1	0,45	10	1

Table.3.3.6. Statistical results about the 'g' index observing the whole pool of the 898 founders who have accessed Equity Crowdfunding in Italy

This index 'g' has been used in the course of our network analysis to study the network but also to try to solve the problem of the calculation of 'c' parameter. As previously written, a difficulty of the Closeness parameter is its inability to objectively consider the study of the proximity and of the positioning of the node within the network. In fact, if a node has fewer links it assumes by default a value of c higher than one that has a more complex relational structure. For this reason, the introduction of the parameter 'g' in the equation has allowed the insertion of the info 'connection weight' that the node has, guaranteeing a more detailed explanation about the positioning of the node. This has created a new index called 'c.2'.
In fact, if the node has many connections, the parameter g increases and as consequence even the index 'c.2' increases. If the node has no connections, the parameter g is low and therefore the value of the index 'c.2' remains low. In this way we have tried to better catalogue those nodes associated with many connections trying to find a solution for enhancing their position of node with many connections and instead on the other side to discriminate those who held a more isolated position.

The value of ‘c.2’ remains the same of ‘c’ for those nodes that are not associated with serial founders and with the founders linked to serials because the value of their ‘g’ parameters is 1.
The equation for the computation of c.2 is represented in Fig.3.3.6.

$$c.2(\mathrm{i}) = \frac{n}{\sum_{j=1}^{m} \mathrm{s}(\mathrm{i},\mathrm{j})} \times g(i)$$

Fig.3.3.5. Equation for the computation of ‘c.2’ parameter

The index ‘g’ is used as multiplier of the previous computed Closeness index. The objective behind the use of this parameter is to provide a qualitative analysis of the network and not a quantitative one because it does not want to study the real number and the volume of connections but it wants to improve the qualitative study of them. The statistical results of this new index are reported in the Table.3.3.7.

Mean	*Median*	*Std Dev.*	*Max*	*Min*
513,82	402,75	340,25	1790	130,52

Table.3.3.7. Statistical results about the ‘c.2’ index observing the cluster of serial entrepreneurs and those related to them

The analysis through SNA indexes and the observation made by the parameter ‘g’ has shown that the serial entrepreneurship network is strongly disconnected, thusly demonstrating what was initially understood thanks to the initial adjacency matrix.
For this reason the focus of the thesis work has been shifted from the study of serial entrepreneurs in equity crowdfunding to the study of the general startup network.

CHAPTER 4
THE NETWORK AND ITS EVOLUTION

4.1 Methodology

In this chapter we are going to focus our attention on the network itself, its characteristic and its evolution through the years. This part is more a visual compendium to the work done through spreadsheets and econometrics studies and it wants to put into an easy-to-understand form what the whole work was about. Of course, even this part is done focusing on the study of interconnected startups in the Italian Equity Crowdfunding space. It was not something strictly required in order to investigate the effects of social capital on the success of a campaign, but it was thought that it might be of interest for the topic discussed and useful in order to provide a more complete study about the network analysis. In addition, it may provide value and be the ground work for future studies on the matter.

As introduced in previous chapters, the network is comprised of 141 startups that present at least a link with another one. They are not all interconnected and not belonging to the same cluster, but they vary from connections of just two startups to much bigger clusters where a single entity may be connect up to seven companies. Just like the Founder-Founder connection, the thought of the authors was that also other kind of connections across startups would generate and foster the circulation and blending of social capital across the equity crowdfunding ecosystem. For this reason, from now on the investigation is broadened to all the 6 types of connections presented in Chapter 3.2 and of course the network itself is built taking all of them in consideration.
What is noteworthy to understand in the construction and in the visualisation of this network is that individuals generate connections, therefore they are the bridges and the glue of this network. For this connecting reason, if an individual links 4 startups because he/she has either the same role in all four, we will connect all of those startups among each other, generating a total of 6 connections because a single individual is the bonding element. This was the way that the authors have thought to provide a practical approach in order to show the existing connections and to maintain the privacy right of individuals. Below in Fig.4.1.1 there is a sketch for an easy visual representation of the concept.

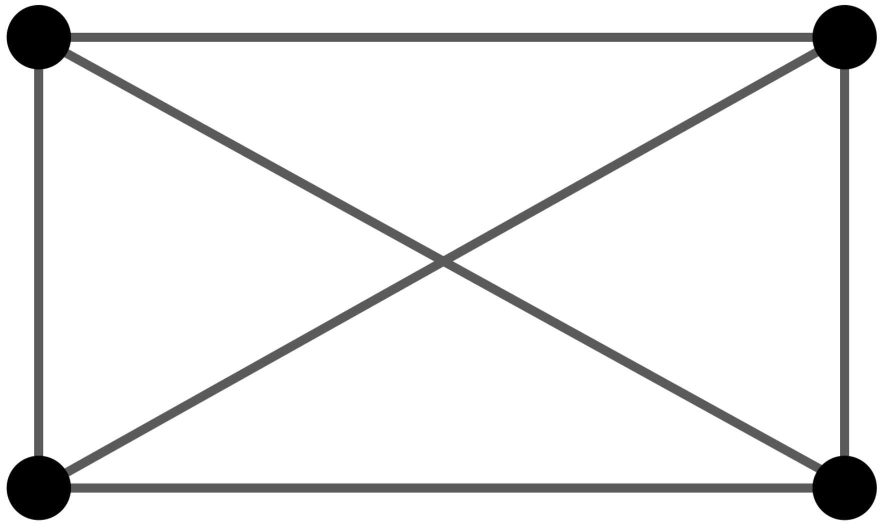

Fig.4.1.1 Connections among startups

The graph doesn't take into account the direction so, for example, a Founder-Team connection is treated identical to a Team-Founder. The arrows present in the coming pages indicate only temporality in the network, meaning what startup joins and anchor itself to another one already present in previous years.

As specified in chapter 3, it is important to note that in some cases the bonding entity may also be another company. It has been decided to manage this situation without differentiating if the link is formed by an individual or by company because the key concept of Social Capital and Intellectual Capital diffusion is applied regardless the nature of the linking entity and because behind each company there are always people involved who share their competencies, knowhow and skills. It could be interesting for further studies to breakdown and analyze this possible differentiation and its implications. If the bonding entity is a corporation instead of a single individual, it generates a condition in which the volume of involved people in the connections would be multiple by definition and so the flowing of Social and Intellectual capital assumes a bigger scope.

For the construction of the network everything started from the table 1.3.1 in which are listed all the startups that present connections among each other and so the entities that populate the network. With that information, an Excel spreadsheet for the Nodes of the network has been created. Additional information has been added including the year in which the campaign occurred, if the fundraising was successfully run or not and the platform used for running the campaign. These information can be used to filter through the network in different ways.
A portion of that spreadsheet is presented on the side. Fig 4.1.2.

62	Bikee Bike	2018	Yes	MamaCrowd
63	AR Market	2018	No	CrowdFundMe
64	Eligo	2018	Yes	200Crowd
65	EYS BA	2018	Yes	WeAreStarting
66	ShapeMe	2018	Yes	MamaCrowd
67	Traction Manageme	2018	Yes	BackToWork24
68	My Lab Nutrition	2018	Yes	MamaCrowd
69	JustMary	2018	Yes	CrowdFundMe
70	Green Idea Technol	2018	No	CrowdFundMe
71	Seed Money	2018	Yes	CrowdFundMe
72	Revotree	2018	Yes	CrowdFundMe
73	Wiralex	2018	Yes	Opstart
74	Soisy	2018	Yes	200Crowd
75	Eattiamo	2018	Yes	MamaCrowd
76	You are my guide	2018	Yes	MamaCrowd
77	Fol the best	2018	Yes	Opstart
78	Racine Caree	2018	No	CrowdFundMe
79	InkDome	2018	Yes	MamaCrowd
80	WindEnergyEfficien	2018	Yes	WeAreStarting
81	Domoki	2018	No	200Crowd
82	Japal	2018	Yes	Opstart
83	Sportit	2018	Yes	CrowdFundMe
84	Locare	2018	Yes	WeAreStarting
85	My Credit Service	2018	Yes	Fundera
86	TiAssisto24	2018	Yes	BackToWork24
87	Autentico	2018	Yes	BackToWork24
88	Growishpay	2019	Yes	200Crowd
89	Gardenstuff	2019	Yes	Opstart
90	Wonderstore	2019	No	MamaCrowd
91	Vidoser	2019	Yes	200Crowd
92	Recrowd	2019	Yes	Opstart

Fig.4.1.2 Nodes table

Concurrent to this one, another spreadsheet for the Edges has been generated, including all the connections present among the companies. For how it has been built when a startup raises through a campaign and in it there's at least one entity already present in other starups, then the node of the new startup connects to all the others where that entity is present. That's why it's written that a company "joins" a cluster of other ones, because it connects to all the ones in which the entity is in common. Additional information are the year in which the connection was generated, the connection type and the weight. The weight is equal to the number of bonding entities in that specific connection. All the edge are Directed and as said in previous chapters the arrows start from the Startup that join the network and "anchor" itself to another one, showing direction that is indicative about the time component of the network. Colors in the table has been used to identify a group of links generated by the same entity. A frame of the used spreadsheet is shown below, Fig 4.1.3.

54	8	Directed	1	2018	SS	Sthimaty and Inpolitix Join P2R - Nano - Nettowork	
54	14	Directed	1	2018	SS	Sthimaty and Inpolitix Join P2R - Nano - Nettowork	
54	36	Directed	1	2018	SS	Sthimaty and Inpolitix Join P2R - Nano - Nettowork	
54	44	Directed	1	2018	SS	Sthimaty and Inpolitix Join P2R - Nano - Nettowork	
76	13	Directed	1	2018	SS	You are my guide joins Parterre - Sync - Scloby - YouDroop	
76	23	Directed	1	2018	SS	You are my guide joins Parterre - Sync - Scloby - YouDroop	
76	41	Directed	1	2018	SS	You are my guide joins Parterre - Sync - Scloby - YouDroop	
76	42	Directed	1	2018	SS	You are my guide joins Parterre - Sync - Scloby - YouDroop	
73	12	Directed	1	2018	SS	Sharewood - Wiralex	
55	7	Directed	1	2018	SS	CleanBNB - Marshmallows Game	
57	25	Directed	1	2018	SS	Domoki and Eggup and MyCredit Service join Taskhunters - WeBeers	
57	34	Directed	1	2018	SS	Domoki and Eggup and MyCredit Service join Taskhunters - WeBeers	
81	25	Directed	1	2018	SS	Domoki and Eggup and MyCredit Service join Taskhunters - WeBeers	
81	34	Directed	1	2018	SS	Domoki and Eggup and MyCredit Service join Taskhunters - WeBeers	
81	57	Directed	1	2018	SS	Domoki and Eggup and MyCredit Service join Taskhunters - WeBeers	
85	25	Directed	1	2018	SS	Domoki and Eggup and MyCredit Service join Taskhunters - WeBeers	
85	34	Directed	1	2018	SS	Domoki and Eggup and MyCredit Service join Taskhunters - WeBeers	
85	57	Directed	1	2018	SS	Domoki and Eggup and MyCredit Service join Taskhunters - WeBeers	
85	81	Directed	1	2018	SS	Domoki and Eggup and MyCredit Service join Taskhunters - WeBeers	
60	8	Directed	1	2018	SS	P2R -Verum	
100	35	Directed	1	2019	FF	Welfare Efficient Piemonte joins Sustainable Mobility - EYS BA - WindEnergyEfficiency	
100	65	Directed	1	2019	FF	Welfare Efficient Piemonte joins Sustainable Mobility - EYS BA - WindEnergyEfficiency	
100	80	Directed	1	2019	FF	Welfare Efficient Piemonte joins Sustainable Mobilit	Double Person
104	84	Directed	2	2019	FF	Locare-Salva Assistance	
101	39	Directed	1	2019	FF	Quomi-Leo Nardi Milano	Two people having different roles in both
95	133	Directed	2	2019	FF + FA	Start&Partners - Bio Investments	
107	45	Directed	1	2019	FF	Leark -Olzemusic	
110	29	Directed	1	2019	FF	Verso Technologies - Pickmeapp	
109	3	Directed	1	2019	FA	Fremslife - InSono	
89	12	Directed	1	2019	FA	Garden Stuff Joins Sharewood - Wiralex	
89	73	Directed	1	2019	FA	Garden Stuff Joins Sharewood - Wiralex	Triple Person
94	45	Directed	3	2019	FA	Olzemusic - LiveSonar	
107	94	Directed	1	2019	FA	Leark/Olzemusic - LiveSonar	
112	7	Directed	1	2019	FS	CleanBNB/Seed Money - Repup	
112	71	Directed	1	2019	FS	CleanBNB/Seed Money - Repup	

Fig.4.1.3 Edges table

These two files were necessary for the creation and visual representation of the network, as they were the inputs for Gephi, an open source software for network analysis (Gephi.org), which has been used for all the images that follows.

4.2 Evolution of the network

In this section will be presented the visual representation of the network and its evolution year after year, with some comments along the way. The network creation started in 2014 when the first two startups that are part of it, DiamanTech and Fannabee, raised capital for the first time through equity crowdfunding. In this moment, these companies entered in the network space but there were not connections among them, as the first connections will occur only in 2016. For this reason, it is possible to say that for now the network is composed only by isolated nodes. In 2015 four more companies appear. They are Inoxsail, Insono, Cartina and Open Tail, but still no connection were generated among them, causing a condition in which there is not already overlaps between the Social Capital of companies. The state of the network at the end of 2015 is shown below, Fig. 4.2.1.

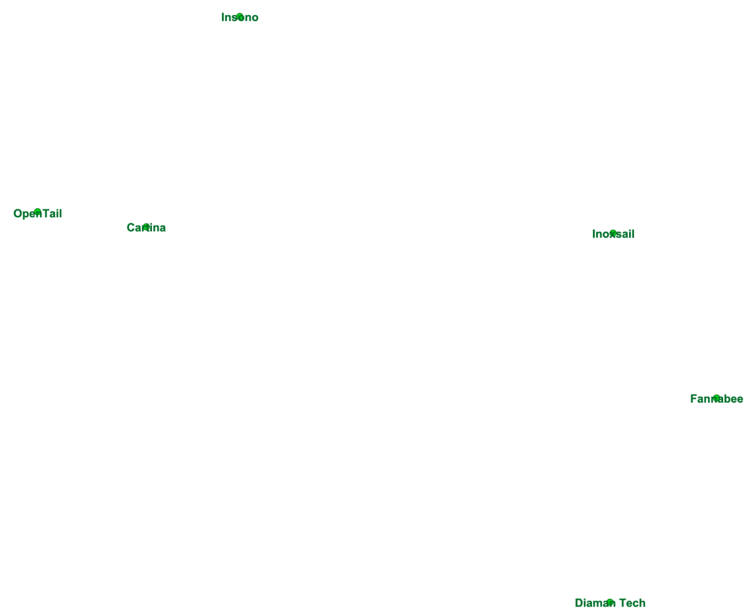

Fig.4.2.1 Network in 2015

The following year, 12 more companies joined the network. Among them there is an important component of the network that is InfinityHub, which has raised money for the first time in that year. InfinityHub is a business that aims at developing energy efficiency solutions for public and private real estate projects. It's a holding company which every time it launches a new project creates a new SPV (Special Purpose Vehicle) and uses equity crowdfunding to raise more funds for its projects. Sustainable Mobility, BicySolar and Wind Energy Efficiency are some of those. 2016 represents an important moment for the network as during this year the first connections started to appear. These forerunner connections are Inoxsail and Forever bambù thanks to a Founder-Team connection, Xnext and DiamanTech that present team members in common and finally P2R and Nano which have commonality of Investors. The state of the network at the end of 2016 is shown below, Fig.4.2.2.

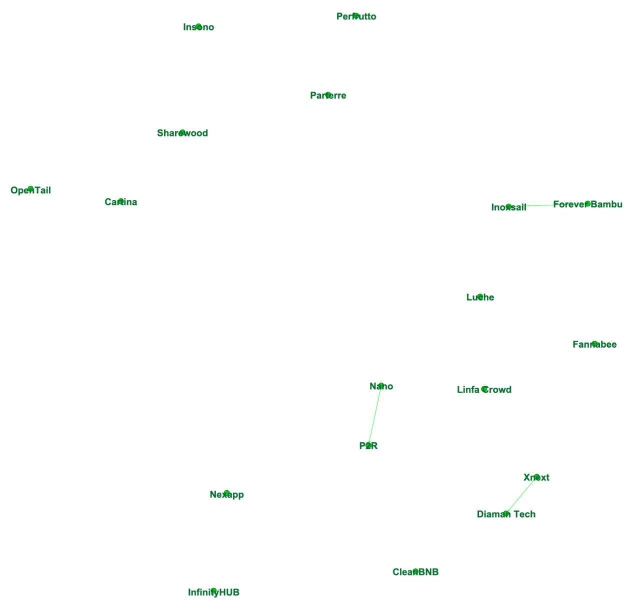

Fig.4.2.2 Network in 2016

In 2017 there's an acceleration in the Equity Crowdfunding phenomenon as it started to become popular and to get the attention of small investors, who wanted to find alternatives to an almost zero-yielding bank account. From just 33 campaigns launched in 2016 ,the year closes at 74 for the whole EC Italian landscape; the same year 26 new startups join the proto-network and 12 more bonding entities are present, creating more interconnections.The network continues to enlarge its dimension and the first clusters, lumps where more than just two companies are linked, started to appear. From now on, for every year, will be also presented the Matrix of connection in order to present the network through both a visual representation and the list of interconnections among the startups. Connections are shown in Fig.4.2.3.

<u>Overlaps Dec 2017</u>

	Founder	Team	Investor
Founder	Glasstopower-Green Energy storage	Green Energy Storage -SoundofThings SoundofThings -Green Energy Storage Raft -P2R Inoxsail - Forever Bambu	
Team		Bermat - Melixa Xnext - Diaman Tech Perfrutto - Socopet - Graphene XT	
Investor			Qaplà - Sync Green Energy Storage - Glasstopower Yakkyo - Babaiola - Bloovery - sync Bermat - Melixa P2R - Nano - Nettowork Parterre - Sync - Scloby - YouDroop Taskhunters - WeBeers

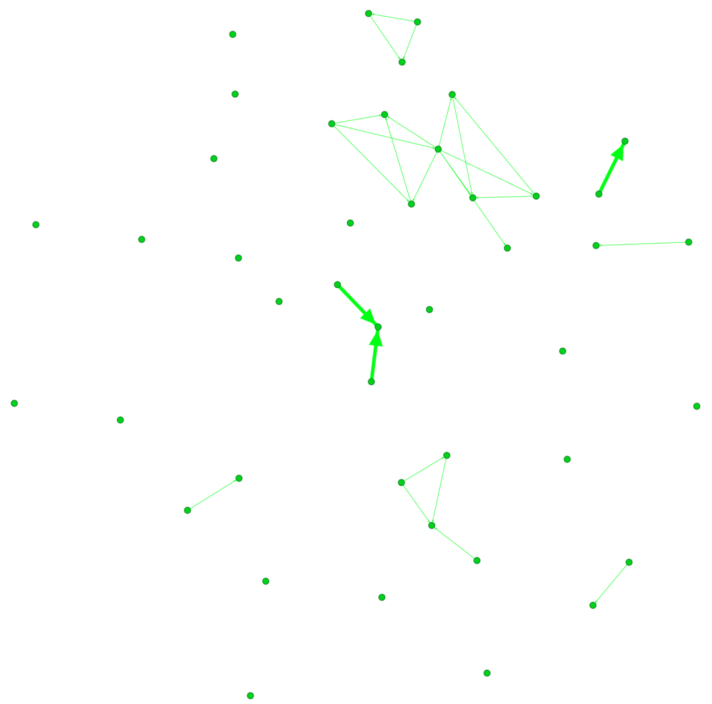

Fig.4.2.3 Connections present in 2017

The following year (2018), the Equity Crowdfunding phenomenon explodes in popularity as a way to raise funds for newly formed startups. 143 new campaigns were launched and of these 115 (80%) were successful with a total raise of €36 millions. Just the year before the total amount raised was €11 millions. It's the biggest year for the expansion of the network, as 46 new startups joined it. Connections are reported in Fig 4.2.4.

Overlaps Dec 2018

	Founder	Team	Investor
Founder	CleanBNB-Seed Money Sustainable Mobility - EYS BA - WindEnergyEfficiency Glasstopower-Green Energy storage JustMary-Criptomining JustMary-Criptomining Revotree-Fol the best Japal-Leo Nardi Milano Japal-Leo Nardi Milano AR Market -Findmylost Japal- Userbot	Glasstopower/Green Energy Storage - Green Idea Technology Green Energy Storage -SoundofThings SoundofThings -Green Energy Storage Japal - Classup Raft -P2R LinfaCrowd - Biovecblok Inoxsail - Forever Bambu Sharewood - Wiralex	Traction Management -Babaiola Japal/Userbot - Prestofood
Team		Green Idea Technologies - TaskHunters Bermat - Melixa Coco - Sportit Xnext - Diaman Tech Perfrutto - Socopet - Graphene XT	Open Tail - Shape Me Open Tail - Shape Me Verum - Nettowork
Investor			InfinityHub - EYS BA InfinityHub - EYS BA Locare - TAEBioenergy Fannabee - Eattiamo - InReception Live Based Value - Xnext Luche - Autentico Luche - Autentico - Eligo Luche - Autentico Sfrecciando - Live Based Value TAEBioenergy - Prestofood Qaplà - Edgar Qaplà - Sync Maid Service - Sin Tesi Forma Green Energy Storage - Glasstopower Verum - Nettowork Biovecblok - Linfa Crowd Yakkyo - Inkdome - MyLab Nutrition - Babaiola - Tiassisto24 - Karaoke One - Bloovery - sync Bermat - Bikee Bike - Melixa P2R - Sthimaty - Inpolitix - Nano - Nettowork You are my guide - Parterre - Sync - Scloby - YouDroop Sharewood - Wiralex CleanBNB - Marshmallows Game Taskhunters - Domoki - Eggup - WeBeers - MyCredit Service P2R - Verum

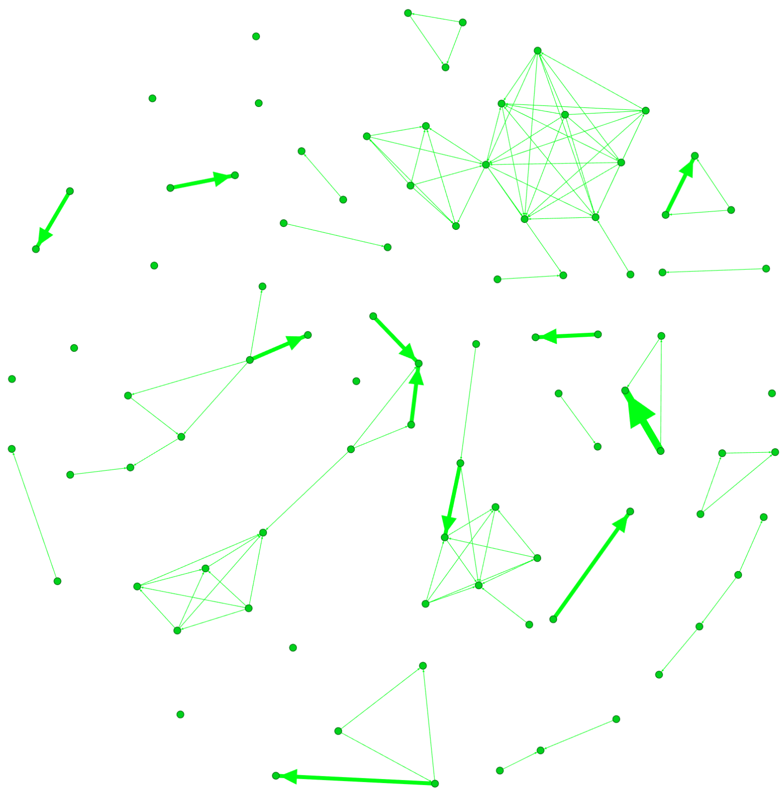

Fig.4.2.4 Connections present in 2018

Overlaps Dec 2019

	Founder	Team	Investor
Founder	CleanBNB-Seed Money Sustainable Mobility - EYS BA - WindEnergyEfficiency - Welfare Efficiency Piemonte Glasstopower-Green Energy storage JustMary-Criptomining JustMary-Criptomining Locare-Salva Assistance Locare-Salva Assistance Quomi-Leo Nardi Milano Revotree-Fol the best Start&Partners - BioInvestments Japal-Leo Nardi Milano Japal-Leo Nardi Milano Leark -Olzemusic AR Market -Findmylost Verso Technologies - Pickmeapp Japal- Userbot	Glasstopower/Green Energy Storage - Green Idea Technology Start&Partners -BioInvestments Green Energy Storage -SoundofThings SoundofThings -Green Energy Storage Japal - Classup Raft -P2R LinfaCrowd - Biovecblok Inoxsail - Forever Bambu Fremslife - InSono Sharewood - Wiralex/GardenStuff Olzemusic - LiveSonar Leark/Olzemusic - LiveSonar Olzemusic - LiveSonar	CleanBNB/Seed Money - Repup Traction Management -Babaiola Nuova Industria Torinese - Sin Tesi Forma Start&Partners - BioInvestments Japal/Userbot - Prestofood /Vidoser /SEO Tester Start&Partners- OIP Start Gogobus - Biogenera
Team		Green Idea Technologies - Recrowd - TaskHunters - Quomi Bermat - Melixa Coco - Sportit Xnext - Diaman Tech Perfrutto - Socopet - Graphene XT Verum - Nuova Industria Torinese Recrowd - Green Energy Sharing	Open Tail - Shape Me Open Tail - Shape Me Verum - Nettowork
Investor			RentApp - Repup Green Idea Technologies - Recrowd Green Idea Technologies - Recrowd Racine Caree - Quomi InfinityHub - EYS BA InfinityHub - EYS BA Locare - TAEBioenergy Fannabee - Eattiamo - InReception Live Based Value - Xnext Luche - Autentico Luche - Autentico - Eligo Luche - Autentico Sfrecciando - Live Based Value TAEBioenergy - Prestofood - Axieme Qaplà - Edgar Qaplà - Sync Maid Service - Sin Tesi Forma Green Energy Storage - Glasstopower Verum - Nettowork Noixa - Soisy Sportclubby - Pickmeapp Leo Nardi Milano - Vintag Biovecblok - Linfa Crowd Yakkyo - Inkdome - MyLab Nutrition - Babaiola - Social Academy - Tiassisto24 - Karaoke One - Bloovery - sync Bermat - Bikee Bike - Melixa P2R - Sthimaty - Inpolitix - Nano - Nettowork You are my guide - Parterre - Sync - Scloby - YouDroop Sharewood - Wiralex - Gardenstuff CleanBNB - Marshmallows Game - MySecretCase Taskhunters - Wonderstore - Axieme - Domoki - Eggup - Growishpay - WeBeers - MyCredit Service SEO Tester - Vidoser - Cartina SEO Tester - Vidoser P2R - Verum

In 2019 €65 millions are raised through ECF for a total of 138 successful campaigns out of 184 launched. Looking the observed network, 27 new startups entered in it. The Fig. 4.2.5 shows data about it.

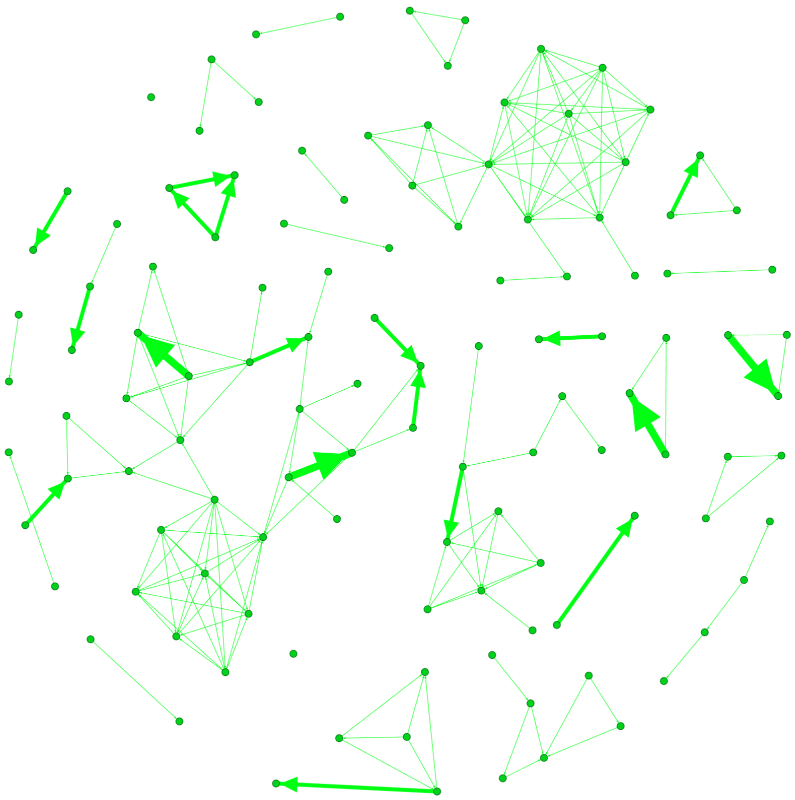

Fig.4.2.5 Connections present in 2019

Overlaps Dec 2020

	Founder	Team	Investor
Founder	ByciSolarStreet Sardegna-InfinityHub Spa- 110 Efficiency Sustainable Mobility - EYS BA - WindEnergyEfficiency - Welfare Efficiency Piemonte - Retail Efficiency Venezia - WEY Dolce ER - 110 Efficiency Glasstopower-Green Energy storage JustMary-Criptomining JustMary-Criptomining Locare-Salva Assistance Locare-Salva Assistance Quomi-Leo Nardi Milano Revotree-Fol the best Olivone-Green Energy Sharing Olivone-Green Energy Sharing Petzolla-Petsempre Petzolla-Petsempre Start&Partners - BioInvestments Japal-Leo Nardi Milano Japal-Leo Nardi Milano Leark -Olzemusic AR Market -Findmylost NexApp -Elsilab Verso Technologies - Pickmeapp Sterify - Eutronica	Glasstopower/Green Energy Storage - Green Idea Technology Start&Partners -BioInvestments Green Energy Storage -SoundofThings SoundofThings -Green Energy Storage Japal - Classup Raft -P2R LinfaCrowd - Biovecblok MeetMyPet - Apping Inoxsail - Forever Bambu Fremslife - InSono Sharewood - Wiralex/GardenStuff Olzemusic - LiveSonar Leark/Olzemusic - LiveSonar Olzemusic - LiveSonar	CleanBNB/Seed Money - Repup Traction Management -Babaiola Nuova Industria Torinese - Sin Tesi Forma Start&Partners - BioInvestments Japal/Userbot - Prestofood /Novatek /Vidoser /SEO Tester Sustainable Mobility Umbria - ByciSolarStreet Sardegna Start&Partners- OIP Start Gogobus - Biogenera The Hundred - MySecretCase Take OFF - Verum
Team		Green Idea Technologies - Recrowd - TaskHunters - Quomi Bermat - Melixa Coco - Sportit Xnext - Diaman Tech Prestito Super - Everyware Perfrutto - Socopet - Graphene XT Verum - Nuova Industria Torinese Recrowd - Green Energy Sharing - Ener2Crowd Elsilab - Nexapp Elsilab - Nexapp	Open Tail - Shape Me Open Tail - Shape Me Verum - Nettowork DesignItaly - Deliveristo Infinity Hub - ByciSolarStreet Sardegna Infinity Hub - ByciSolarStreet Sardegna/WEY Dolce ER Eligo- MPD SME Capital Eligo- MPD SME Capital
Investor	Double name = Two people or more link the two companies In diagonal cells "-" separate the different SU linked by the same entity In extra diagonal cells "-" separates the row to the colum for the different roles		RentApp - Repup Green Idea Technologies - Recrowd Green Idea Technologies - Recrowd Racine Caree - Quomi InfinityHub - EYS BA InfinityHub - EYS BA Locare - TAEBioenergy - Coffinardi e Delpanno Industries - Interweb Fannabee - Eattiamo - InReception P2R - Apping Live Based Value - Xnext Luche - Autentico Luche - Autentico - Eligo Luche - Autentico Sfrecciando - Live Based Value TAEBioenergy - Prestofood - Axieme Qaplà - Edgar Qaplà - Sync Maid Service - Sin Tesi Forma Green Energy Storage - Glasstopower Verum - Nettowork Flowdron - Elsilab Noixa - Soisy Sportclubby - Pickmeapp Leo Nardi Milano - Vintag Biovecblok - Irides - Linfa Crowd Biovecblok - Irides Yakkyo - Inkdome - MyLab Nutrition - Babaiola - Social Academy - Tiassisto24 - Karaoke One - Bloovery - sync -AvvocatoFlash Bermat - Bikee Bike - Melixa P2R - Sthimaty - Ener2Crowd - Inpolitix - Nano - Nettowork You are my guide - Parterre - Sync - Scloby - YouDroop Sharewood - Wiralex - Gardenstuff CleanBNB - Marshmallows Game - MySecretCase Taskhunters - Affitto Certificato - Wonderstore - Axieme - Domoki - Eggup - Growishpay - WeBeers - MyCredit Service Axieme - Alterego SEO Tester - Vidoser - Cartina SEO Tester - Vidoser Smart Mobility - Vintag 110 Efficiency - Retail Efficiency Venezia 110 Efficiency - InfinityHub Spa Eligo- MPD SME Capital Eligo- MPD SME Capital P2R - Verum

Finally in 2020 the growth of ECF continues and tops the €100 million mark, standing at €103 millions with 159 campaigns financed. In this year the last 24 startups joined the network, reaching the total of 141 startups connected in the network with 248 edges. Fig 4.2.6.

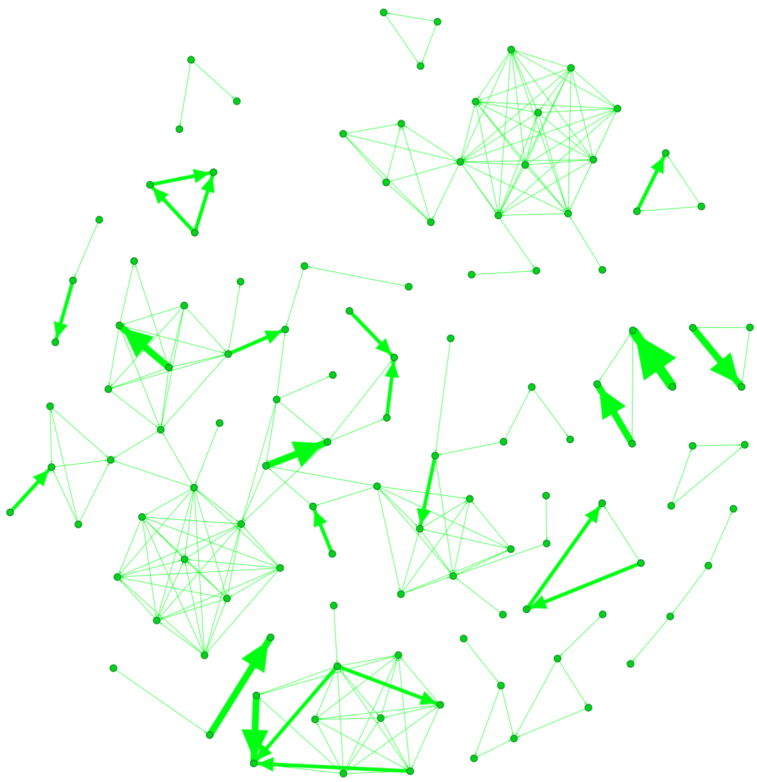

Fig.4.2.6 Connections present in 2020

Observing the network as of December 2020, it can be seen that a good portion of connections involve just two or three startups, as only 24 entities are responsible for linking more than two companies therefore showing that the network has not a very cohesive structure. Meaning that there's not much consistent seriality for now among stakeholders. This is to be expected since the Equity Crowdfunding phenomenon is relatively new, it started in 2014 in Italy, less than 10 years ago, for this reason it has not passed enough time for a relevant portion of people involved in each startup to transition from a company to the next one, or starting to have different positions in multiple companies. Just few entities link more than 4 companies. There are 11 connections that pair two startups that would otherwise present no other connections with any other company and 9 triplets, three interconnected startups that present no further links among other nodes. It has been decided to include them anyway because it's still a form of seriality nonetheless. In the following pages these non-cluster interconnections, meaning links that bond together 4 or less nodes, will be gradually removed to clearly show heavy interconnections among startups.

If these pairs are removed, then the network appears like in Fig 4.2.7.

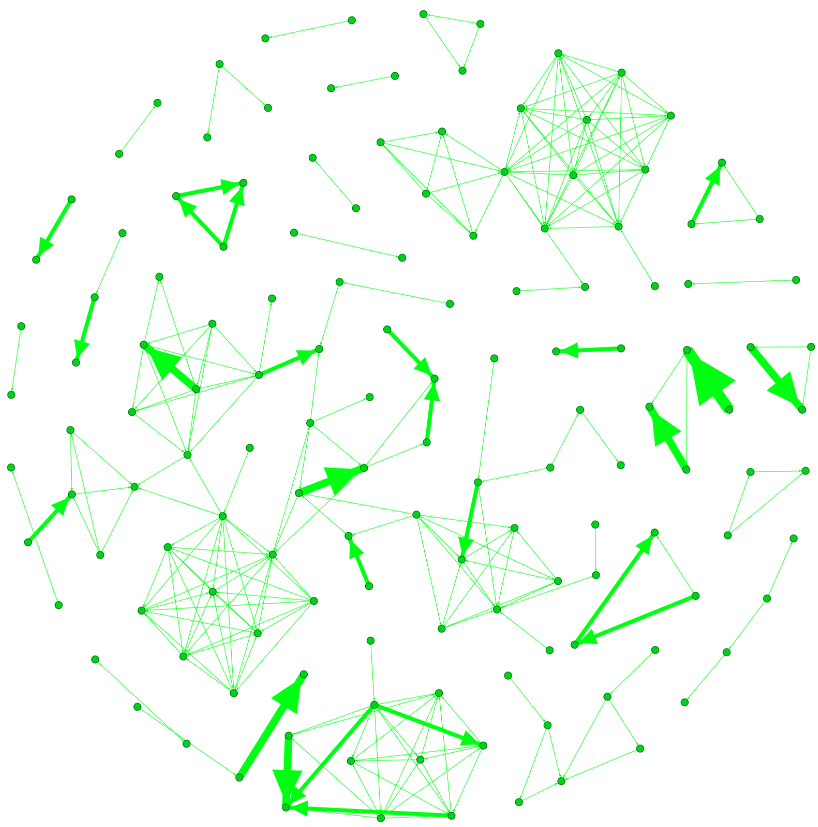

Fig.4.2.7 Network removing pairs

If also isolated triples are removed, both the ones in which two startup are connected to a third one without having a direct link between them, and also the ones in which all three startups are connected among each other, then the network evolves into Fig.4.2.8.

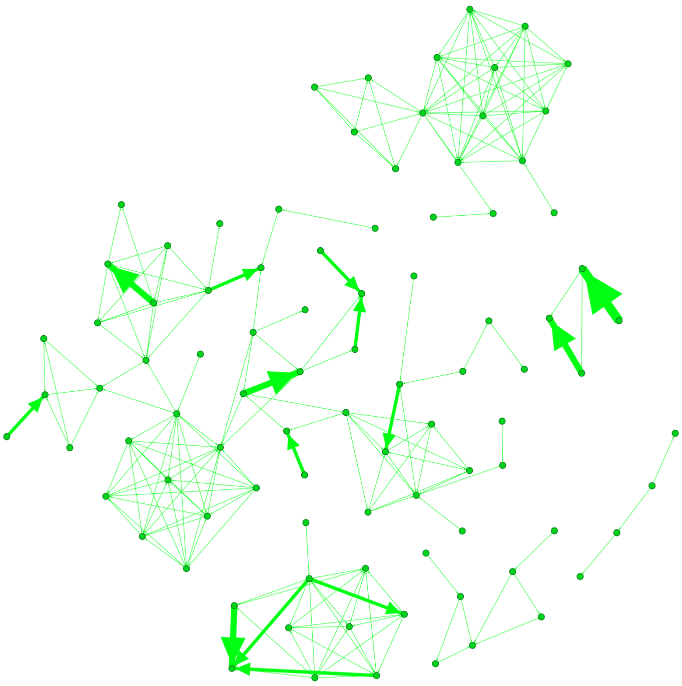

Fig.4.2.8 Network removing pairs and triplets

Finally if also the two isolated connections between four startups, visible on the right part of the network, are removed, then it is possible to identify the four separated clusters that make up the bulk of the network. In this case the network involves just 83 startups. This situation is shown in Fig.4.2.9.

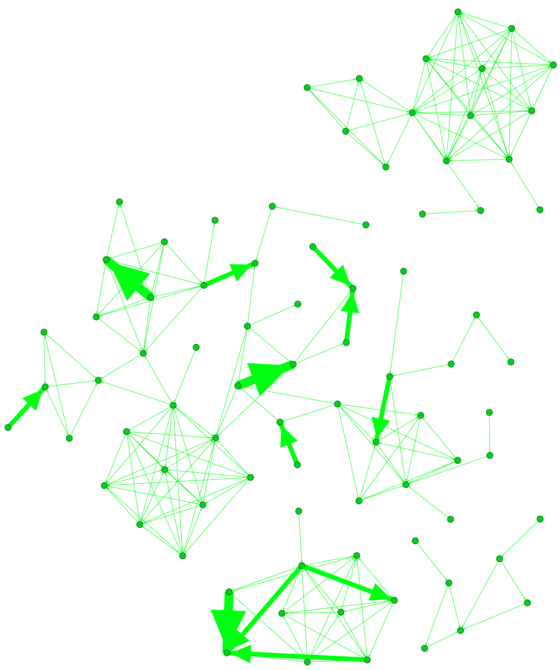

Fig.4.2.9 Network removing non-clusters

It’s immediately visible how there are mainly three groups of heavily interconnected startups. Those are the ones generated by Infinity Hub, LVenture Group and Digital Magics. This grouping situation has to be expected because the latter two are incubators, while the first one creates new SPVs for the new projects and uses Equity Crowdfunding as raising method. Additionally MNS Capital, which is a fund that aims at providing early stage seed funds to startups, is also responsible for creating a smaller and less dense group, that belongs to the same cluster of Digital Magics. The smaller cluster comprised of 7 startups, bottom right, in contrast to the other three, is made up only by multiple separated entities that bond those startups together, without big entities linking together a multitude of them and thus creating a group. Same dynamic for the small group in the top left part of the cluster of Digital Magics and MNS capital. The 4 clusters with the 4 main groups are presented below. Fig.4.2.10.

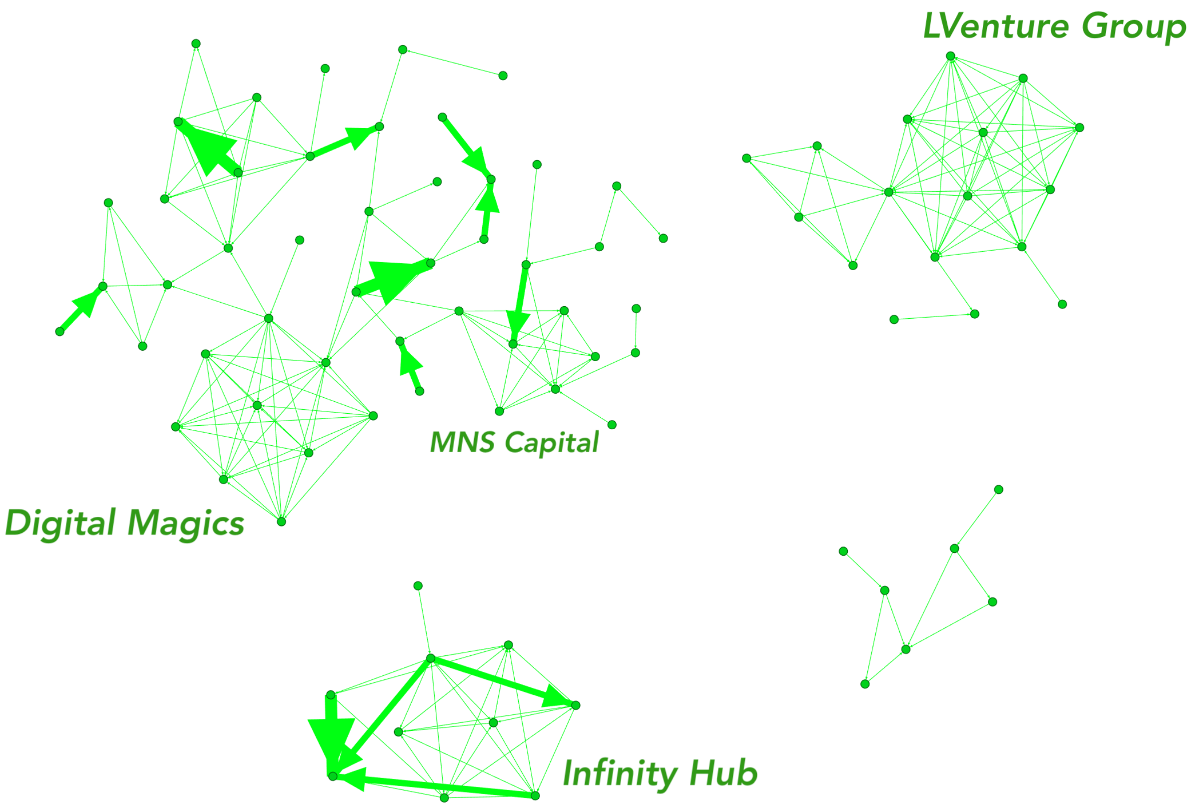

Fig.4.2.10 The four clusters with their groups

In the following part is going to be briefly presented also the evolution over time of the singles clusters, only the three dense ones will be presented, the smaller with just 7 nodes won’t be covered given its relative small size compared to the others. To avoid confusion the top left one will be called Digital Magic, the bottom one Infinity Hub and the top right one LVenture, the name of course derives by the company that generates the biggest groups inside each cluster. Fig.4.2.11.

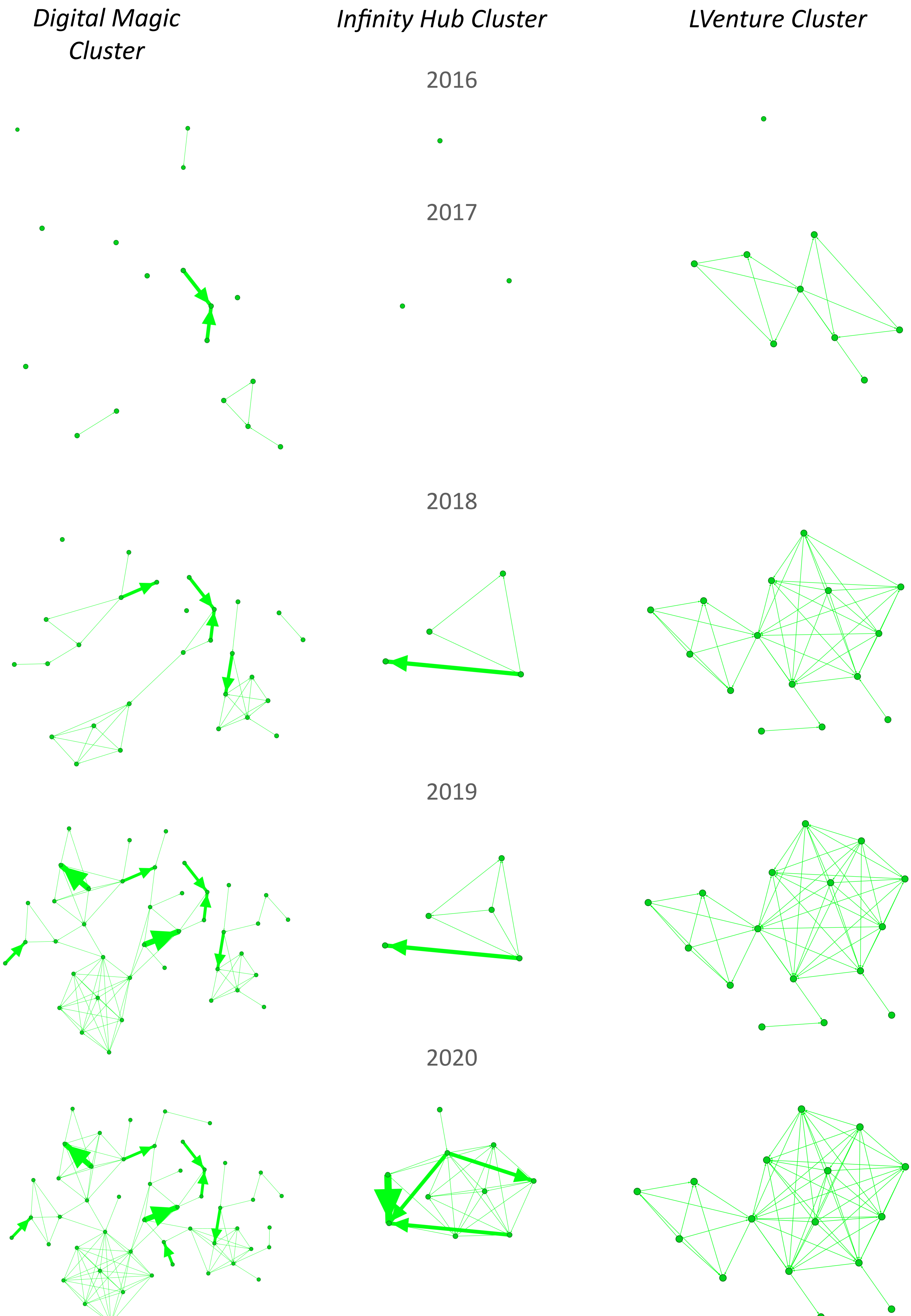

Fig.4.2.11 Cluster Evolution

Finally a full page of the evolution and breakdown of the network presented in the previous pages, from 6 nodes in 2015 to 141 in 2020 and then 83 once interconnections involving less than five nodes are removed.

The network disposition has been done using a force-directed graph approach. The core idea to this graphic representation is that all the edges are characterized by more or less equal length and there are as few crossing edges as possible. To achieve this, an attractive force is assigned to two nodes at the endpoint of each edge, creating the "gluing" component for the network. At the same time an opposite and repulsive force is assigned to each node to give spacing and distancing among them. The combination of attractive forces among adjacent vertices, and repulsive forces on all other vertices, was first theorized by Eades (1984). More in particular the program Gephi offers the possibility to organize the network following the additional work done by Fruchterman and Reingold (1991) who further studied force directed layouts.

4.3 Network density

The 'network density' is a parameter useful to understand the cohesiveness of the network. It includes in the computation the existing interconnections among the nodes and the overall structure of the network as it is defined as the ratio between the connections present between the nodes in the actual network over all the total potential ones that would connect all the nodes among each other. A high density coefficient close to 1, which is the possible maximum value, means a high level of interconnectivity among all the nodes. It means that not just few nodes present connections but the majority of them is highly interconnected. On the other hand a value of density close to 0 represents that the network is very disconnected, it's thin, and with only few nodes that present a high number of connections. The indirected density has been investigated, given the fact that in the network has not been given importance to the direction of the connection, the arrows as said before, only indicate the time component.
The mathematical computation of the Indirected Density is presented below in Fig.4.2.13.

$$Density = \frac{Actual\ connections}{Potential\ connections} \qquad Potential\ Connections = \frac{n \cdot (n-1)}{2}$$

Fig.4.3.1 Density computation

In the total universe of startups that have used equity crowdfunding as a funding venue in Italy, which is comprised of 442 companies, the density parameter assumes a value equal to 0,00254. It represents a very low value as this means that only the 0,254% of all the potential connections are actually present, furtherly showing the absence of consistent seriality among stakeholders. On the other hand, in the complete network of interconnected startups presented the density is 0,025, meaning that only 2,5% of all the potential connections are present. Again given the recency of the Equity Crowdfunding phenomenon not enough time has elapsed since its inception to have a consistent flowing of Human Capital and Intellectual Capital across the different companies that decide to raise funds through crowdfunding, a backbone of serial stakeholder interested in the space and participating on multiple levels to the newly created startups, Founder,Team, Investor, has yet to emerge in Italy.

If the network removed of the double connections is analysed the density increases to 0.034 or 3,4%, an increase which has to be expected because isolated parts of it, that were remote and isolated has been cut out. Eliminating also the triple connections the density jumps to 5,2% and finally by removing the two isolated connections of four startups and having only the four clusters the density tops at 6%.

Looking the network populated by innovative startups that are characterized by seriality, it is possible to observe that there is an evolution of density index in years. Using the computation method defined in Fig.4.3.1, it is possible to compute the density index for all the years and this has shown how the parameter value switches from an initial value equal to 1,96% in 2016 to a value equal to 2,513% in 2020. During the intermediary years the value of the index remained fairly stable, taking the value of 2,748% in 2017, 2,671% in 2018 and 2,623% in 2019.

Finally, it was observed the density condition of the four clusters. As it is to be expected, the density parameter rises a lot, particularly in the ones where the group generated by a single entity is clearly visible and encompass a good portion of the overall cluster.

The top left one of Digital Magic has a density of 9,2%, slightly higher than the one taking into account all four cluster, that's it is the largest but also the most branched out, it's not a compact lump of highly interconnected nodes. The Infinity Hub one, bottom left, is the one that presents the highest density of all, 68,9%, given the fact that it's almost made up of a single group originated by Infinity Hub itself it's not surprising; just from a visual inspection at a glance one notices the compactness of it compared to the others.LVenture cluster, top right, is the second most dense standing at 42,6%. Again here like in the Infinity Hub one almost every one is incorporated in the group or is directly linked to it. Concluding with the smaller one, composed of just 7 startups, the density stands at 38.1%.

CHAPTER 5
BEING IN THE NETWORK

5.1 Positioning in the network

In this chapter, the objective is to study through econometrical models how the fundraise performance is affected by the position and by the seriality cases that characterize the studied startup. In particular, this is done observing the network of connected startups in the equity crowdfunding environment.

As already contextualized in the previous chapters, every single node occupies a certain position in the network 'space' which can be identified through both graphical and numerical ways thanks to the use of SNA discipline. In this case, the analysis of the startup's positioning was conducted focusing on two important parameters such as 'Centrality' and 'Closeness'.

Centrality is an important parameter which is strongly linked with the concept of Degree (Stawinoga, 2014). The Degree idea has been already introduced in this thesis work and it can be easily summarized as the number of direct interactions that a node has with other nodes within the network. The correlation between the two parameters 'Centrality-Degree' is positive and therefore it means that an increase of the degree associated with a generic node 'i' generates a subsequent increase of its centrality index. This highlights the fact that if a node has many interactions with many other nodes, it covers a central position within the network (Stawinoga, 2014).

Then, the equation used for the computation of the Centrality associated to each individual node is the one represented in Fig.5.1.1.

$$Centrality(\mathrm{i}) = \frac{d(i)}{(g-1)}$$

Fig.5.1.1 Equation for the computation of 'Centrality' parameter

The d(i) is the Degree value of the node i, while the value g represents the total number of nodes in the network.

During the investigation, we wanted to go into details of direct connections. In fact, the relationships have not been considered only in their totality, but they have also been categorized in order to understand which are the types of connection and which is the total number of links per each category. In this way the relationships of type FF, FS, FA, SS, SA and AA have been quantified for each startup in the network. This disaggregation of the Degree parameter provides a very important analysis which was crucial because it allowed us to understand which are the type of antecedent seriality cases that characterize the startup. This distinction between the various type of direct seriality correlation was introduced into the econometric models, thus obtaining an useful analysis to understand which are the relationships that really influence the studied dependent variable.

The other important parameter for the analysis is the 'Closeness' (Stawinoga, 2014). Its meaning is the study of the position of the node within the entire network, considering the distance between the studied node and all the other nodes of the network related to it. The more a node is central in the group, the closer it is to many other, which results in a greater possibility of interaction and so a more favorable location for building relationships with the other nodes in the network space.
Therefore, the concept of Closeness is inversely proportional to the length of the geodesic paths that are linked with the observed node. It means that the less the node is distant in relation with the others, the more it is central and vice versa.
In this second analysis, we wanted to refer to a different equation than the one used in the 'Serial entrepreneurship' study. The equation for the computation of this index is described in Fig.5.1.2.

$$Closeness(\mathrm{i}) = \frac{1}{\sum_{j=1}^{m} \mathrm{d}(\mathrm{i},\mathrm{j})}$$

Fig.5.1.2 Equation for the computation of 'Closeness' parameter (Stawinoga, 2014)

The parameter d represents the length of the geodesic path between the studied node 'i' and the associated node 'j', while 'm' represents the number of linked to the node 'i' considering both direct and indirect correlations. Before undertaking the econometric studies, the parameters have been calculated for all the startups in the studied network in order to provide a qualitative analysis on the condition of the startups at the end of 2020.
The relevant statistical data are reported in the Table.5.1.1, while the computed values for each startup are given by Table.5.1.2.

	Mean	*Median*	*Std. dev*	*Max*	*Min*
Centrality	0,0282	0,0214	0,0194	0,0786	0,0071
Cloeness	0,2579	0,1111	0,3314	1,0000	0,0028

Table.5.1.1 Basic statistical data referred to Centrality and Closeness computation

	2020	DEGREE.ff	DEGREE.fs	DEGREE.fa	DEGREE.ss	DEGREE.sa	DEGREE.aa	DEGREE.tot	Sum[d(i),(j)]	CENTRALITY	CLOSENESS
1	CleanBNB	1	2	0	2	0	0	5	8	0,0357	0,1250
2	Seed Money	1	2	0	0	0	0	3	11	0,0214	0,0909
3	BykiSolarStreet Sardegna	2	1	0	2	3	0	8	16	0,0571	0,0625
4	InfinityHub	2	0	0	3	3	0	8	16	0,0571	0,0625
5	110 Efficiency	8	0	0	3	0	0	11	15	0,0786	0,0667
6	Sustainable Mobility	6	1	0	0	0	0	7	9	0,0500	0,1111
7	EYS BA	6	0	0	2	0	0	8	10	0,0571	0,1000
8	WindEnergyEfficiency	6	0	0	0	0	0	6	10	0,0429	0,1000
9	Welfare Efficiency Piemonte	6	0	0	0	0	0	6	10	0,0429	0,1000
10	Retail Efficiency Venezia	6	0	0	1	0	0	7	10	0,0500	0,1000
11	WEY Dolce	6	0	0	1	2	0	9	9	0,0643	0,1111
12	GlassToPower	1	0	2	1	0	0	4	191	0,0286	0,0052
13	Green Energy Storage	1	0	4	1	0	0	6	191	0,0429	0,0052
14	JustMary	2	0	0	0	0	0	2	2	0,0143	0,5000
15	Criptomining	2	0	0	0	0	0	2	2	0,0143	0,5000
16	Locare	2	0	0	3	0	0	5	207	0,0357	0,0048
17	Salva Assistance	2	0	0	0	0	0	2	253	0,0143	0,0040
18	Quomi	1	0	0	1	0	2	4	128	0,0286	0,0078
19	Leo Nardi Milano	3	0	0	1	0	0	4	154	0,0286	0,0065
20	Revotree	1	0	0	0	0	0	1	1	0,0071	1,0000
21	Fol the best	1	0	0	0	0	0	1	1	0,0071	1,0000
22	Olivone	2	0	0	0	0	2	4	161	0,0286	0,0062
23	Ges Site Zero	2	0	0	0	0	2	4	146	0,0286	0,0068
24	Start&Parteners	1	2	1	0	0	0	4	4	0,0286	0,2500
25	BioInvestments	1	1	1	0	0	0	3	5	0,0214	0,2000
26	Japal	3	5	1	0	0	0	9	115	0,0643	0,0087
27	Leark	1	0	2	0	0	0	3	5	0,0214	0,2000
28	OlzeMusic	1	1	4	0	0	0	6	5	0,0429	0,2000
29	NexApp	1	0	0	0	0	2	3	5	0,0214	0,2000
30	Elsilab	1	0	0	1	0	2	4	4	0,0286	0,2500
31	Verso Technologies	1	0	0	0	0	0	1	3	0,0071	0,3333
32	Pickmeapp	1	0	0	1	0	0	2	2	0,0143	0,5000
33	Userbot	1	6	0	0	0	0	7	176	0,0500	0,0057
34	Sterify	1	0	0	0	0	0	1	1	0,0071	1,0000
35	Eutronica	1	0	0	0	0	0	1	1	0,0071	1,0000
36	Green Idea Technologies	0	0	2	2	0	3	7	141	0,0500	0,0071
37	SoundOfThings	0	0	2	0	0	0	2	234	0,0143	0,0043
38	Classup	0	0	1	0	0	0	1	214	0,0071	0,0047
39	Raft	0	0	1	0	0	0	1	246	0,0071	0,0041
40	P2R	0	0	1	7	0	0	8	175	0,0571	0,0057
41	Linfa Crowd	0	0	1	2	0	0	3	3	0,0214	0,3333
42	Biovecblock	0	0	1	3	0	0	4	4	0,0286	0,2500
43	MeetMyPet	0	1	1	0	0	0	2	272	0,0143	0,0037
44	Apping	0	1	1	1	0	0	3	272	0,0214	0,0037
45	Inoxsail	0	0	1	0	0	0	1	1	0,0071	1,0000
46	Forever Bambuu	0	0	1	0	0	0	1	1	0,0071	1,0000
47	Fremslife	0	1	1	0	0	0	2	2	0,0143	0,5000
48	InSono	0	1	1	0	0	0	2	2	0,0143	0,5000
49	Sharewood	0	0	2	2	0	0	4	4	0,0286	0,2500
50	Wiralex	0	0	2	2	0	0	4	4	0,0286	0,2500
51	GardenStuff	0	0	2	2	0	0	4	4	0,0286	0,2500
52	LiveSonar	0	1	4	0	0	0	5	5	0,0357	0,2000
53	Traction Management	0	1	0	0	0	0	1	15	0,0071	0,0667
54	Babaiola	0	1	0	7	0	0	8	8	0,0571	0,1250
55	Nuova Industria Torinese	0	1	0	0	0	1	2	262	0,0143	0,0038
56	SinTesiForma	0	1	0	1	0	0	2	306	0,0143	0,0033
57	Prestofood	0	5	0	2	0	0	7	151	0,0500	0,0066
58	Novatek	0	6	0	0	0	0	6	195	0,0429	0,0051
59	Vidoser	0	5	0	3	0	0	8	195	0,0571	0,0051
60	SeoTester	0	5	0	3	0	0	8	195	0,0571	0,0051
61	OIP Start	0	1	0	0	0	0	1	5	0,0071	0,2000
62	Gogobus	0	1	0	0	0	0	1	1	0,0071	1,0000
63	Biogenera	0	1	0	0	0	0	1	1	0,0071	1,0000
64	The Hundred	0	1	0	0	0	0	1	15	0,0071	0,0667
65	MySecretCase	0	1	0	2	0	0	3	10	0,0214	0,1000
66	Verum	0	1	0	2	1	1	5	220	0,0357	0,0045
67	TAKE OFF	0	1	0	0	0	0	1	268	0,0071	0,0037
68	Recrowd	0	0	0	2	0	5	7	133	0,0500	0,0075
69	Task Hunters	0	0	0	8	0	3	11	128	0,0786	0,0078
70	Melixa	0	0	0	2	0	1	3	3	0,0214	0,3333
71	Coco	0	0	0	0	0	1	1	1	0,0071	1,0000
72	Sportit	0	0	0	0	0	1	1	1	0,0071	1,0000
73	Xnext	0	0	0	1	0	1	2	4	0,0143	0,2500

Table.5.1.2 First half of the table which shows the computed value of parameters Centrality and Closeness

74	DiamanTech	0	0	0	0	0	1	1	6	0,0071	0,1667
75	Ener2Crowd	0	0	0	5	0	2	7	153	0,0500	0,0065
76	Open Tail	0	0	0	0	2	0	2	2	0,0143	0,5000
77	ShapeMe	0	0	0	0	2	0	2	2	0,0143	0,5000
78	Nettowork	0	0	0	6	1	0	7	174	0,0500	0,0057
79	DesignItaly	0	0	0	1	1	0	2	1	0,0143	1,0000
80	Deliveristo	0	0	0	1	1	0	2	2	0,0143	0,5000
81	Eligo	0	0	0	6	2	0	8	8	0,0571	0,1250
82	MPD SME Capital One	0	0	0	4	2	0	6	10	0,0429	0,1000
83	RentApp	0	0	0	1	0	0	1	11	0,0071	0,0909
84	Racine Caree	0	0	0	1	0	0	1	177	0,0071	0,0056
85	TAEBioenergy	0	0	0	5	0	0	5	161	0,0357	0,0062
86	Interweb	0	0	0	3	0	0	3	209	0,0214	0,0048
87	Fannabee	0	0	0	2	0	0	2	2	0,0143	0,5000
88	Eattiamo	0	0	0	2	0	0	2	2	0,0143	0,5000
89	InReception	0	0	0	2	0	0	2	2	0,0143	0,5000
90	LiveBasedValue	0	0	0	2	0	0	2	4	0,0143	0,2500
91	Luche	0	0	0	4	0	0	4	6	0,0286	0,1667
92	Autentico	0	0	0	4	0	0	4	4	0,0286	0,2500
93	Sfrecciando	0	0	0	1	0	0	1	1	0,0071	1,0000
94	Axieme	0	0	0	11	0	0	11	139	0,0786	0,0072
95	Qaplà	0	0	0	2	0	0	2	10	0,0143	0,1000
96	Maid Service	0	0	0	1	0	0	1	352	0,0071	0,0028
97	Flowdron	0	0	0	1	0	0	1	3	0,0071	0,3333
98	Noixa	0	0	0	1	0	0	1	1	0,0071	1,0000
99	Soisy	0	0	0	1	0	0	1	1	0,0071	1,0000
100	Sportclubby	0	0	0	1	0	0	1	3	0,0071	0,3333
101	Vintag	0	0	0	2	0	0	2	197	0,0143	0,0051
102	Irides	0	0	0	3	0	0	3	3	0,0214	0,3333
103	Yakkyo	0	0	0	7	0	0	7	9	0,0500	0,1111
104	Inkdome	0	0	0	7	0	0	7	9	0,0500	0,1111
105	MyLabNutrition	0	0	0	7	0	0	7	9	0,0500	0,1111
106	Social Academy	0	0	0	7	0	0	7	9	0,0500	0,1111
107	Ti Assisto 24	0	0	0	7	0	0	7	9	0,0500	0,1111
108	Karaoke One	0	0	0	7	0	0	7	9	0,0500	0,1111
109	Bloovery	0	0	0	7	0	0	7	9	0,0500	0,1111
110	BikeeBike	0	0	0	2	0	0	2	2	0,0143	0,5000
111	Bermat	0	0	0	2	0	1	3	3	0,0214	0,3333
112	Inpolitix	0	0	0	5	0	0	5	183	0,0357	0,0055
113	Nano	0	0	0	4	0	0	4	183	0,0286	0,0055
114	You are my guide	0	0	0	4	0	0	4	9	0,0286	0,1111
115	Parterre	0	0	0	4	0	0	4	9	0,0286	0,1111
116	Sync	0	0	0	5	0	0	5	7	0,0357	0,1429
117	Edgar	0	0	0	1	0	0	1	1	0,0071	1,0000
118	Sclooby	0	0	0	4	0	0	4	9	0,0286	0,1111
119	YouDroop	0	0	0	4	0	0	4	9	0,0286	0,1111
120	Marshmallows Game	0	0	0	2	0	0	2	11	0,0143	0,0909
121	Affitto Certificato	0	0	0	8	0	0	8	153	0,0571	0,0065
122	Wonderstone	0	0	0	8	0	0	8	153	0,0571	0,0065
123	Domoki	0	0	0	8	0	0	8	153	0,0571	0,0065
124	Eggup	0	0	0	8	0	0	8	153	0,0571	0,0065
125	We Beers	0	0	0	8	0	0	8	153	0,0571	0,0065
126	Italian Waves	0	0	0	1	0	0	1	185	0,0071	0,0054
127	Cartina	0	0	0	2	0	0	2	232	0,0143	0,0043
128	Smart Mobility	0	0	0	1	0	0	1	242	0,0071	0,0041
129	Repup	0	2	0	1	0	0	3	10	0,0214	0,1000
130	Coffinardi e Delpanno	0	0	0	3	0	0	3	209	0,0214	0,0048
131	Sthimaty	0	0	0	5	0	0	5	183	0,0357	0,0055
132	Growishpay	0	0	0	8	0	0	8	153	0,0571	0,0065
133	MyCredit Service	0	0	0	8	0	0	8	153	0,0571	0,0065
134	Horticultural Knowledge	0	0	0	0	0	2	2	2	0,0143	0,5000
135	Socopet	0	0	0	0	0	2	2	2	0,0143	0,5000
136	GrapheneXT	0	0	0	0	0	2	2	2	0,0143	0,5000
137	FindMyLost	1	0	0	0	0	0	1	1	0,0071	1,0000
138	EveryWare	1	0	0	0	0	0	1	1	0,0071	1,0000
139	AR Market	1	0	0	0	0	0	1	1	0,0071	1,0000
140	PrestitoSuper	1	0	0	0	0	0	1	1	0,0071	1,0000
141	AvvocatoFlash	0	0	0	7	0	0	7	9	0,0500	0,1111

Table.5.1.2. Second half of the table which shows the computed value of parameters Centrality and Closeness

5.2 Preparation of data for the econometric models

For the econometric study, it was not sufficient to use the data reported in the Table.5.1.1 and in the Table.5.1.2 since they do not take into account an important factor which is the ‘time’.

The focus of the elaborated econometric models is the impact generated by the conditions of centrality, closeness and of the antecedent seriality cases on the fundraising. As the above parameters refer to end of 2020, these are not important for our study as they don’t reflect the conditions of these parameters exactly before the round. If they were used, it would not be clear what is the real condition of the startup at the moment of the round and therefore the econometric model would lose value because it would not be based on reliable explanatory variables. For this reason, it was important to introduce the factor ‘time’, and this was done photographing the situation of the startup at the exact moment of the fundraising. In this way, it was possible to understand which were the actual values of the parameters that really have influenced the startup at the moment of the fundraising.

As far as the seriality cases are concerned, the introduction of time is fundamental because if it was not taken into account they will be considered as a whole without considering which are the specific cases that really affect the round. What really happens is that a seriality case ‘A’ generates an impact on a startup ‘B’ if and only if the ‘A’ case predates the ‘B’ one. This consideration is crucial as we want to study the impact of human capital on the startup which is developed by the experience.

This idea about time is not important just in case of ‘seriality case interaction’. In fact, even if we want to consider the parameters related to the positioning of the node it is fundamental to observe in detail the image of the network at the exact round’s moment. In different time moments we can have different positions because new startups could enter in the network generating new connections. Therefore, it is important to consider the positioning at the precise moment for better understanding the real condition of the startup and in order to study with the greatest level of detail the impact of this on the round. This detailed study was possible because the data collection was carried out in cooperation with a time-table that was created by us and which allows to sort the startups in chronological order according to the round’s date. By doing so, it was possible to understand which startups are present at the time of the round simply comparing the rounds’ dates. Therefore, if a startup ‘X’ has carried out the round after the studied startup, then this ‘X’ is not considered in the parameters computations either if we are talking about seriality cases and/or if we want to study the positional ones.

5.3 Introduction to the used econometric models

The econometric models used in this analysis are linear regressions, so they are studies in which a certain dependent variable Y is interpreted through a straight line defined thanks to a series of explanatory variables X. A simple theoretical example of 'linear regression' can be explained in Fig.5.3.1.

$$Y = \beta 0 + (\beta 1 \times X1) + (\beta 2 \times X2) + \varepsilon$$

Fig.5.3.1. Basic example of linear regression

Y is the studied dependent variable, Xs are the explanatory variables (even called regressors), β coefficients are the slopes and the last term is the error term.

All the dependent variables Y defined in our model are linked to the success of the startup's fundraise seen in the Italian equity crowdfunding space. The first dependent variable introduced in the model is the percentage of round collection, so the initial aim is to study the impact of the previously mentioned relational and positional parameters on the collection of the fundraising activity. Sequently, we have expanded the study by deciding to introduce two other variables Y, always keeping attention on the concept of round success. The first of this second category of dependent variable is the log transformation of the fundraise %, while the second is a binary variable that takes value 0 in case of round failure and value 1 in case of success. The transition to logarithmic function is based on an econometric reasoning. In fact, passing to the log transformed allows the transition from 'absolute error' to 'percentage error'. The issue of having an absolute error is its possible divergent behavior in case of high values of the predicted variable Y, so this means that if the prediction of the dependent variable and the values of X increase, the error increases. Instead, having a percentage error guarantees a more stable behavior of this parameter, guaranteeing a greater predictive ability of the model in case of high values of Y.

The X variables used in the models are several. We have decided to use variables both related to the physical positioning of the startup in the network (previously discussed Closeness and Centrality) but also relational variables (seriality case), so variables that want to study in qualitative and quantitative ways the relationships that a studied node has with others. Considering the latter, it has been possible to study which is the magnitude of the impact created by the seriality cases as well as the types of relations that impact with most effect within our study. Of course, all these variables have been measured maintaining in strong consideration the 'time' factor as previously discussed in the paragraph 5.2.

The seriality cases are considered as 'relational variables' because through seriality we can have connection of two or more startups thanks to the presence of a common individual, or a group of them, who first plays a role in one and then in another. This means that this individual is working as a sort of bridge between the two observed startups.

Initially, the seriality cases were considered in their overall, observing only their total number. The value of this X variable called 'SerialityCases' is calculated for each startup through the sum of the direct relationships that a startup has in the network at the precise moment of its round. Subsequently, this parameter was 'opened' trying to study in more depth which were the types of seriality links and their personal volume. Therefore, the initial regressor called 'SerialityCases' has been transformed into a set of other X variables such as: FFsum, FSsum, FAsum, SSsum, SAsum and AAsum. Each variable of this group quantifies the number of direct links per each single relationship category, thus providing a quantitative and a qualitative study.

At the same time, purely qualitative variables were also used as regressors for the study. These are part of a pool of dummy variables called FF, FS, FA, SS, SA and AA whose purpose is only to show the presence of certain typology of relationship. These binary variables take the value 1 in case that the relationship exists and value 0 in case the relationship doesn't exist. In other words, they focus only on communicating presence or not without studying the relative quantity. In this way the dummy variables have been used as categorical variables because the value 1 is a symptom that the relationship belongs to a defined category.

For instance, if two nodes are correlated through two Founder-Founder relationships, the variable FFsum is measured as 2 while all the other variables of that cluster are 0, and at the same time the dummy FF assumes value 1 and the other variables of the second described group are 0.

As mentioned above, it was also considered a log transformed study. This requires to involve in the transformation process not only dependent variables Y but also the various X variables. However, this situation has highlighted a problem, as the massive presence of null values in the clusters of variables mentioned above has increased the difficulty of switching to the logarithmic version, being the log function not defined for value of X equal to 0. To solve this problem, the value 0 has been approximated to 0,1x10(-7). The intention was not to lose the meaning of the logarithm, thus trying to use a value of X that tended to the value 0. In this way it has been possible to consider as X variable also all the logarithmic transformations of all the regressor variables previously defined.

Instead, the values related to the positional parameters as Closeness and Centrality that are introduced within the various econometric models were calculated simply by relying on the equation described in paragraph 5.1 and considering what was said in the paragraph 5.2 about time influence. The only aspect to underline is the calculation of the parameter Closeness where this cannot be done for analytical reason. In some cases, due to the absence of interconnections between the node and the network, the denominator of the equation assumes vale equal to 0 making impossible the computation. Therefore, to make the idea of excessive distance and total disconnected position and knowing the negative correlation between the index value and the proximity condition of the node with the rest of the network, we have decided to associate to the index Closeness the value equal to 5. Associating a value totally outside the range of the confidence interval in that direction allows us to associate to the node the idea of absolute distant position from the surrounding network.

All the parameters discussed above have been calculated for each startup present in the network defined in CHAPTER 4. In addition, data about the second round of startups have been included in the econometric model data set as well. In this way the study can rely on a larger amount of data increasing the level of detail, and also it can show additional information about how the changes in seriality and in positioning conditions create effect on the round's performance.
The basic statistical data about these variables are defined in the table below (Table.5.3.1). Data about categorical variables and the relative log transformed are not reported in the table.

DEPENDENT V.	***Mean***	***Median***	***Std. dev***	***Max***	***Min***
Fundraise %	202,213	156,850	194,448	1666,670	0,000
Log (Fundr. %)	1,965	2,195	1,314	3,222	-8,000
Binary Success	0,821	1	0,385	1	0
EXPLANATORY V.	***Mean***	***Median***	***Std. dev***	***Max***	***Min***
Centrality	0,015	0,007	0,016	0,075	0,000
Closeness	1,883	0,500	2,216	5,000	0,004
FFsum	0,324	0,000	0,949	7,000	0,000
FAsum	0,117	0,000	0,417	3,000	0,000
FSsum	0,186	0,000	0,540	3,000	0,000
SSsum	1,152	0,000	1,912	9,000	0,000
SAsum	0,069	0,000	0,326	2,000	0,000
AAsum	0,124	0,000	0,455	3,000	0,000
SerialityCases	1,966	1,000	2,181	10,000	0,000
LOG (FFsum)	-6,642	-8,000	3,061	0,845	-8,000
LOG (FAsum)	-7,275	-8,000	2,318	0,477	-8,000
LOG (FSsum)	-6,888	-8,000	2,790	0,477	-8,000

LOG (SSsum)	-4,494	-8,000	4,133	0,954	-8,000
LOG (SAsum)	-7,608	-8,000	1,749	0,301	-8,000
LOG (AAsum)	-7,326	-8,000	2,251	0,477	-8,000
LOG (SerCases)	0,000	0,000	3,887	1,000	-8,000

Table.5.3.1. Collection of basic statistical data based on collected dependent and explanatory variables

Additionally, three control variables have been introduced in the study to verify and ascertain the causal effects of the explanatory variables onto the dependent ones, meaning the effect of the positioning and connections that a company has in the network may have on its success.

The variables that have an influence on the success of a crowdfunding campaign are multiple and they have been already studied in the literature (Mochkabadi and Volkmann 2018) (Vulkan et al. 2016), in particular factors that have been investigated as influencing the success are: human capital attributes (Piva and Rossi-Lamastra 2018), third party signals (Bapna 2017), the funding dynamics of the campaign (Hornuf and Schwienbacher 2018; Vismara 2018), the engagement with the crowd by providing regular updates (Block et al. 2018) but also the amount of equity offered (Ahlers et al. 2015) (Vismara 2016), the time duration of the campaign on the portal (Cordova, Dolci, Gianfrate, 2015) and the number of founders present in the startup (Ralcheva ,Roosenboom 2019). In this study, it has been decided to use the last three as control variables.

The 'percentage of equity' that is offered during the campaign, or its complement which is the percentage of equity retained, has been shown in different studies as a very strong influencing factor on the success of the campaign (Mollick 2014) (Ahlers et al. 2015) (Vismara 2016) (Ralcheva and Roosenboom 2019). A high level of equity being offered in the campaign has a very consistent negative impact on its success, that's because in the framework of signaling theory, retaining equity is as a strong sign of quality. The actions by the entrepreneurs to offer a reduced amount of equity "speak" for the quality of company and their willingness to maintain substantial ownership in their own project, therefore sending a positive signal to investors (Leland and Pyle (1977). By retaining more equity, entrepreneurs can signal their confidence in the future potential and prospects of their startup. On the contrary, entrepreneurs who are less dedicated to their company are likely to sell a higher amount of equity, that way shifting a higher proportion of potential future losses onto investors. This behavior is likely to be taken into account by equity crowdfunding investors thereby impacting the success probability of equity crowdfunding campaigns. The statistical data for the equity offered by the 141 startups present in the network analyzed are shown in table 5.3.2.

	Mean	*Median*	*Std. dev*	*Max*	*Min*
Equity Offered	0,104	0,061	0,127	0,990	0,010
Log Equity Offered	-1,166	-1,218	0,378	-0,004	-2,013

Table.5.3.2 Basic statistical data referred to equity offered

Second used control variable is the 'duration window of the campaign'. It's another important parameter that has been found to have a positive impact on the success of the campaign (Cordova, Dolci, Gianfrate, 2015). The further in time the fundraising closure is, the higher the likelihood contributions will add up to an amount equal or above the one originally requested by the found thus making the capital raise successful. This occurs because more people are able to participate in it. Moreover, an investor who has invested in the early days of the campaign, is able to speak about it to his acquaintances and so thanks to word of mouth mechanism there is bigger awareness toward the company, which can be translated in more potential capital because a portion of the contacted people will decide to invest. Additionally, the startup may update the crowd on his own developments while the crowdfunding campaign is still on-going thus stimulating more investments from the crowd and moving the undecided investors to the investment decision. Below are presented the statistical data for the duration of the campaign for the startups belonging to the network, Table 5.3.3.

	Mean	*Median*	*Std. dev*	*Max*	*Min*
Duration	80,166	77,000	45,307	365,000	3,000
Log Duration	1,822	1,886	0,306	2,562	0,477

Table.5.3.3 Statistical data on campaign duration

The third and last adopted control variable is the 'number of directors' in the startup that is raising funds, in particular the founding directors, in other words the number of founders. It has been found in two studies (Vismara 2016) and (Ralcheva ,Roosenboom 2019) that there is a strong positive correlation associated with the success of a campaign and the number of directors with founding positions that are involved in this raising startup. These dynamics reflect how investors are more willing to invest in startups where there's a plethora of skills and knowhow coming from different individuals in a leading role, which ties in with concepts discussed in previous chapters of human capital and competence sharing inside the company between different individuals. Founder's social capital plays a crucial role in attracting investors during the early days of the campaign (Colombo et al. 2016) and (Mollick, 2014) showed that the number of a founder's social network connections is associated positively with the capital raised from a project, thus the higher the number of individuals covering the role of founding directors the larger and more inter winded the social capital is in a given firm. The statistical data about the number of founder for our dataset is shown below. Table 5.3.4.

	Mean	*Median*	*Std. dev*	*Max*	*Min*
N. Founders	2,283	2,000	1,262	7,000	1,000
Log N. Founders	0,298	0,301	0,23	0,845	0,000

Table.5.3.4 Statistical data on number of founders

Subsequently, it has been verified that also in the analyzed network, with a dataset of 141 startups belonging to it, these three control parameters have a significant impact on the success of the crowdfunding campaign. This confirms that the results of previous studies (Ralcheva ,Roosenboom 2019) (Vismara 2016)(Cordova, Dolci, Gianfrate, 2015) can be applied also to a subsection of the Italian equity crowdfunding space referred to startups that present seriality and interconnections among their human capital structures. In order to show the relevance of these variables on our study, it was decided to investigate the correlation that these have with the dependent variable 'Percentage'. The obtained results have shown that there is always a significant correlation between the variables and therefore the rejection about the null hypothesis on the correlation value. Data about the correlation study between control variables and 'Percentage' Y variable, and relative data about null hypothesis are reported in Table 5.3.5.

CONTROL V.	*Correlation*	*T-Ratio*	*P-Value*
Equity Offered	-0,240	-2,950	0,370%
Duration	0,296	3,705	0,030%
N. Founders	0,398	5,188	0,000%

Table.5.3.5 Econometric data about correlation between control variables and 'Percentage' dependent variable

5.4 Econometric study and results

As previously mentioned, the type of reference model used in our study is 'linear regression'. The objective of this model is to create a straight line defined by a series of explanatory variables X, which allows to interpret the behavior of the observed and independently collected dependent variable Y. The intention is to create a dense network of linear models involving different types of study, in order to clarify in the most efficient way what is discussed at the theoretical level.

In addition to the initial data collection, the important point of this process is the creation of the model by estimating the parameters β that multiply the variables X within the equation. In this way it is possible to understand and to size the direct impact of the explanatory variables X and the impact from eventual changes in X on the dependent one.

The parameter estimation is performed through a statistical model called 'Ordinary Least Squares', OLS. The operation of this process is based on the maximization of the Likelihood function in the respect of the β parameters. During the development of the computation there is a logarithmic transformation, as being the log a monotonic function its use makes easier the process of maximization. The maximization process ends by defining the resulted parameters β (also called slopes) as the only ones that are able to respect the minimization of the summation shown in Fig.5.4.1.

$$\sum_{i=1}^{n} \{\mathrm{y(i)} - \left[\beta 0 + \left(\beta 1 \times X1(i)\right) + \left(\beta 2 \times X2(i)\right)\right]\}^2$$

Fig.5.4.1. Summation which requires the minimization for the computation of slopes' values

This summatory clearly shows how the estimates of β parameters are based on the minimization of the squared distance between the observed variable Y and the relative predicted value calculated with the collected explanatory variables. Therefore, the aim is to associate to the slopes the value which allows to have a model with as much efficiency as possible since it provides a value of Y as close as possible to the real observed one.

The analytical equation that provides the estimates of the β parameters that respect the minimization process can be defined by the simple equation shown in Fig.5.4.2.

$$\beta = (X'X)^{-1}X'Y$$

Fig.5.4.2. Equation for the computation of the β parameter through OLS

X is the matrix that contains all the values of all the explanatory variables of each single observation, X' is its transposed and Y is the vector that encloses all the values of all the observed dependent variables.

The strength of this model is not just the computation of the values of the slopes associated with the X variables, but it is also related to the ability to go furtherly into detail thanks to a comparison between the computed parameter and the statistical annulment hypothesis. In this way it is possible to study if a certain slope parameter accepts the associated hypothesis of cancellation, despite it has a not null value in the regression. The acceptance of the annulment hypothesis is symptom of how the parameter can be associated to zero value within the linear regression, showing that this doesn't impact significantly in the model and thus allowing its removal.

The result of the cancellation hypothesis is shown through two statistical results: t-ratio and p-value. The hypothesis is accepted if the t-ratio assumes value lower than 2 in module and p-value larger than 0,05. During our analysis, the linear modeling process was carried out thanks to Gretl software. This has allowed us to understand how the linear relationships between the dependent and the explanatory variables that have been mentioned above are developed, but also to understand the results of the null hypothesis in order to have a more detailed view of the study.

What was searched during this analysis is an econometrical and analytical confirmation that the seriality cases and the positioning of the node within the network generate a positive effect on the fundraising of the startup. Therefore, a confirmation of how the social-intellectual capital combination is able to be beneficial on the startup during the process of equity crowdfunding.

5.5 Econometric studies about seriality effect and relative results

The first studied model involves as dependent variable the % of fundraise collection, which is studied as function of the total number of antecedent seriality cases that characterize the startup ('SerialityCases' variable).

Obviously, the variable Y and the relative variable X have been found for all the cases of seriality that are present in the network, considering also the double rounds. As mentioned above it is of fundamental importance to take into account the time factor, because it is crucial to understand the situation at the exact moment of the round.

Before building the econometric model, the analysis was focused on understanding the existence of a correlation between the two observed parameters. From this initial study, it was possible to understand the existence and the positivity of the correlation. Moreover, what has been found is furtherly confirmed by the rejection of the 'null hypothesis' on the correlation. Data about the correlation value and about the null hypothesis are shown in Fig.5.5.1.

```
corr(Percentage, SerialityCases) = 0.20574797
Under the null hypothesis of no correlation:
 t(143) = 2.51418, with two-tailed p-value 0.0130
```

Fig.5.5.1. Results of the simple correlation analysis

Later the analysis was based on the creation of a linear regression that allows to understand the behavior of the studied dependent variable Y in relation to the collected variable 'SerialityCases' and the used control variables that were defined for the econometric study. This linear model has confirmed the existence of a positive impact of this variable X on the studied Y, and it has confirmed again that this impact cannot be overlooked. The latter detail is shown by the not acceptance of the 'null hypothesis' on the β4 parameter, which is the slope of X4 that is the explanatory variable associated to the 'SerialityCase' variable. The results of the linear regression are reported in Fig.5.5.2. In this case all the controls variables are included in the model.

Dependent variable: Percentage

	coefficient	std. error	t-ratio	p-value	
const	−23.3134	43.0278	−0.5418	0.5888	
NumFound	57.5870	11.0692	5.202	6.85e-07	***
Days	1.10134	0.307055	3.587	0.0005	***
EquityOff	−219.811	111.671	−1.968	0.0510	*
SerialityCases	14.3251	6.43444	2.226	0.0276	**

Fig.5.5.2. Econometric results on explanatory variables from OLS method

The parameter 'const' indicates the constant term of the linear regression, this is the parameter β0 of the Fig.5.3.1 and of the Fig.5.4.1. The associated coefficient to the considered independent variable 'SerialityCases' is positive, and it assumes value equal to 14,3251. This shows that there is a positive impact from the variable X on the variable Y, analytically demonstrating what was previously discussed at a theoretical level and during the study of the pure correlation among the two variables. Additionally, it is possible to observe that in this analysis the further assumption of 'null hypothesis' on the parameter β4 is not accepted. This further consideration demonstrates that the behavior of this variable X is not passive, but it has a specific impact on the studied variable Y. At the econometric level, this is understood thanks to the values of t-ratio equal to 2,226, so greater than 2, and of p-value equal to 0,0276, therefore lower than 0,05.

The only issue that the model shows is an unclear behavior of the control variable 'EquityOff', which deals of showing the % of Equity capital offered during the round. This unclear behavior is demonstrated by values of t-ratio and p-value at the limit if compared to the accepted target values. However, being this a control variable whose reliability is demonstrated by previous empirical and theoretical studies (Cap.5.3) and being econometric values very close to the limit of acceptance, it was decided to maintain it into the model and so to confirm the validity of this model for the study. A further econometric analysis has been carried out for showing the behavior of the observed variable X 'SerialityCases' on the studied Y in absence of this discussed control variable. Data of this last model are reported in Fig.5.5.3.

Dependent variable: Percentage

	coefficient	std. error	t-ratio	p-value	
const	−60.3818	39.0802	−1.545	0.1246	
NumFound	59.9587	11.1150	5.394	2.83e-07	***
Days	1.16403	0.308497	3.773	0.0002	***
SerialityCases	16.1885	6.42897	2.518	0.0129	**

Fig.5.5.3 Econometric results on explanatory variables of the second study from OLS method

In this way, it has been possible to underline again the nature of the impact of the observed variable X on the dependent one, also in absence of the controversial situation that characterized the used control variable 'EquityOff'.

Remaining on the analysis of how the total number of antecedent seriality cases impact the performance of the startup fundraising, a further model has been developed with the objective to show again that exists a positive relationship between success and seriality. The difference with the previous model is in the studied dependent variable Y, while the used variable X on which the study is based is the same as the linear regression previously discussed. In this case, the studied Y is a binary variable that assumes value 0 in case of failure and value 1 in case of success. In this way the model doesn't want to study the 'size' of the success, but it just wants to understand whether it comes success or not providing a sort of qualitative round's analysis. Therefore, it can be seen as an easier model than the previous one as this study stopes at the definition of the dummy variable, without trying to size the studied success. Even in this case all the control variables were included in the model maintaining the same numerical values used in the previous linear regression. The result of the linear study on the binary success variable with all the control variables and the observed explanatory variable 'SerialityCases' is reported in Fig.5.5.4.

Dependent variable: BinarySuccess

	coefficient	std. error	t-ratio	p-value	
const	0.517360	0.0901144	5.741	5.60e-08	***
NumFound	0.0719149	0.0231826	3.102	0.0023	***
Days	0.00182761	0.000643076	2.842	0.0052	***
EquityOff	−0.609184	0.233876	−2.605	0.0102	**
SerialityCases	0.0282523	0.0134759	2.097	0.0378	**

Fig.5.5.4 Econometric results from OLS for the studied linear regression with the binary variable as Y

Considering the numeric value of the slope parameter β4 (equal to 0,0282523) and observing the values of t-ratio and p-value linked to the null hypothesis of β4, it is possible to additionally demonstrate that the volume of the seriality cases has a positive and not irrelevant impact on the considered analysis, even if it involves a qualitative analysis of the round success. This further communicates that this explanatory variable affects the fundraising performance, continuing to show what was discussed at theoretical level.
Working in this direction, it is possible to notice that this used explanatory variable can be positively considered both for a study on the fundraising collection and for a study only based on fundraising's success, as this last used Y variable communicates just this information of success or failure.

Keeping the focus on the dependent variable Y 'Percentage', another linear regression model has been carried out with the objective of increasing the level of detail of the study. In fact, this model has been developed with the objective to study how the dependent variable 'Percentage' is influenced by the variables FFsum, FSsum, FAsum, SSsum, SAsum and AAsum. These are defined through a qualitative analysis of the initial overall variable 'SerialityCases', that can be achieved by breaking down the regressor 'SerialityCases'. Having available these variables, the objective of the model is to study the variable Y trying to understand which are the types and the relative volume of serial cases that really impact on it. In the initial analysis of this linear regression, all the previously mentioned variables have been inserted inside the regression in a bid to observe how all of them impact on Y. Obviously the variable 'SerialityCases' was not introduced in the regression

as it is a linear combination of the other six variables. However, the found result has highlighted that not all the six variables are able to affect the studied Y. Indeed, it can be possible to note that the values resulting from the null hypothesis related to the FFsum, FSsum, FAsum, SSsum and SAsum lead to the acceptance of the cancellation hypothesis. The unique variable that is not included in this group is the AAsum. Due to this, it was necessary to thin out the number of variables. By doing this and observing the behavior of the X variables in different cases, we arrived at a penultima and not definitive model which considered only the pure seriality cases as FFsum, SSsum and AAsum. However, this regression has highlighted through the acceptance on the null hypothesis that the variable SSsum is excluded from the model, as it has an associated too large p-value equal to 0,6538. Removing this variable, we have reached the final model in which the Y is studied as function of just two variables: FFsum and AAsum. This removal of variables up to the final model only with FFsum and AAsum communicates that just these two qualitative-quantitative variables have an impact on the fundraising performance. Therefore, applying the numerical result to the real context it is possible to extrapolate the information that only the two pure seriality cases FF and AA can positively impact the volume of the fundraising.
Data about this studied linear regression are shown in Fig.5.5.5.

Dependent variable: Percentage

	coefficient	std. error	t-ratio	p-value	
const	−3.01789	39.7685	−0.07589	0.9396	
NumFound	54.5607	10.7654	5.068	1.26e−06	***
Days	1.11410	0.297989	3.739	0.0003	***
EquityOff	−306.226	107.910	−2.838	0.0052	***
FFsum	42.1447	14.2667	2.954	0.0037	***
AAsum	74.2883	29.5907	2.511	0.0132	**

Fig.5.5.5 Econometric results of regressors of the linear regression model by OLS method

The elaborated linear regression shows that the impacts from the two X variables are positive, symptom that the increase of serial cases of both types will contribute to have an improvement of the round's performance. The low p-values show that the null hypothesis on both two variables cannot be accepted, further underlying that there is an impact from these two regressors.

Observing the last introduced linear regression, it is possible to identify as the AA relationship contributes with a more significant effect on the dependent variable Y than the parameter related to the FF interaction. In particular, the relative β4 parameter of the regressor FFsum is around the half of the β5, which is the slope associated to the AAsum variable. This shows that FFsum has a half-impact on the variable Y compared to the explanatory variable AAsum. Having understood that relationships have different effects, it was decided to investigate in depth the impact of each single type of relationship by introducing categorical variables that are only focused on the relationship presence.

Maintaining the attention on the same Y variable 'Percentage', another model has been developed switching the focus of the study on a pure qualitative analysis. The objective of this analysis is achieved thanks to the introduction of the purely qualitative binary variables in the regression, therefore those variables in the group FF, FS, FA, SS, SA and AA which are useful only to signal the presence of a certain relationship typology. In this way, this fourth generated linear regression wants to study how the dependent variable 'Percentage' is only correlated to the presence of the seriality cases, therefore without considering the relative volume of the seriality. In other words, the study focuses on showing how the only presence of certain seriality cases can influence the volume of raising of capital during the round. This results in a pure qualitative study of the seriality variables.

Data about this fourth linear regression are reported in Fig.5.5.6.

Dependent variable: Percentage

	coefficient	std. error	t-ratio	p-value	
const	−9.67195	39.8138	−0.2429	0.8084	
NumFound	55.4627	10.7109	5.178	7.70e-07	***
Days	1.09967	0.297121	3.701	0.0003	***
EquityOff	−288.400	107.180	−2.691	0.0080	***
AA	157.439	48.5370	3.244	0.0015	***
FF	79.6828	35.5896	2.239	0.0267	**

Fig.5.5.6 Econometric results of qualitative studied linear regression by OLS method

The outcome of this linear regression gives the possibility to emphasize two important factors. The first is that seriality in general is important and at econometric level it is shown because just the presence is seen as positively impacting on the model through qualitative variables. The second is that FF and AA seriality cases are resulted again as most relevant cases, but in particular for the second time the relevant seriality case is the AA, so an individual who is in common between two different startups as he/she has worked in both as team member. This result has confirmed what was understood by the analysis of the third studied linear regression model.

Looking the result of this econometric model and applying what was understood from theoretical study, it is possible to observe that the most relevant seriality case is represented by the AA typology as the figure of the team member is active and very responsible about the operation of the startup. For this reason, having an experienced individual in this position is crucial, as he/she plays a very important role in the startup orchestration. This condition allows backers to be reassured, reducing asymmetry information issues. This conclusion will be better discussed in the next chapter.
On the other hand, if we wanted to apply this pure qualitative study on the binary dependent variable we would have problems, as any resulted model based on this binary Y variable and studied through the qualitative X variables mentioned above has shown an econometric relevance. Arriving at this point, it is possible to consider the qualitative study about seriality as linked to the analysis of the fundraising's volume and not related to the pure study of success.

As discussed in the theoretical part of the econometric study, the log transformation of variables allows a series of advantages such as reduction of negative impacts thanks to the change from 'absolute residual error' to 'percentage' one. For these reasons, the authors have decided to involve this mathematical transformation in the econometric study, deciding to transform in logarithm the collected dependent and explanatory variables. However, this mathematical change did not bring significant results for the study. First of all, it was not possible to identify a model with econometric relevance that contains all the three control variables, because if these were all included in one model then there would always be cases of acceptance of the null hypothesis and this is a problem as this allows the removal of the parameter from the model. Second, to achieve a result with an econometric sense it was necessary to remove the constant parameter inside the regression. This decision has a strong impact on the slopes because without $\beta 0$ the regression line is forced to pass through the origin axis point, causing the distortion of the slopes' values. In fact, the regressive model without the intercept erroneously shows that there is a negative impact from the logarithm of the 'SerialityCases' variable on the logarithmic dependent variable 'LogPercentage'. Data about this model are reported in Fig.5.5.7. The same misleading analysis is seen in the case that are considered the logarithms of the variables of the group FFsum etc… In this case the econometric model shows a negative impact from the logarithm of FFsum and AAsum on the dependent variable Y, totally revolutionizing what was defined by the models before.
The problem is that in order to obtain a result with econometric sense, it was necessary to consider these two decisions but as written before they bring problems on the validity of the model. For this reason, we do not consider any logarithmic model as relevant in our study.

Dependent variable: LogPercentage

	coefficient	std. error	t-ratio	p-value	
LogSerialityCases	−0.203177	0.0382227	−5.316	3.96e−07	***

Fig.5.5.7 Econometric results of the studied logarithmic linear regression without intercept term by OLS method

Econometric example to show the previously discussed problems is given by Fig.5.5.8. In this linear model, it is possible to note that the positive effect generated by parameters on the dependent variable is recovered, but at the same time most of them accept the assumption of annulment.

Dependent variable: LogPercentage

	coefficient	std. error	t-ratio	p-value	
const	−0.273135	0.478828	−0.5704	0.5693	
LogNumFound	1.07850	0.335669	3.213	0.0016	***
LogDays	1.09516	0.250314	4.375	2.36e−05	***
LogEquityOff	−1.07800e−07	4.15896e−06	−0.02592	0.9794	
LogSerialityCases	0.0142116	0.0201329	0.7059	0.4814	

Fig.5.5.8 Econometric results of the observed logarithmic linear regression by OLS method, considering the intercept and the log transformed control variables in the model

5.6 Econometric studies about position effect and relative results

The study of how the network impacts the performance of the startup's equity crowdfunding performance has been expanded through new econometric linear studies with the aim of understating the impact from positioning parameters on the mentioned above dependent variable 'Percentage' and 'BinarySuccess'. The parameters used as explanatory variables are the 'Centrality' and the 'Closeness' indexes, which were already introduced in paragraph 5.1.

For what concerns Centrality, a correlation between seriality and this index is easily ascertained since the calculation of this parameter involves as numerator the Degree of the observed node, that is the total number of relationships with other startups. Therefore, considering this overall number of relationships is the same to consider the volume of seriality cases because these carry out a bridge function among nodes. For this reason, it is possible to expect an impact by the Centrality parameter on the same line as the 'SerialityCases' variable.

Despite this correlation, an econometric model has been developed in order to understand how the parameter Centrality works on the mentioned Y variables. This is useful for having a study purely related to information arising from positioning data about the startup. Of course, also the control variables are included in the linear regression in a bid to provide a more detailed analysis.

As for the other involved parameters, also in this case the 'time' factor was taken into account. Therefore, the calculation of the explanatory variable Centrality of each startup was done photographing the network situation at the exact moment of the round. In this way it was possible to understand which were the existing relationships, then those to consider in the X value, and those instead born later. Combining the observed Y variables ('Percentage' and 'BinarySuccess'), the control variables and the Centrality variable calculated in the above way, it has been possible to develop two linear modes whose data are shown in Fig.5.6.1 and Fig.5.6.2.

Dependent variable: Percentage

	coefficient	std. error	t-ratio	p-value	
const	−24.8407	43.0435	−0.5771	0.5648	
NumFound	57.9868	11.0577	5.244	5.68e−07	***
Days	1.10223	0.306625	3.595	0.0004	***
EquityOff	−218.425	111.541	−1.958	0.0522	*
Centrality	1972.64	855.505	2.306	0.0226	**

Fig.5.6.1 Econometric results of the linear regression by OLS method, considering in the model 'Percentage' as Y variable and 'Centrality' index as explanatory

Dependent variable: BinarySuccess

	coefficient	std. error	t-ratio	p-value	
const	0.515540	0.0902188	5.714	6.37e−08	***
NumFound	0.0726830	0.0231768	3.136	0.0021	***
Days	0.00183077	0.000642683	2.849	0.0051	***
EquityOff	−0.607914	0.233788	−2.600	0.0103	**
Centrality	3.81443	1.79313	2.127	0.0352	**

Fig.5.6.2 Econometric results of the linear regression by OLS method, considering in the model 'BinarySuccess' as Y variable and 'Centrality' index as explanatory

The two models are very similar as they use the same variables X and two variables Y that although different indicate more or less the same thing using different approaches.

As expected, the Centrality of the startup positively affects the performance of the crowdfunding round. This can be easily understood because the centrality is directly proportional to the relationships of the startup with the rest of the network. Under the econometric perspective, the positive impact of this explanatory parameter is demonstrated by the positive slope β4 which multiplies the variable X 'Centrality'. This means that an increase in Centrality leads to an increase in Y. Moreover, the existence of influence by this regressor X on the Y variable is further shown by the values of t-ratio and p-value which communicate the reject of the null hypothesis on the parameter β4.

The other parameter introduced in the regression model is the Closeness. This parameter has been computed for each node in the network as the reciprocal of the summatory of all the distances of each geodesic path between the studied node 'i' and the nodes 'j' that are related to the studied one. Therefore, it is necessary to find all the direct and indirect interactions for each node in order to have all the information for computing the sum of the each geodesic path's distance. As before, for a detailed computation it was necessary to introduce the time component and then consider which startups were present or not at the moment of the round. Proceeding in this way, has given the opportunity to find all the direct and the indirect interactions in the instant of the round, guaranteeing the exact computation of the summatory and so of the parameter per each case.
The message that this index wants to communicate is that if the distance between a node and the others in the network increases, then the parameter value decreases showing that the relationship interaction among nodes is made more complicated. In this way the possibility of relationship between startups decreases resulting in a reduction in the movements of social and intellectual capital. However, this concept is upset by the econometric model introduced in the thesis work. According to this linear regression, the impact generated by Closeness on 'Percentage' and 'BinarySuccess' variables is negative. This means that an increase in Closeness value generates a decrease in the Y variable. Even in this case, all the used control variables have been introduced in the model maintaining them constant in relation with previous cases.
Data about econometric linear models are reported in Fig.5.6.3 and Fig.5.6.4.

Dependent variable: Percentage

	coefficient	std. error	t-ratio	p-value	
const	21.7408	41.1906	0.5278	0.5985	
NumFound	61.0756	11.1000	5.502	1.73e-07	***
Days	1.13391	0.304959	3.718	0.0003	***
EquityOff	−185.538	113.306	−1.637	0.1038	
Closeness	−16.4496	6.43745	−2.555	0.0117	**

Fig.5.6.3 Econometric results of the linear regression by OLS method, considering in the model 'Percentage' as Y variable and 'Closeness' index as explanatory

Dependent variable: BinarySuccess

	coefficient	std. error	t-ratio	p-value	
const	0.601692	0.0868025	6.932	1.40e-10	***
NumFound	0.0777507	0.0233915	3.324	0.0011	***
Days	0.00189315	0.000642651	2.946	0.0038	***
EquityOff	−0.562059	0.238774	−2.354	0.0200	**
Closeness	−0.0276899	0.0135659	−2.041	0.0431	**

Fig.5.6.4 Econometric results of the linear regression by OLS method, considering in the model 'BinarySuccess' as Y variable and 'Closeness' index as explanatory

The negative impact of index 'Closeness' on both dependent variables Y is reported by the negative value of the slope β4, which is the parameter that multiplies the explanatory variable 'Closeness'. In addition, the existence of an influence generated by the 'Closeness' on Y is clarified by the values of t-ratio and p-value that are below the critical values for the acceptance of the null hypothesis of the parameter in both the studied linear regression models.

What the model wants to communicate through this linear regression, is that the increase in the number of interactions should not be seen only as an increase in distances but also a way to increase the size of the relational structure of the node, allowing a more advantageous condition of intellectual and social capital diffusion for the startup during the fundraising.

5.7 Application of econometric models results on theory

The aim of this last chapter is to emphasize the importance of these two capitals on the fundraising through an econometric study, thus confirming in a more detailed way what was shown at theoretical level. The objective is to highlight how social capital can have positive impact as it acts as 'mean of transport' of the intellectual capital, which is beneficial for the startup as it is able to give a performance boost to the company and a reduction of information asymmetry issues that characterize the fundraising phase. This combination of the two capitals is represented by the concept of 'seriality case', therefore people who have created intellectual capital thanks to previous experience and who then enter in a second startup establishing relationships through which they can disseminate the previous acquired skills and knowledge. In particular, the econometric analysis wanted to adopt both quantitative and qualitative variables with regard to the theme 'seriality' in order to provide a deep analysis about this. Econometric results highlight that these binding figures are really beneficial for the CF round's performance, in fact all the elaborated linear regressions show a positive correlation between the volume of seriality cases and the campaign success. The essence of social interactions can be metaphorically seen as bridges able to connect cities. In absence of bridges, the cities cannot interact causing the stop of any flow of information and goods. The same metaphoric concept can be applied also applied to people, because thanks to these relationship 'bridges' they can interact with each other in order to disseminate knowledge and capabilities.

Sequently, further qualitative analyses have increased the level of detail on the elaborated result, showing that only certain serial figures positively impact the success. Such figures are pure serial cases which involves only two types of relationships: AA and FF. Associating this result to the theoretical dimension, it is possible to recognize that being in 'pure case' condition is important for the elaboration of a good level of knowledge and experience, while these typologies of connections are crucial as they are active roles within the startup because they are responsible about the organization and they cover key roles in the managing of the overall orchestration process. For this reason, having a good level of human capital in these positions favors a beneficial impact on the performance of the fundraising, as there is an increase of knowledge and capabilities level about the CF round management and also because there is a lowering of the level of information asymmetry thanks to these active serial figures who behave as signaling tools.

The positive effect on the startup's fundraising was also found by observing two introduced positional parameters Closeness and Centrality, which focus on communicating the location of the node inside the network. The generated linear regressions have shown that the positioning has an influence on the round performance, and in detail the more central a node is and the greater is the number of interactions, then the better will be the impact of the network on this. In this way it is possible to define that both are important for influencing the fundraising success.

What is relevant to take into account during the study is the change in the concept of Closeness. Being this network very disconnected, it is not possible to understand the proximity in a detailed way because so many nodes are really far away among each other. Therefore, the Closeness parameter should be revolutionized in an index that shows the ability to have interactions. The smaller the volume of overall interactions, the lower is the amount of ways to receive or share information. In fact, this parameter has an associated negative value in the elaborated econometric model, symptom of how an increase in Closeness tends to negatively influence the studied Y variables. Closeness is different than Centrality because it considers the whole amount of interactions, including both direct and all the indirect ones.

From the qualitative analysis about seriality, it has been emerged that the concept of 'supporting crowd's better performance' can be put under critical investigation. The analysis from the qualitative-quantitative models have highlighted how the most relevant serial cases are FF and AA, so founder that replicates the activity of CF for his/her startup and/or managers who operate in multiple startups as administrative figures. Therefore, the type of SS interaction is not accounted, and the value of the slope associated to it is then removed due to the acceptance of the null hypothesis, showing the not relevant impact of this variable inside the linear regression. The case of supporting crowd consists in a case of SS, since it reflects a situation in which an individual invests several times in startups following a specific founder. After having analyzed the results from the linear models, it is possible to see that even if a certain positive impact from this crowd exists, this case of investment seriality do not lead to a significant impact on the performance of the round. Therefore, what emerges from the analysis is that the crowd can lead to have a psychological positive impact on investors, but it is not considered as a relevant factor for the success of the equity crowdfunding round. The results of the models revolutionize the concept of investors' crowd, moving the attention from the volume of the crowd towards who is inside the crowd and inside the startup. For this reason, after the econometric results it would be more correct to not speak about positive effect from the overall mass of investors, but positive effect from the mass of individuals who cover key and active roles within the startup, as founder and/or as team member because the models have demonstrated that these are the real generators of added value. Of course, this must be done maintaining strong attention not only on the volume but also on the quality level of people.

Therefore at the end of the analysis, is it possible to say that social and intellectual capital are effective on the round's performance? Yes, they are but it is not possible to define a general rule according to which the success is linked only to seriality cases. These generate a positive impact, but they cannot be seen as the only parameter for which success is achieved. For example, a big effort for the success comes from the contribution of factors that have not been considered in the models such as idea's quality, economic surrounding context, the platform and the business in which the idea is applied.

CHAPTER 6

CONCLUSION PART

6.1 CONCLUSIVE SUMMARY

Based on the analysis of Chapter 4 regarding how the equity crowdfunding landscape has evolved over the years, it can be argued that this phenomenon is constantly developing, and it will involve more and more players over time. This dimensional growth will allow to observe a continuous increase in both Social and Intellectual capital during future years. The first increase is due to the fact that startups will constantly increase their personal relationships, not only thanks by personal cooperation with other startup entities but also through the use of serial individuals who act as link between two or more startups. In this way, it can be seen that there will be an increase of both capitals, since the relationship, the knowledge, the know-how and the experience can be increased thanks to the presence of these interaction figures who will increasingly populate startups. The basic concept is that the Social capital must work as bridge for the diffusion of the Intellectual, because without relationships there is not communication and so there is not knowledges sharing. Therefore, considering this overpopulation of binders, it is possible to imagine that over the years this network will be increasingly characterized by a denser information flow inside it.

Associated to the theoretical study, an econometric analysis was carried out with the aim of empirically and analytically showing how seriality cases, how the position inside the network and how certain typologies of interactions are important to influence the success of the fundraising run by the startup. The analyzed linear models have shown that the prominent serial figures are AA and FF, while there is a less influent relevance from other serial figures that have been considered as 'null impact entities' during the study. Except for SS, which will be discussed later, the leading serial figures have been defined during the analysis as 'pure' because the individual works in both the startups in the same stakeholder category. In this way, it is shown how important it is to have an increase in experience, since covering in the two startups the same position or at least the same positional stakeholder category allows to have an initial phase of information and experience acquisition that is acquired in the first startup going to hold a certain position. Then, this individual works in the second startup maintaining the same role, so having already acquired the experience for that work allows to have a good effectiveness on the second startup. For this reason, these seriality cases were positively viewed during the econometric analysis, considering both qualitative and quantitative studies. In this way, it was possible to demonstrate how the concept of Intellectual capital is important to define the influence of this person on the startup's fundraising. This happens because thanks to the first experience the serial elaborates Intellectual capital that is subsequently disseminated in the second and in the sequent ones. Therefore, the study has pointed out that the combination 'Social capital plus Intellectual capital' is very important because Intellectual is generated through experiences as mentioned above, while Social capital is created thanks to the social interactions present between the serial and the startups. As previously said, Intellectual is more important but in order to be efficient it mandatorily needs Social capital. The econometric study has moved in this direction since it has highlighted as positive impacting the number of serialities (increase of Social capital) and the volume of specific pure seriality cases (high level of Intellectual capital), therefore putting under positive light what has been discussed at theoretical level.

Having shown the benevolent effect from the individual AA, it could be thought that over the years there will be a strong increase of these specialized figures in the management of startups. Unlike other figures such as Venture Capitalist and Business Angels who participate in both financing and managing sides, these AA individuals are more focused on the management dimension without actively participating in its financing. These allow to have a dissemination of their knowledge and experience, going to cover management positions in different startups over time. Then, looking the graphical analysis conducted by authors for the network representations in Chapter 4, it is possible to expect an increase of AA inter-relationships within the network. This statement is a hypothesis made by the authors after having identified the positive effect of this type of seriality. Therefore, there is not any theoretical-mathematical study that explains the evolution of the volume of these relationships over time. This statement was simply made taking into account the findings of the econometric study and the study of the evolutionary trend of the network over years.

The study has showed that this positive effect due to the seriality is not produced by 'not pure' serial figures as well, as they do not sufficiently develop a personal experience that will then be useful in the second startup. This occurs as they do not play a role that is categorized in the same stakeholder category within the startups. Therefore, the first experience in the startup contributes to create knowledge and know-how, but the issue is that in the second startup the serial individual doesn't operate in that stakeholder category and therefore what was previously acquired is not so relevant. Obviously, the increase in experience is always positive. In fact, during the econometric study all the parameters related to all the serial cases have always been associated to a positive slope, always showing the existence of a positive influence on the studied dependent variable. Since the studied variable is always associated to fundraising success, it is possible to say that there is always a positive effect generated by them on the fundraising performance. The additional point is that a more detailed study of the linear models has led us to the analysis of the 'null hypotheses' on the slopes parameters, which has been accepted for all the X variables related to 'not pure' seriality cases as FS, FA and SA. This cancellation is a symptom of how these parameters do not generate a significant impact on the studied Y variable, allowing their removal from the model. The conclusion concerning 'not pure' cases is that they contribute positively to success but their effect is not considered as relevant.

An additional important aspect to say about AA and FF is that they are not just 'pure' serial cases, but they cover serial positions that have an active and important role within the startup because they actively work in it. The founder creates the idea and in most of the cases it is involved in the highest managerial levels, while the manager takes care of the management side of the startup going to be the responsible of the orchestration of the company. In this way, it is possible to identify how the effect of the combination 'Intellectual capital plus Social capital' is more effective if it involves more active and more management-related positions, as these have a direct effect on the performance of the startup. This is not only important for increasing the overall performances of the startup, but it is crucial to reassure supporters that the startup is conducted by good quality people, increasing the probability of fundraising success.

Another identified serial position is the SS. The SS individual is a pure serial figure that indicates an investor who has repeatedly invested in different startups, thus working as link between them. Considering the above, this 'bridge' between startups does not hold an active position within the startup as if she/he maintains the investor position, then limiting only to the financing investment. For this reason, this case can be considered as an entity that does not generate a significant effect on the round's performance as it doesn't significantly diffuse Intellectual capital, but it just contributes to produce the Social one. As in the other cases, this result has also been demonstrated at econometric level. In fact, all the studied models have led to the cancellation of the parameter associated to SS through the acceptance of the relative null hypotheses.

This case of seriality goes along with the concept of 'supporting crowd' (Cap.2.4), in which the mass of serial investors tends to have an impact on the campaign as it influences people to invest, working as a sort of remedy for information asymmetry issues. Therefore, analyzing the econometric result, it is possible to say that this crowd generates a psychological effect on other investors due to the influence from 'information cascade', but it has not been identified as statistically relevant. About SS, it is possible to say that in the statistical analysis has happened exactly what was observed for 'non pure' serialities, so the observation of a positive effect of the seriality case which however can be removed from the model if a study on the null hypothesis is

carried out. As in the previous case, this is symptom of no statistical relevance on the studied dependent variable by this parameter, even if the influence exists and it is positive.
Leaving the concept of supporting crowd and considering just a single investor individual, it is possible to say that a single serial investor can develop his personal ability of good quality investment identification among those proposed on platforms thanks to his different investing experiences. This means that he/she will have greater chance of personal success, but this doesn't mean to positively create impact on round performance. The achieved outcome is the same of the 'supporting crowd'. The key concept is that observing people that invest personal money can have a positive effect on human psychology, but the link between psychological impact and round success doesn't find a mathematical value in this study. Working in this way, it is possible to say that for the reduction of information asymmetry, then for attracting more investors, and for boosting the startup's round performances the best way is not through the supporting crowd but through the increase of serial figures as AA and FF. Therefore, as written in Cap.5.7, "it is not important the volume of the crowd, but it is more crucial the quality of serial members who actively participate in the startup orchestration".
Having identified a series of possible serial cases, but having shown that only certain are really impacting on the performance of the fundraising, it is possible to say that the real importance is in the hands of the spread of Intellectual capital and not of Social capital. This happens because it is not enough to have social relationships, but it is fundamental to have knowledge and skills. For this reason, it is possible to consider that the Intellectual capital is more important, but the issue is that Social is fundamental to have Intellectual capital spread generating benefits within the network. Therefore, the presence of Intellectual is obligatorily linked to the Social because the positive effect created by the Intellectual is generated only if there is Social capital. This leads to the demonstration of the importance of these two capitals on the startup, however considering that is absolutely fundamental that they work together in a cooperative manner.

After graphing the network, considering the nodes (the startups) and the connections between them, it was possible to identify that some startups covered a peripheral position remaining isolated while others were more central. For this reason, it was important to study the existence and the type of impact that this positioning generates on the startup's fundraising performance, directly answering to the question "What does it mean to be in the network?". The study was conducted by observing two indicators from the Social Network Analysis that are 'Centrality' and 'Closeness'. The first parameter studies the direct links of the startup while the second quantifies the total number of links related to that observed startup.

What has been found, it is that the positioning has a positive influence on the startup, in particular the closer a startup is to the others the more positively it is influenced and the more the connections the more positive the influence is. The concept is the same as before, so positioning and the relationships are important for the dissemination of Intellectual capital. Therefore, so much is central and so many are the relationships among startups, so greater is the Social capital volume and the more is the subsequent possible diffusion of Intellectual capital. The result is more or less the same as before, only that it was studied using parameters from the SNA. Even in this case, the analysis was conducted by combining to the theoretical study an econometric analysis.

As final conclusion, it is possible to observe that the carried-out study has highlighted how the Social and Intellectual capitals generate positive effects on the startup's crowdfunding round but at the same time it is possible to observe that these are not the only factors to be taken into account to determine the success or failure of the campaign. For this reason, it is not possible to identify a general rule that associates success with seriality cases and/or positioning, but it is possible to consider in the future how these are factors to be taken in consideration if someone wants to increase the probability of success of the startup's fundraising.

6.2 POSSIBLE FURTHER FUTURE STUDIES

This thesis work can be used as source of information and inspiration for future works, with the aim of providing more information about the network of startups and the influence that it creates on them. A series of possible future studies have been thought by the thesis' authors, with the aim of understanding how their work can be additionally developed to provide a better level of information.

Starting from the econometric models and their elaborated results, a first additional study that can be carried out is based on a 'further opening' of the X variables, going to catalog serials not only as FF and AA but trying to define additional explanatory variables associated with them. The split of the variable FF can be made by identifying some variables X that consider some additional information as if the business of the first startup is the same of the second one therefore quantifying the experience of the founder in that competence business, whether the first startup has successfully carried out a round, if the first founded startup is having good results in its business, if the founder has experience in CF as he/she has realized more than one round and finally any previous work/study experience of the founder before the startup foundation. In this way it is possible to give further information about the FF individual, without stopping at a simple cataloging of the case of seriality. The same thing can be done even for AA serials, so also in this case can be done an additional share of information about the single serial individual considering past experience in both work and university, the precise managerial position in which the serial has worked in the previous experiences, the success of the previous campaigns and also in this case the trend of the startup in the business of competence. The idea is to not stop at a simple analysis of the categorization of seriality, but to go deeper analyzing what is the true competitive advantage of this individual and what can be really exploited in a bid to increase the round success. Keeping the focus on the concept of correlation, it would be interesting to study the possible difference in the performance of the crowdfunding process if the entity that creates the correlation is a person, as the classic representation of seriality case discussed, or it is a company as a VC fund.

Another further study can be done considering a structural point of view. This can be conducted trying to provide a theoretical and mathematical study about the evolution of the global network considering which relations will develop more in the future and in what quantity. It would be interesting to correlate the structural development of the network with external economic parameters, understanding what really influences the development of this alternative source of financing and especially in which way. For example, it could make an analysis of how the trend of interest rates impacts on the total volume of CF fundraising in a given region, thus considering how many new startups enter the business and also how these are associated to the already existing.

Finally, an analysis can be carried out to study how the network influences the development and the value of the startups over the years, moving the focus from the effect of the network at the time of round to the effect on the startup during future years. This study is interesting for investors as they have an interest in the revaluation of the startup over time, as this gives value to their investment. Therefore, this additional analysis would allow to study how the startups within the network subsequently develop thanks to the help provided by the network itself, so thanks to the series of interactions that the observed startup has with the others. Interesting would be to make a comparison between the development path of startups in the network and those outside, going to understand in detail whether the presence in the network is benevolent or not for the future of the startup. In this way, investors have additionally information for the choice of startup in which decide to invest, because if they know that being within the network generates advantage in the future performances, then they will tend to have more interest in startups within the network . At the same time, also startups will prefer to enter the network creating interactions, because being inside the network means to have a positive impact on their personal development.

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