The role of social networking in capital sourcing

Ameeta Jaiswal-Dale[1], Fanny Simon- Lee[2], Giovanna Zanotti[3], Peter Cincinelli[4]

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Abstract

The aim of this research is to apply the tool of social network analysis to situations in capital sourcing, including early stage financing. The study is conducted within the social network of Medical Alley Association of Minnesota (MAA). We investigate the correlation between the main *centrality measures*: *closeness*, *degree* and *betweenness* and the amount of funding received by the 163 MAA members during 2009 - 2012. Companies benefit from their social network to get access to better financing. The empirical results also provide a road map to encourage the sponsored or spontaneous growth of other social networks in related fields. Despite the financial crisis, the empirical results show how competition works when firms have established relations with others. Where an intersection occurs is merely an empirical curiosity and the causation resides in the intersection of relations. The relation that intersect on an organization determines the player's competitive advantage.

Key words: Social Network; entrepreneurship; innovation; entrepreneurial finance; early stage sourcing of capital for medical technology innovations; financing within social networks.
JEL Classification: N 70; O 31; O 33; O 44; O 57; P 31; Q 58.

1 Introduction and literature review

The network of relations that intersect in a player have their casual effect in what Burt (1992) defined as "*Structural Holes*". The social structure in a competitive arena, within a specific network, creates entrepreneurial opportunities for certain players to influence the terms of their relationships.

Network Analysis (hereafter, NA) is a field of interdisciplinary research exploring the structure of relationships among social entities, firms and associations (Butts, 2008). A network represents the set of relations that can be drawn upon to get access to resources, financial and non-financial, along with several forms of support (Johannisson, 1990). Several studies, related to entrepreneurial success, have highlighted the importance of social network to new ventures creation (Aldrich and Zimmer, 1986; Liao and Welsch, 2003; Witt, 2004; Hite, 2005; De Carolis and Sapatito, 2006; De Carolis *et al*., 2009; Andrieu and Staglianò, 2016; Xue *et al*., 2018). New venture growth depends on the entrepreneur's ability to capture tangible resources such as capital (Liao and Welsch, 2003). Yet, as new ventures evolve in an uncertain environment, it may be difficult for potential investor to assess the viability of their projects. Consequently, trust and personal relationships will play a key role in getting access to financing. Thus, companies having management team(s), who maintain relationships with numerous other companies as well as having contacts with key actors, may have a privileged access to financing.

[1] Department of Finance, Opus College of Business, Terrance Murphy Hall, University of St. Thomas, Minneapolis.
[2] University of Caen, France.
[3] Department of Management, Economics and Quantitative Methods, University of Bergamo - Corresponding author at University of Bergamo - giovanna.zanotti@unibg.it
[4] Department of Management, Economics and Quantitative Methods, University of Bergamo.

The aim of this research is to apply the tool of social network analysis to situations in capital sourcing, including early stage financing. We define new ventures as early stage and small companies seeking funding in a social network of companies of all sizes and many with established records. The study is conducted within the social network of Medical Alley Association of Minnesota (hereafter, MAA). This is a cluster of companies mostly in the Greater Minneapolis/St Paul area. We want to demonstrate that the companies within this cluster benefit from their social network to get access to better financing. We investigate the correlation between three main *centrality measures* (i.e., *closeness*, *degree* and *betweenness* centrality) with the amount of funding received by 163 MAA members during the time period 2009 - 2012. Particularly, we want to investigate the following research question: *Do companies seeking funding, if connected to major companies in the network as defined by centrality measures(s), have better funding?*

To address this research question, we construct a set of network measures that capture a firm's centrality in interfirm network. Within a network, the position of an actor may also affect its access to financial resources and its behavior in relation to the other players. Therefore, the central actors in a network of relationships are those that control the allocation of resources or who have an authority.

Using the software *Ucinet*, we study network development within the MAA context investigating the most important centrality measures (Otte and Rousseau, 2002): *closeness*, *degree* and *betweenness* centrality.

Each of them captures how important an individual is bridging the global network, reflecting a sense of her capacity to access resources sparsely located in the network. The *closeness centrality* measures the connections among the actors according to the distance between a given actor and the other members of the network. Also recognized as a *centrality of proximity*, the *closeness* provides the extent to which the communication performs within the network in terms of distance to go to ensure that information passes from one point to another. In this way, we determine if some players are better positioned to receive information or other resources well before their counterparts in optimized paths ways. *Degree centrality* indicates the degree to which the activity is concentrated around certain dominant points. The players with the highest levels of *degree* of centrality are those who have more links with other players. *Betweenness centrality* measures the number of paths connecting two individual entities that the player is connected with. In other words, it measures the network's dependence compared to some nodes in terms of information control. Thus, a central player will be able to have faster access to information; more easily interact with others and/or control the flow of resources. Moreover, this measure assesses control that individuals can exercise in the network, especially if they are located on touch points of information between two members (if they are located on the path between two actors).

We look at the different types of calls for financing of companies in this social network and examine their success in obtaining their desired levels of financing with respect to their positioning and strength in the social network. Indeed, in an uncertainty situation, investors will be inclined to trust the managers who have more direct connections with other companies. Relationships that managers have will give them legitimacy (DiMaggio, 1992) and this latter plays an important role in the sustainability of the new company. Investors will also consider them as trustworthy owing to the positive signal that entrepreneur's network sends.

The empirical results provide two main results: a) highlight the paths to improve the social network within the MAA cosmos; b) provide a road map to encourage the sponsored or spontaneous growth of other social networks in related fields within the USA and outside.

The rationale of these results are corroborated by other researches which have demonstrated the efficiency of using network ties for early venture financing. In particular, previous research has investigated three complementary perspectives to explore the effects of the networks on firms' invention productivity: a) the ego network perspective (Ahuja, 2000; Zaheer and Bell, 2005); b) the global network perspective (Abrahamson and Rosenkopf, 1997; Schilling and Phelps, 2007; Uzzi and Spiro, 2005); c) network communities (Knoke, 2009). We decide to follow the network communities perspective, since is the best way to capture how heterogeneous knowledge is redistributed through an interorganizational system over time. Particularly, in our paper, we detect specific measures which capture, in various ways, the interconnections among actors.

Researches have demonstrated the efficiency of using network ties for early venture financing (Shane and Cable, 2002; Zhang *et al.*, 2008; Talavera *et al.*, 2012) whether this financing is achieved through bank or private investors. Social network allows overcoming the lack of information that investors have to face when deciding whether they want to invest into a new venture (Uzzi, 1999; Shane and Cable, 2002). The network can also be perceived as a "pipe" that would conduct information on the company's reputation (Podolny, 2001) and thus enhance its legitimacy to get resources. The fundamental concepts of network analysis, as interdisciplinary tool, are examined in detail in Butts (2008). Whereas the notion of centrality, whether model or graph specific is examined by Newman (2003), Borgatti (2005), Borgatti and Everett (2005) and Bonacich (2007). Most researches focus on network properties and their consequences for entrepreneurs. One of those properties, which are widely used is network size (i.e., direct contact between the entrepreneur and other actors). Furthermore, researchers try to assess the set of resources that an entrepreneur can access (Hoang and Antoncic, 2003). Another network characteristic that has been discussed is the network cohesion and ties *embededness*. This measure refers to the fact that the entrepreneur can be embedded in a set of relations with actors who already have contact with each other. Those cohesive networks would bring trust and obligation among players (Coleman, 1988), which facilitates the information flow. Consequently, governments in several countries have emphasized the setting up of clusters to enhance relationships among different companies. Through event organizations, training, or coordination initiatives, clusters should bring an opportunity for management teams of different companies to meet and exchange. This would increase start-ups embeddedness in a specific location. Although the entrepreneur's social network is perceived as playing a key role in accessing capital, most researches focus on the selection process from the investors' perspective and we have little understanding on the way entrepreneurs develop their network to seek financial support (Steier and Greenwood, 2000). Moreover, those researches depend on specific context: for example, Talavera *et al.* (2012) demonstrate that participating to charities and business association increase the probability to get a bank loan in China. Other researches, such as the one conducted by Steier and Greenwood (2000), demonstrate that relationships to get financing become multiplex and may involve different types of contacts. The network tends to increase in size and becomes more complex to manage. Clusters of social networks rely on proximity among companies to enhance the development of relationships and spillover among them (Koha *et al*., 2005). Thus, firms' embeddedness enhances knowledge access and financing support. As pointed out in the literature review, start-ups or early stage companies should be able to develop an extended network and set up new ties. The entities in the central node within a network of relationships are those who control the allocation of resources or have some authority over the other elements of the cluster (Lazega, 2008).

The paper is organized as follows. The section that follows the introduction provides the empirical strategy in which data and methodology are presented along with results. Conclusion follows.

2 Empirical Strategy

2.1 Context: The Medical Alley Association

Our sample is a unique dataset obtained from the Medical Alley Association (MAA). LSA (before becoming MAA), since 1950's, has spread over a corridor extending between Rochester and Duluth in Minnesota. The MAA encourages incubation and acts as broker to identify financing options for start-ups introducing entrepreneurs and investors.[5] Training programs are set up, furthermore, within the network of investors, positive signs as well as negative data about entrepreneurs and their team can strengthen or ruin stat-ups reputation.[6] The association attracts

[5] We interviewed with the officials of MAA. The interviews established the validity and robustness of the social network and the data sources.

[6] As described in the following quote from an MAA official: *"And what happens is the investor picks up the phone and calls all his investor buddies and says, "hey, this person is going to call you up, it's a waste of time, don't even bother." They get blacklisted.*

several sources of funding, public domain grants, private and public equity, a network of business angels, venture capitalists is accessible to the cluster and several programs and services are provided to new companies to help them find investors.

The dataset is composed of the MAA member companies from 2009 to 2012 along with the funds raised among the members. Over this time period, we identified companies that received funding at least once. This allowed us to create a cluster of 163 companies.

Table n. 1 - Amount of funding received by MAA members during 2009 - 2012

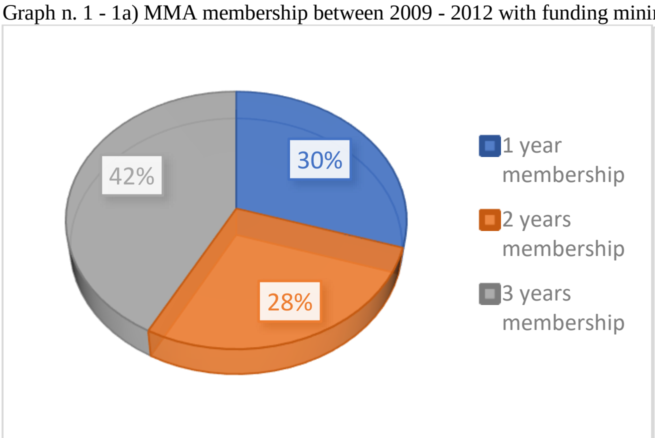
Years	Total amount received	Mean	N. of beneficiary companies	% of beneficiary companies
2009	326,885,504.00	5,272,346.84	62	38.04%
2010	213,120,193.00	3,674,486.09	58	35.58%
2011	269,545,634.00	4,492,427.23	60	36.81%
2012	251,844,817.00	2,679,200.18	94	57.67%
2009-2012	1,061,396,148.00	16,118,460.34	69	42.33%

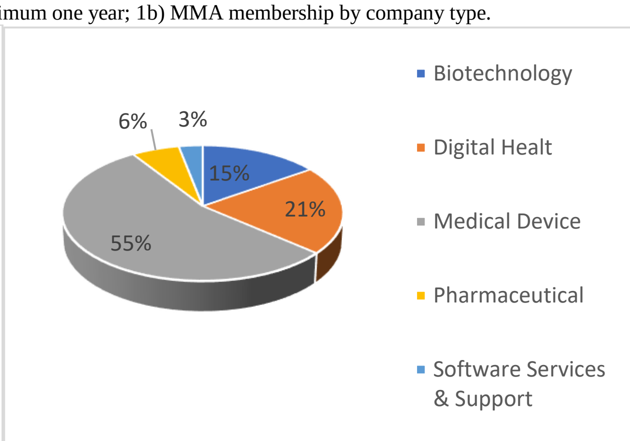
Source: Authors data processing

Table 1 presents the total amount received by the MAA members along the time period 2009 - 2012. The beneficiary companies which received once the funding reached the highest percentage in 2012.

In a different perspective, graph n. 1a and 1b report the MMA membership between 2009 - 2012 with funding minimum one year and with regard the type of the company. Over the time period, 42% of the company is a MMA membership for at least three years and more than 55% companies belong to medical device sector.

Graph n. 1 - 1a) MMA membership between 2009 - 2012 with funding minimum one year; 1b) MMA membership by company type.



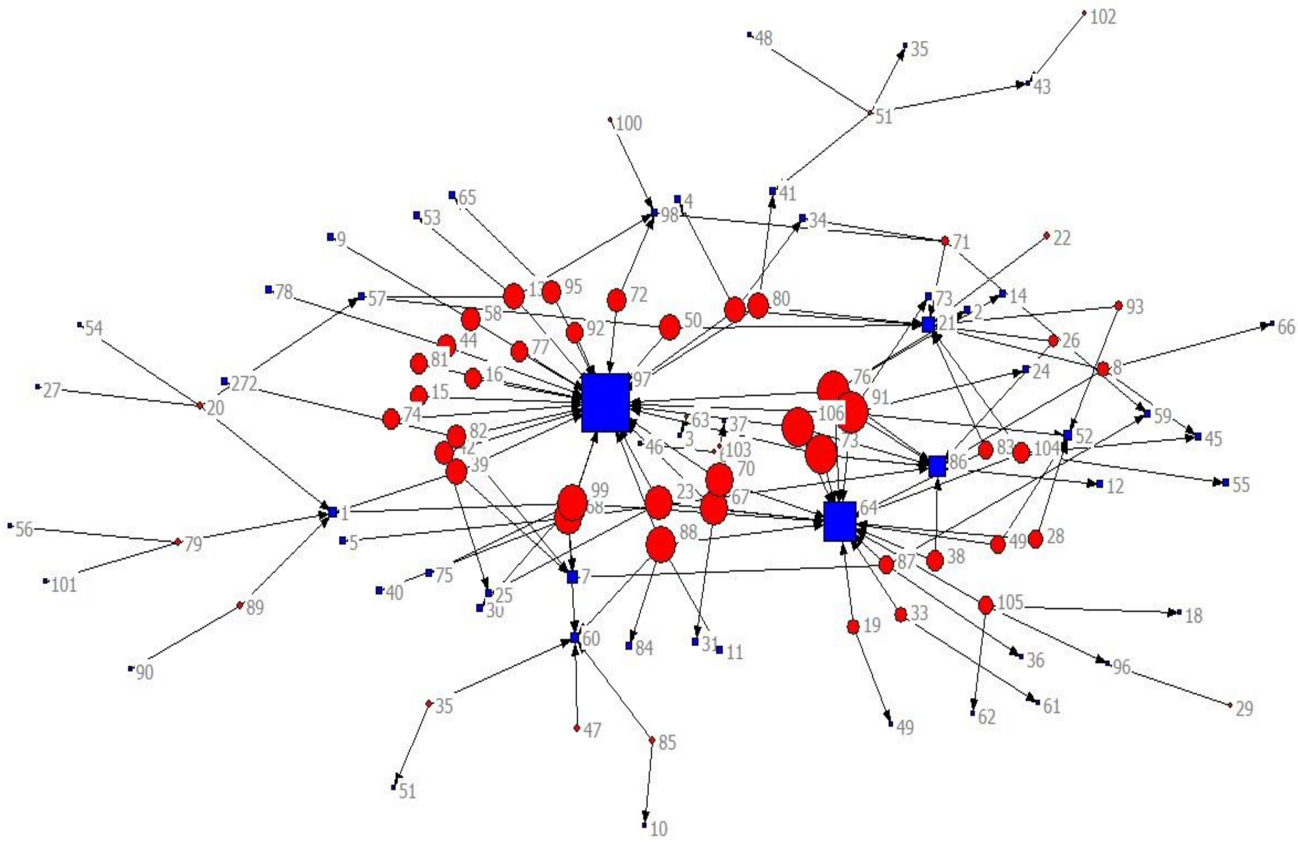


Source: Authors data processing

To set up a social network among our cluster, we collected publicly available management information (with cross check information data coming from Bloomberg) to identify the management team of each company. We define management team as a Chief Executive Officer (CEO), founder, Vice President (VP) of marketing and/or regulatory affairs, Chief Operating Officer (COO), Chief Financial Officer (CFO) and members of the executive team. The management team is often predominant in a new venture. In particular, we focus on the relationships maintained by the management team, in the past as at present, with other units in this cluster.[7] Then, we look at the career of each management team member and determine whether the member worked previously for a different company which belonged to the cluster at that time or is presently working for another company belonging to the cluster. We consider that any two companies have a relationship when a management team member from one of the companies has worked in another one. This form of network community of 163 companies that are connected over the three years through their top management relations.

We then create and formalize the network of relationships using the softwares Ucinet and Netdraw.[8] To ensure that the best measures of centrality are used for testing our research question, we employed Ucinet to obtain all measures of centrality for our 163 units – *closeness*, *degree* and *betweenness centrality* measures.

Graph n. 2 – The Medical Alley Association (MMA)



Source: Authors data processing with UCINET software

[7] According with Mauer and Ebers (2006), the social network of the venture can be considered as similar to the management team.

[8] Ucinet, Social Network Analysis Software, 6 for Windows (2002), Analytical Technologies, Harvard, MA; NetDraw Network Visualization (2002), Analytical Technologies, Harvard, MA. Ucinet computes the scores on the different types of centrality while identifying the central nodes within the network.

2.2 Empirical model

Our main goal is to investigate the correlation between each centrality measures with the amount of funding received by MAA members during the time period 2009 - 2012. Particularly, we want to investigate the following research question: *Do companies seeking funding, if connected to major companies in the network as defined by centrality measures(s), have better funding?*

To address this research question, we construct a set of network measures that capture a firm's centrality in interfirm network. Within a network, the position of an actor may also affect its access to financial resources and its behavior in relation to the other players. Therefore, the central actors in a network of relationships are those that control the allocation of resources or who have an authority.

Before carrying out the empirical analysis, we outline some notions from graph theory. Particularly, a directed graph *G* consists of a set of nodes, denoted *N(G)*, and a set of links (also called arcs or edges), denoted as *L(G)*. The words "network" and "graph" are synonymous. In sociological research nodes are often referred to as "actors". A link *e* is an ordered pair *(i,j)* representing a connection from node *i* to node *j*.

We implement a cross section analysis by estimating the following regression:

$$Fund_i = \alpha_i + \beta_1 Closeness_i + \beta_2 Degree_i + \beta_3 Betweenness_i + \beta_4 Times\ Funds_i + \gamma_1 Company\ life_i + \varepsilon_i \quad (1)$$

where:

$Fund_i$ is the dependent variable in terms of the total amount in logarithm terms of the funding received by a company; $Closeness_i$ is the first main explanatory variable which measures the centrality of the company (i.e., the node) within the network. In particular *closeness centrality* measures if a node is equal to the total distance (in the graph) of this node from all other nodes. As a mathematical formula, *closeness centrality*, $c(i)$, of company *i* can be written as: $c(i) = \sum_i d_{ij}$ where d_{ij} is the number of links in a shortest path from node *i* to node *j*; $Degree_i$ is the second main explanatory variable which measures the number of ties that a node has (i.e., in graph-theoretical terminology, the number of edges adjacent to this node). In mathematical terms, *degree centrality*, $d(i)$, of company *i* can be written as: $d(i) = \sum_j m_{ij}$ where m_{ij}=1 if there is a link between nodes *i* and *j*, and m_{ij}=0 if there is no such link. We use a normalized degree measure, which refers to the percentage of all other firms a specific firm is connected to during the holding period. $Betweenness_i$ is the third main explanatory variable which gauges the extent to which a company facilitates the flow in the network. It can be shown that for an *N*-node network the maximum value for $b(i)$ is $(N^2 - 3N + 2)/2$ and the standardized *betweenness centrality* is: $b_s(i) = \frac{2b(i)}{N^2-3N+2}$. The betweenness measure, proposed by

Freeman (1979), captures how often a firm happens to be positioned on informational linkages between pairs of other firms. A firm is between two firms if it lies on the shortest possible path between them. We examine the robustness of the results by controlling for other independent variables such as: *Times Funds*$_i$ which measures how many times a company got funding during the holding period 2009 - 2012; *Company life*$_i$ measures the years of a company activity, from its foundation till 2012, expressed in natural logarithm.

Table 2 presents the correlations between all the variables used in the model. The possibility of multicollinearity among the explanatory variables is tested using the Variance Inflation Factors (VIFs). The maximum VIF that results from any of the models is 2.65, which is far below the generally employed cut-off of 10, or more prudently, 5 for regression models. Therefore, the results show that the absence of multicollinearity can be accepted.

Table n. - 2: Matrix correlations

Variables	*Fund$_i$*	*Closeness$_i$*	*Degree$_i$*	*Betweenness$_i$*	*Times Fund$_i$*	*Company life$_i$*
Fund$_i$	**1**					
Closeness$_i$	0.2434*	**1**				
Degree$_i$	0.3752*	0.6320*	**1**			
Betweenness$_i$	0.3542*	0.5090*	0.6491*	**1**		
Times Fund$_i$	0.4848*	0.2183*	0.2100*	0.1406	**1**	
Company life$_i$	0.0527	0.0493	0.0949	0.1239	-0.0408	**1**
Variance Inflation Factors (VIFs)	**1.54**	**1.74**	**2.15**	**1.71**	**1.07**	**1.02**

Note: Pearson's correlation coefficient with Variance Inflation Factors (VIFs). *Fund$_i$* is the dependent variable in terms of the total amount in logarithm terms of the funding received by a company; *Closeness$_i$* is the first main explanatory variable which measures the centrality of the company (i.e., the node) within the network. In particular closeness centrality measures if a node is equal to the total distance (in the graph) of this node from all other nodes. As a mathematical formula, *closeness centrality*, $c(i)$, of company *i* can be written as: $c(i) = \sum_i d_{ij}$ where d_{ij} is the number of links in a shortest path from node *i* to node *j*; *Degree*$_i$ is the second main explanatory variable which measures the number of ties that a node has (i.e., in graph-theoretical terminology, the number of edges adjacent to this node). In mathematical terms, degree centrality, $d(i)$, of company *i* can be written as: $d(i) = \sum_j m_{ij}$ where m_{ij}=1 if there is a link between nodes *i* and *j*, and m_{ij}=0 if there is no such link; *Betweenness$_i$* is the third main explanatory variable which gauges the extent to which a company facilitates the flow in the network. It can be shown that for an *N*-node network the maximum value for $b(i)$ is $(N^2 - 3N + 2)/2$ and the standardized *betweenness centrality* is:$b_s(i) = \frac{2b(i)}{N^2-3N+2}$. We also control for other independent variables such as: *Times Funds*$_i$ which measures how many times a company got funding during the holding period 2009 - 2012; *Company life*$_i$ measures the years of a company activity, from its foundation till 2012, expressed in natural logarithm. * denotes significance at the 5% level.

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2.3 Empirical Results

We examine if firm network characteristics helps companies to have better funding, particularly for firms belonging to the MAA network. We estimate the regression (1) on total funding received using firm network variables along with standard control variables. In table 3, the estimated coefficients on all the network variables are statistical significant in Models (1) - (3). As the coefficients on the centrality measures show, the more centrally located firm *i* is in the interfirm network, the better the funding will receive. This is consistent with the premise that greater network centrality is more conducive for information diffusion (Chuluun *et al*., 2017). A strong centrality of proximity (i.e., *closeness centrality*) means that some actors, in relation to their peculiar positions within the network, benefit from significantly shorter routes than others, so they will certainly have faster access to information. A strong centrality of the degree (i.e., *degree centrality*) of the network indicates that some actors are more closely connected than others, consequently these nodes are considered able to concentrate the activity. A strong centrality of intermediation (i.e., *betwenness centrality*) means that some actors can exercise control over the network because they can choose not to diffuse some information (they are on more paths than the other actors). When all the centrality measures are regressed, the closeness is not anymore statistical significant whereas, degree and betwenness measures keep the positive relationship and the high statistical significant.

In relation to the sign and the significance of the control variable *Times Fund* confirms that the number of times a company got funding is strictly and positively correlated with the amount of funding. However, the company life is not significant in any models. This suggests that how older a firm is does not matter as previously outlined by Xue *et al*. (2018). Moreover, in all model estimated, the goodness of the estimations is higher when the all measures of centrality are taken into account.

Table n. - 3: Baseline regression

Variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
Closeness$_i$	3.7752*			-2.4064
	(2.0214)			(2.4444)
Degree$_i$		0.1922***		0.1445**
		(0.0354)		(0.0578)
Betweenness$_i$			0.2655***	0.1859**
			(0.0578)	(0.0805)
Times Fund$_i$	1.0117***	0.9401***	0.9873***	0.9538***
	(0.1527)	(0.1446)	(0.1425)	(0.1427)
Company life$_i$	0.1272	0.0855	0.0702	0.0589
	(0.1417)	(0.1325)	(0.1332)	(0.1318)
Constant	12.0993***	12.2375***	12.2452***	12.3250***
	(0.3933)	(0.3743)	(0.3772)	(0.3870)
N. Observations	163	163	163	163
R^2	0.26	0.32	0.32	0.34
R^2 Adjusted	0.25	0.30	0.31	0.32

Note: The table shows the empirical results in relation to the equation n.1. *Fund*$_i$ is the dependent variable in terms of the total amount in logarithm terms of the funding received by a company; *Closeness*$_i$ is the first main explanatory variable which measures the centrality of the company (i.e., the node) within the network. In particular closeness centrality measures if a node is equal to the total distance (in the graph) of this node from all other nodes. As a mathematical formula, *closeness centrality*, $c(i)$, of company *i* can be written as: $c(i) = \sum_i d_{ij}$ where d_{ij} is the number of links in a shortest path from node *i* to node *j*; *Degree*$_i$ is the second main explanatory variable which measures the number of ties that a node has (i.e., in graph-theoretical terminology, the number of edges adjacent to this node). In mathematical terms, degree centrality, $d(i)$, of company *i* can be written as: $d(i) = \sum_j m_{ij}$ where m_{ij}=1 if there is a link between nodes *i* and *j*, and m_{ij}=0 if there is no such link; *Betweenness*$_i$ is the third main explanatory variable which gauges the extent to which a company facilitates the flow in the network. It can be shown that for an *N*-node network the maximum value for $b(i)$ is $(N^2 - 3N + 2)/2$ and the standardized *betweenness centrality* is:$b_s(i) = \frac{2b(i)}{N^2-3N+2}$. We also control for other independent variables such as: *Times Funds*$_i$ which measures how many times a company got funding during the holding period 2009 - 2012; *Company life*$_i$ measures the years of a company activity, from its foundation till 2012, expressed in natural logarithm. Robust standard errors are reported in parentheses. *, **, *** denote significance at the 10-, 5-, and 1- percent levels, respectively.

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3 Concluding Remarks

The importance of membership and the strength of the medical device in the analysis validate the characteristics of the network and underline the network's relevance and potential. The role of the *centrality measure* that measures substantive importance of the connection, rather than just regular connections, as measured by the centrality measure of degree, clearly demonstrates the relevance and potential of the network. Our main goal is to investigate the correlation between each centrality measures with the amount of funding received by 163 MAA members during the time period 2009 - 2012. Particularly, we want to investigate the following research question: *Do companies seeking funding, if connected to major companies in the network as defined by centrality measures(s), have better funding?*

To address this research question, we construct a set of network measures that capture a firm's centrality in interfirm network. Within a network, the position of an actor may also affect its access to financial resources and its behavior in relation to the other players. Therefore, the central actors in a network of relationships are those that control the allocation of resources or who have an authority. Within the network it is the "quality" of who you are connected to rather than the number of connections itself, that count for the success in getting the word out for obtaining the desired level of funding. (underling that this is the main result). The empirical results provide two main results: a) highlight the paths to improve the social network within the MAA cosmos; b) provide a road map to encourage the sponsored or spontaneous growth of other social networks in related fields within the USA and outside. Networks analysis has the potential to investigate many business situations. We chose but one situation, that of sourcing of funding for an established network, the MAA.

We conduct the analysis during the financial crisis and despite it we identify how competition works when players have established relations with others. Firms are connected to certain others, trusting of certain others, obligated to support certain others, dependent on exchange with certain others. Where an intersection occurs is merely an empirical curiosity and the causation resides in the intersection of relations. The relation that intersect on an organization determines the player's competitive advantage.

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