Private Equity Centrality and Club Deal Formation: Evidence from a Social Network Analysis - Subsample Analysis and Social Network Analysis in the Nordic Countries

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Abstract

In this paper, we investigate the structure of the network of relationships established between private equity firms when they form acquisition consortiums. We collected information on 1562 private equity transactions, including both sole-sponsored and club deals, across the period 2000-2017. We analyse the consortiums within a social network framework, investigating the prominence and centrality of private equity firms inside the network. In particular, we performed two subsample analysis for the likelihood of consortium formation. In the first one we tested our model in the two subsamples of Public to Private transactions and Private to Private ones, while in the second one we tested our model across different quartiles of Deal Size transactions.
Furthermore, we performed a third subsample analysis which aim to analyse, from a social network point o view, the structure of relationships existing between private equity firms when they form acquisition consortium, in the Nordic countries. The results we got from these subsample analyses were in line to the findings of the main research paper and increased their robustness. In particular, we were able to confirm the "information and knowledge sharing" motivation, in addition to the financial motivation, already tested in the literature. We also found that our model which aim to predict the conditional probability of consortium formation works better in the context of Private to Private and small (first and second quartile) transactions.

To my parents, my sister and my brother.
To my grandmothers, grandfathers
and all my closest relatives.

1. Introduction

Before explaining the subsample analyses performed in this thesis we would like to give an introduction to the main thesis. In particular, after describing the private equity club deal environment, we will outline the relevant literature review, the data and methodology description, the research questions and the key findings of the main research paper.

Private equity club deals are consortia in which two or more private equity funds acquire together a target company. This kind of deals are not uncommon in the industry, in 2017 they represented 17% of all the private equity transaction, as reported in Table 1. The number of announced club deals reached a peak in 2006, and in the same year, the US Department of Justice started an investigation into the potentially anticompetitive behaviour of such transactions.

The majority of the criticisms to club deals in private equity are related to the claim that the consortiums' participants only cooperate in order to lower the purchasing price (anticompetitive behaviour). Other opponents claim that this kind of deals further increases the governance problems in the acquired firms, due to coordination problems and "clash of egos" between members of the consortium (Lockett, Meuleman and Wright, 2011). On the other hand, supporters of this form of investment, claims that club deals enhance the transferability of knowledge, skills, and expertise between investors, both ex-ante, in the process of selecting the target prior to the actual investment takes place, and ex-post in term of operational improvement of the acquired company.

Various aspects of club deals have been studied in the past. The anticompetitive hypothesis, together with other motivations for club deal formation, and the effect of club deals on acquisition pricing, have been analysed mainly by Officer, Ozbas and Sensoy (2010) and by Boone and Mulherin (2011).

So far, little focus has been given in the literature to the relationships between private equity firms arising from club deals. In particular, as noted for other industries, the network of repeated relationships, represents a valuable, albeit intangible, asset for the network participants.

The purpose of the thesis is indeed the study of this network of relationships arising when multiple private equity firms build consortiums. With the tools of social network analysis, we aim to study the characteristics and the structure of the whole network of relationships and consider the role played by the single players in it.

1.1 Literature Review and Main Theories on Social Capital Theories

The determinants of club deal formation in Private Equity have been analysed by Officer, Ozbas and Sensoy (2010) and by Boone and Mulherin (2011). The two papers, both focused on leverage buyout transactions (public to private takeovers), analyse broadly whether Private Equity consortiums (club deals) facilitate the collusion bidding and whether the prices and premiums paid by a consortium are lower compared to the one of sole-sponsored deal. In both studies, the authors begin their analysis by building an empirical model for the determinants of club deal formation. In their study, Boone and Mulherin (2011) find that the size of the target has a positive and significant effect on the likelihood of consortium formation. Book leverage of the target (assumed by the author as a measure of risk of the target firm) is a significant determinant of consortium formation. However, the sign of the latter coefficient is negative, going against the VC literature about portfolio diversification motive, according to which a riskier firm is more likely that will be bought out by a consortium rather than a sole investor (Smith and Smith, 2000).

Officer, Ozbas and Sensoy (2010), build a similar model to analyse the determinants of club formation. The study finds that the size of the transaction has a positive and significant impact on the probability of club formation, while the effect of the risk is not significant. Finally, is worth mentioning that both the two studies use a dummy variable to control if the deal was concluded before 2006. Indeed, 2006 represents the year in which the US Department of Justice announced an investigation into the potentially anticompetitive behaviour of club deals in private equity transactions (Jackson, 2008).

The previous two papers mainly analyse the motives of consortium formation between private equity firm from a financial perspective, not considering the networks that these repeated relationships create. The social network perspective is instead considered by the studies of Meuleman *et al.* (2009) and of Huyghebaert and Priem (2016). Using a sample of management buyout transactions in UK between 1993 and 2006, Meuleman *et al.* (2009) find evidence that the network centrality of a PE firm (measured with Degree Centrality) has a positive and significant effect on the likelihood of consortium formation. Moreover, the study finds evidence that better networked investors have the ability to moderate the agency costs arising from the syndication of the investment.

Using a sample of European private equity transactions between 1999 and 2009, Huyghebaert and Priem (2015) investigate how lead private equity funds select their co-investors when deciding to form an investment consortium. The study provides evidence that the measures of network centrality have a significant effect on the choice of which partner to select in a buyout syndication.

In the context of social network of private equity firms, it is essential to briefly mention the relevant theories related to social capital, that explain how partnership choices help to create and sustain network of relationships.

According to Colemann (1988)'s view of social capital, repeated relationships among the same group of players, increase the level of closure of the network, and this is beneficial as it facilitates trustworthy cooperation and diminishes the incentives for opportunistic behaviour. Therefore, according to this theory, the higher the level of closure of a network, the larger is the amount of social capital available for the participants of this network. In the context of club deals, this means that private equity firms may seek to build relationships with similar players within their close network, avoiding "new" potential partners in order to reduce the likelihood of opportunistic behaviour and minimize coordination costs.

A completely opposite approach to social capital is given by Burt (1992) Structural Hole theory. According to the Structural Hole theory, information flow in cohesive networks tends to be redundant and does not provide much value to the players. Sparse and well diversified networks, on the contrary, are beneficial to social capital because each player acts as a broker towards non-redundant source of information. Holding a brokerage position inside the network is therefore beneficial as it allows to get access to a large amount of social capital available in the network. Again, in the context of club deals, Burt (1992) theory suggests that private equity firms are more likely to build relationship with "diverse" players with complementary skills especially in term of geography, industry or process.

The literature does not provide a definite answer on which of the two theories finds more evidence in practice, and very often the two theories appear to be complementary rather than opposite. This is exactly the "paradox of embeddedness" expressed by of Uzzi (1997), which states that players inside a network have constantly to find a balance between safety (strengthening trustworthy relationships with players in the close network), and adaptability (building new relationship to access complementary resources).

1.2 Data and Variables Description

Data was collected using several sources and databases. Private equity transactions data were collected from Zephyr. Zephyr is the database of Bureau van Dijk which contains a comprehensive set of information about M&A, IPO, Private Equity and Venture Capital transactions. For each deal, Zephyr provides all the details about the transaction, the players involved, a commentary of the deal and a link to the official press release of both the bidder and the target. It is important to notice that when reporting a transaction, Zephyr always discloses the private equity firm that completed the transaction but rarely specifies which specific funds of the private equity firm was involved. Therefore, like many other analyses on club deals (Officer, Ozbas and Sensoy, 2010) in the literature, our study focuses on private equity firms and not their funds.

Private equity features like age and funds under management were collected via Thomson One Banker. It is important to remark that each database has its own drawbacks and biases. In our case, for example, Thomson One Banker did not report any data for

Our study relies on a unique dataset (hand-collected in part) which includes information on global Private Equity transactions completed in the period 2000-2017, in which the deal value (enterprise value) is greater than $300 million. Using this query, we obtain a sample of 2,533 transactions reported in the Zephyr universe. Since the scope of this thesis is focusing on corporate private equity transaction, we decided to exclude the following transaction classified by Zephyr under Private Equity:[1]

- Private equity Real Estate Transaction
- Private equity Infrastructure Transaction
- Secondaries deals

[1] Real estate and Infrastructure deals were excluded by filtering for the relevant SIC code, while the others categories were manually excluded using the information provided by Zephyr in the commentary as well as in the official press release, when available.

- Debt to Equity Swap, Restructuring transactions and other bankruptcies procedures[2]

In addition to the previous selection criteria, we cross-matched data from Thomson One Banker in order to get information about funds' features. As a consequence, some of the transactions reported by Zephyr were excluded as Thomson One Banker lacked the information on some players.

In the context of club deals, original press releases, official press news, and the deal comments all reported by Zephyr allowed us to identify the lead financial sponsor of the deal, or the financial sponsor that originated the consortium. Most of the times Zephyr reported who was the lead financial sponsor in the consortium, other times it reports the percentage of ownership in the target. In the latter case, the sponsor with the majority or the highest percentage of ownership was considered the lead investor in the club. Transactions, where the lead sponsor could not be identified, were excluded from the sample. This represents the same procedures used by Huyghebaert and Priem (2016), to identify the lead private equity firm in buyout syndicates.

Apart from the centrality measures, for which we will dedicate a chapter below, we inserted in our logit regression model other variables usually tested in the relevant literature.

Target Size

To measure the size of the target when the acquisition took place we decided to use the total Enterprise Value ($m) of the transaction, including both debt and equity arrangements, reported by Zephyr database. In the club deal literature, it is possible to find examples of target size measured only considering the equity value, as did by Officer, Ozbas and Sensoy (2010) or considering the total enterprise value of the transaction (debt plus equity value) as did by Meuleman *et al.* (2009). Since our sample is constituted both by public and private targets, the equity value of the transaction isn't always disclosed, therefore we decided to use the total enterprise value.

Private equity funds are usually constrained for investing more than a certain percentage of their total committed capital in a single investment (Axelson, Stromberg

[2] We exclude any transaction in which the end result consisted in debt holders taking control of the company.

and Weisbach, 2007), therefore we would expect target size to be a significant determinant of club deal formation.

The distribution of this variable in the sample is positively skewed (Table 4), with the presence of big outliers both for sole sponsored deals and club deals. For this reason, in the logitstic regression, we used the natural log of this variable.

Public to Private Dummy

Dummy variable equal to one if the transaction is a takeover of a public traded company and zero otherwise. The majority of previous studies related to consortiums of private equity firm was focused only on public takeovers. In our study, we decided to have a wider scope and include also private company acquisitions and acquisition of divisions of private companies. In our sample, public takeovers account for 34% of the overall number of deals. This percentage is significantly higher for club deals where public takeover accounts for 41% of the deals, while it is lower (32%) for sole sponsored private equity transactions (Table 5). Therefore, we expect this variable to have a discriminatory power in the probability of club deal formation.

Geographic Concentration

Dummy variable equal to 1 if at least one of the private equity firm in the consortium (or the sole sponsor in case of) has an office in the same geographic location where the target is incorporated. This variable tries to capture the tendency international of private equity firm to partner with local players in order to gain access to local expertise and incremental investment opportunities. The average value of this variable is 96% for club deals while 86% for sole sponsored deals (Table 5). We would expect a positive and significant coefficient for this variable, confirming the resource motivation for building consortiums.

Target Industry Dummies

Each target company has been grouped in the ten different industries and ten different industry dummy variables were created accordingly (Table 2). The industries have been identified using the two digits US Standard Industrial Classification (two-digit SIC codes). For any model to be correctly specified and avoid perfect multicollinearity problem only nine of the ten industry dummy variables will be used in the model.

Investor Size

This variable measures the size of each private equity firm in our sample, by considering the amount of funds under management ($m). The amount of funds under management were not directly provided by Thomson One Banker. In fact, the database only provides the characteristics (name of the fund, investment focus, year, committed capital) of the funds raised by each private equity firms through the years. Using the same procedure of Hochberg, Lindsey and Westerfield (2011), we computed the funds under management for each private equity firm as the sum of the total capital committed to its currently active funds, where a fund is considered to be active for ten years since its initial raising. The distribution of this variable positively skewed, with the presence of big outliers (Table 6 and Table 8). For this reason, we considered the natural log of this variable when running the logistic regressions.

1.3 Methodology Description

Since dependent variable of our interest is a binary outcome ($y = 1$ if there is a Club Deal, 0 otherwise) in order to investigate the determinants of club deals formation and test our hypothesis we decide to employ a Logit Model. In particular, we wish to evaluate the impact of our independent variables ($\boldsymbol{x}$) on the probability of Club Deal formation, and to do so , we model $Pr(y = 1|x)$ as a function of $\boldsymbol{x}$.

Since $0 < Pr(y = 1|x) < 1$ a suitable functional form for $Pr(y = 1|x)$ is any cumulative distribution function evaluated at a linear combination of $\boldsymbol{x}$.

$$Pr(y = 1|x) = F\,(x'\beta)$$

In the case of the Logit model we have that the cumulative distribution function is the Logistic distribution with with zero mean and variance $\pi^2/3$:

$$F\,(x'\beta) \equiv \Lambda(x'\beta) \equiv exp\,(x'\beta)\,/\,[1 + exp\,(x'\beta)]$$

Being $F\,(x'\beta)$ a cumulative distribution function, the binary model can be motivated as a latent regression model:

$$y^* = x'\beta + \varepsilon \text{ and } y = 1\,[y^* > 1]$$

where y^* is the latent continuous random variable and ε is a zero mean random variable that is independent from $\boldsymbol{x}$ and with $\varepsilon \sim F$, where F is the Logistic cumulative distribution function. Logit models are also called index models as they restrict the way that the probability depends on x as it depends on $\boldsymbol{x}$ only through the index of $\boldsymbol{x}$.
In a logit model the estimation of the parameters is carried out via Maximum Likelihood Estimation. As common when dealing with a multi-year panel, we include in the Logit model the Year fixed effects. This should help to capture the different level of activity of the Private Equity market across the years of the sample.

The β coefficients presented in the univariate and multivariate regressions (Tables 15 and 16) cannot be interpreted as a marginal effect, as it is done in an OLS setting, as within the Logit model, the relationship between the dependent and independent variables is not linear in nature.
However, in the Logit model, it is possible to work out the marginal effect by using the chain rule of derivation. The marginal effect of x at observation i are estimated by Logit model as:

$$(\partial_x F_i)_{logit} = f_{logit,i} b_{logit} = \Lambda(x_i' \, b_{logit})[1 - \Lambda(x_i' \, b_{logit})] b_{logit}$$

This can be easily implemented with Stata using the post-estimation command *margins* with the option *dydx (varlist)*. We calculated the marginal effects for the main models in Table 18 in Appendix. Marginal effects can be described as a change in outcome (in our case probability of club deal) as a function of the change in the independent variable, holding all other variables in the model constant.
As an alternative to marginal effects, another way to present the results of a binary model (as the Logit model) is to use the odds ratio derived from the logistic regression. However, for the purpose of this thesis, we decided to use marginal effects as we believe they represent a better and more meaningful metrics to describe the results.

A further issue in the context of logit analysis is the lack of a measure analogous to the R^2 statistic as in the Ordinary Least Square Setting. Various alternatives for the goodness-of-fit measures have been developed in the literature. For the purpose of this paper, we will employ the McFadden Pseudo R^2 developed by McFadden (1973) as follow

$$McFadden\ Pseudo\ R^2 = 1 - \frac{L(\beta)}{L(\bar{y})}$$

where $L(\beta)$ is the value of the maximized log-likelihood for the model and $L(\bar{y})$ is the value of the log-likelihood evaluated for the model with only the intercept and no covariates (null model).

As in the traditional OLS setting, also the McFadden Pseudo R^2 always increases as the number of predictors increase. To make the measure more meaningful, is it possible to adjust the McFadden Pseudo R^2 to take into account the number of independent variables in the model (model complexity). Defining k the number of independent variables in the model, the adjusted measure is the following

$$Adjusted\ McFadden\ Pseudo\ R^2 = 1 - \frac{(L(\beta) - k - 1)}{(L(\bar{y}) - 1)}$$

Another way to compare the plausibility of two logit model and taking into account the model complexity is to consider the Bayesian Information Criterion (BIC) and Akaike Information Criterion. For two information measures the smaller the value the better the fit of the model under consideration, and are calculated as follow

$$AIC = -2L(\beta) + 2p$$

$$BIC = -2L(\beta) + \ln(n)\, p$$

where p is the number of predictor in the model and n the number of observations.

1.4 Centrality Measures

Centrality has been defined by Wasserman and Faust (1994) as “the extent to which a central actor is connected with others in a specified network”. In Social Network Analysis centrality metrics allow to identify which are the most important players, in our case private equity firms, inside a network. Therefore, they allow to capture how well connected a particular private equity firm is in the market.

According to Wellman (1983), network centrality allows the player which have a central role to access diverse strategic resources and also play a facilitating role in the integration of knowledge and technology of other participants.

Centrality is a multi-dimensional concept, meaning that there could be multiple reasons for a player to be important inside a network. As a consequence, there exist multiple centrality measures. Among them, we decided to investigate the three centrality measures proposed by Freeman (1979) which are Degree Centrality, the Betweenness Centrality, and Closeness Centrality and the one proposed by Bonacich (1987) which is the Eigenvector Centrality. The Degree Centrality measures the number of direct ties (first degree relationships) that a player has in its peer network. The underlying concept is that the more ties a firm has, the more opportunity for resources exchange has, and so the more centrally located and influential it is within its network. In our context, private equity firms that have many ties with other competitors (completed many club deals together with other players in the network) may hold an advantage position, since they could have access to a broader range of expertise, contacts, capital and improved deal flow (Hochberg, Ljungqvist and Lu, 2007).

Betweenness centrality measures how crucial a player is in connecting other nodes to each other in the network. In our study, it quantifies the frequency with which a particular private equity firm lies along the shortest path between any two other nodes of the network.

Betweenness is a centrality measure that is able to capture the brokerage power of an actor with respect to the whole network. In fact, an actor with a high betweenness centrality measure represents a cut-point along the shortest path connecting two other players in the market (Newman, 2005). Therefore, it might be able to control and direct the flow of information, resources, and opportunities, acting as a “gatekeeper” inside the network.

The Eigenvector Centrality is a measure of prestige of an actor inside the network. Differently from the other centrality measures, the Eigenvector Centrality measures the status of a player in the network depending not only on the number of connections but also on the "quality" of these ties. This centrality measure, introduced by Bonacich (1987), uses an iterative process which weights the centrality of each player by the centrality of its connections. According to this metric, the importance of a player inside the network depends, iteratively, from the importance of the player's neighbours.

In our study of private equity club deals network, it thus measures the extent to which a private equity firm is connected to other well-connected peers (Hochberg, Ljungqvist and Lu, 2007). In a co-investment context, as the one of club deals, high-status investors are likely to receive more invitation to join club deals because of the legitimacy they confer to the other investors involved in a deal.

A second measure of the prominence of a player in the network is the Closeness Centrality measure. Closeness Centrality measures how close a vertex is located to all the others in the network. This measure can be only calculated for fully connected networks, and being a local measure, it is computed for every player.

Closeness Centrality measure the strength of both direct (first degree) and indirect connections, therefore, differently from degree centrality, it is influenced by the position of the player with respect to the whole network. A high value for the Closeness Centrality is associated with an efficient use of information and resources available in the network. In fact, short distances among nodes implies shorter time to reach any other player in the network and ultimately lower transaction costs. Intuitively, the player with the highest closeness centrality (lowest total distance to all other nodes) is the one that relies less on intermediaries to build relationships with other nodes in the network.

1.5 Research Questions and Key Findings

In the thesis we used the tool of the social network analysis to show how the network looks like and investigate whether there is evidence of a “small world” of relationships. (first set of research questions). Moreover, a further set of research question aims to investigate the determinants of club deals formation. In particular, along with other variables already tested in the literature, we want to test if and which of the network centrality measures of private equity firms are significant determinants of club deal formation.

After assessing this structure and the prominence of the players in it using the tools of the social network analysis, we exploited the logit model as a tool to test our hypotheses and we reached interesting conclusions.

Our first finding is related to the low cohesiveness and relatively high centralization for the entire network of private equity firms. In particular, we were able to see that the network is made mostly by indirect ties, and only 2% of all the possible dyads in the network have a direct relationship. Moreover, the relatively high centralization of the network, together with the high standard deviation for all the centrality measures indicates that the network is dominated by few central players, suggesting the existence of a “small world” of relationships.

Our second finding from the social network analysis is related to the different definitions of centrality. For each network centrality measure, we are able to observe a modification of the ranking for the most prominent players. An interesting finding, is related to the brokerage power of some private equity firms inside the network. In particular, we found that some players, despite having a lower number of connections, act as a broker of relationships between many players, increasing the resources exchange in the network. This evidence was confirmed both by the Betweenness Centrality measures and by the Structural Hole Theory.

From the second set of research questions, we were able to confirm the financial motivation for consortium formation. In particular, we found that the size of the target has a positive and significant effect on the likelihood of club deal formation. Moreover, we find evidence that larger private equity funds are less likely to build consortiums, as they will be less capital constrained compared to smaller players.

The key finding of this paper lies on the positive and significant coefficients of the centrality measures on the probability of consortium formation. In particular, we found that the Degree Centrality and Betweenness Centrality have the largest economic effect on the likelihood of club deal formation. This finding supports the idea that private equity consortiums are established not merely for capital constrain motivation or portfolio diversification (financial motivations) but also to increase the social capital and ensure future deal flow.

In conclusion, we believe that this paper gives a contribution to the current literature on club deals in private equity. On the one hand, it confirms some results found by previous researches. On the other hand, it offers many aspects of novelty, especially related to the description of the network of relationships, rarely described in the literature for the private equity industry.

However, sample characteristics and data quality still affect our analysis. Firstly, our database starts from 2000 and ignore all the relationships that private equity firms had already developed in the past. Secondly, our sample is strongly US-biased and we lack information about deals and firms, particularly in Asia and China. These two facts may lead to a misrepresentation of the importance of some funds in the network and to ignore consortiums established with Asian peers.

Finally, we should be aware that also possible misspecifications of our model might affect our analysis. Despite having implemented many of the relevant variables already tested by the previous literature, a large number of variables may have been omitted from the analysis. This is due to the fact that our database is mainly constituted of acquisitions of private companies, for which we do not have any reliable disclosure of accounting metrics. However, we tried to limit this problem of omitted variables using year fixed effects in most of our regressions.

2. Subsample Analysis

We would like to extend our thesis adding three subsample analyses, of which two are referring to the second set of research question and one to the first set. We believe that adding these subsample analyses will increase the robustness of the results of the main research questions and verify if our results hold true also in the two subsample under consideration

2.1. Public to Private Transactions

The first subsample analysis I would like to perform is to run the Multivariate Logit Models to identify the determinant of club deal formation (second set of research question of the thesis) for the subsample of Public to Private (P2P) transaction. The original dataset includes all corporate private equity transactions (LBO on private companies, carve-out transactions and public to private transactions), as the aim of the thesis was investigate the broader universe of private equity transactions. Performing this subsample analysis will allow to control if the results obtained using the broad database hold true also for the subsample of Public to Private transactions that are the most studied transactions in the private equity literature and the most debated from in the private equity world.

Table 12 presents the results of the multivariate logit models that try to predict the conditional probability of consortium formation among private equity firms when pursuing acquisitions. The left-hand side of the chart analyses the conditional probability of consortium formation among “take private” private equity deals, while the right-hand site of the chart reports the results for all the transaction excluding private to public ones. As in the original model, or all these models we included year fixed effect to capture the size of the PE market across the years.

From table 12 the positive and significant coefficient for the Size supports the “financial motive” for organizing a club deal and this result is valid for both the subsample considered in the analysis.

Compared to the results in the original dataset, the Geographic Concentration variable has a positive and significant effect only in the Private to Private subsample and not in the Public to Private one. This mean that the geographic expertise of the PE firms inside the consortium is particularly relevant only among the private deal. A possible explanation could be that since the private deals are more common in

European countries (excluding UK), characterized by smaller public equity market, when forming the consortium, the geographical expertise of the consortium members become more important.

The positive and significant coefficient of the size of the lead investor in both the subsamples under consideration confirm the results of the original model. As explained for our main model the he rationale to add this variable is twofold. First of all, it helps to test the “financial motive” motivation for forming a consortium. In fact we would expect that larger funds will be less likely to syndicate or form a club as they would have enough capital themselves to conclude the acquisition. The second reason to add the variable, as expressed by Hochberg, Ljungqvist, and Lu (2007), is that it is used as a control variable for the Network Centrality measures used later. In fact, it is important to control that our measures of network centrality are not a mere proxy for the size of the private equity firm, but they are relevant indicators of the importance of the position of a player inside their network of relationships. The sign of this coefficient is negative as we would have expected, confirming the abovementioned financial motivation for club bidding.

From regression (1) to (4) we include the four metrics that measure the centrality position of a player inside the network, representing the most interesting findings of this thesis. We decided to include the centrality variables one at a time to mitigate potential problems of multicollinearity, as explained Hochberg, Ljungqvist, and Lu (2007).

The results from these regressions give positive and significant coefficients for all measures of social network centrality in both the subsample, confirming the results obtained in the original model.

However, it is possible to notice that the the Adjusted McFadden R^2 is much higher in the Private to Private subsample (c.8% among the first three model specifications) compared to the Public to Private subsample, meaning that our model, which tries to predict the conditional probability of consortium formation, is much more powerful in a private transaction context compared to a public one.

The outcome of this first subsample analysis again strongly supports the deal-flow motivation of consortium formation, in addition to the financial one in both the two subcategory of the dataset. In fact, it suggests that private equity firms may have used club deals to strength existent relationships or developing new ones with their competitors in order to increase their deal flow, investment opportunities, as well as the exchange of information and sector or geographical capabilities (Huyghebaert and Priem 2016).

2.1. Deal Size

The second subsample analysis we would like to run is related to the size of the transactions. As performed in many studies in the private equity literature in the past, I would like to check if my results hold true, or give different outcomes, also for subsamples of different size deals. We divided our dataset in four different quartiles sorted according to the size of the transaction, from the smallest (first quartile) to the largest (fourth quartile).

Table 13 (first and second quartile) and Table 14 (third and fourth quartile) outline the results of the multivariate logit models that try to predict the conditional probability of consortium formation among private equity firms when pursuing acquisitions, across different quartiles.

First of all, we can notice that the variable referring to the deal size is not significant in the first, second and third quartile. This means that within Q1, Q1, Q3 the size of the transaction is not a significant determinant in of the probability of club bidding. However, we notice that within Q4, containing the deal with latest dimensions, the size coefficient is still statistically significant as in the original model.

Overall we can see that the Geographic Concentration coefficient is positive and statistically significant. This confirms the results obtained in the original model which contribute to support the “resource based” theory of syndication (Bygrave,1987; Lerner, 1994), with international players that seek to build relationships with local ones in the countries where the target is located, independently on the size of the target.

What is important to notice in this subsample analysis is that not all the measures of network centrality are statistically significant across quartiles. In particular, we observe that the Betweenness Centrality, Eigenvector Centrality and Closeness Centrality are no longer significant in Q2. This implies that the ability of a player of acting as a broker inside the network (Betweenness Centrality), having high-quality connections, or in other words having many connections with others well-connected players in the network (Eigenvector Centrality) and being “close” to others players in the network (Closeness Centrality) are positive and significant determinant for the probability of consortium formation only between smaller targets (Q1) and mid-to-large targets (Q3, Q4). The outcome of this subsample analysis again partially supports the deal-flow motivation of consortium formation, in addition to the financial one for almost all the company in the subsample.

It is possible to notice that, across the different quartiles, the the Adjusted McFadden R^2 is much higher in first (between 7 and 8% among the first three model specifications) compared to the other quartiles (between 2 and 4% among the first three model specifications), meaning that our model, which tries to predict the conditional probability of consortium formation, is much more powerful in the context of small transactions compared to larger ones.

Apart from what we observed for the target in the second quartile the overall results of this subsample analysis are broader in line with the results we obtained in the original model, confirming the key finding of our main thesis.

3. Social Network Analysis in the Nordic Countries

We decided to perform a subsample analysis on the structure of the social network for the private equity firms in our dataset which performed a club deal (at least one) in the Nordic countries (Sweden, Norway, Denmark, Finland). We believe it is interesting to perform this subsample analysis to compare the structure of the network in a limited region, as the Nordic countries compared to the global one. It will also give us the chance to see which is the most prominent fund, from a social network (centrality) proprioceptive, in this region.

To calculate all the social network metrics that allow to describe the structure of the social network and the prominence of the single players in it, it was essential to build the Adjacency Matrix or Sociomatrix. In graph theory, a Sociomatrix is a square diagonal matrix that is used to represent a finite graph, and in our study, it represents the matrix of relationships between investors. The rows and columns of this matrix are the 23 Private Equity Firms of our subsample. In the 23x23 matrix, the elements of the main diagonal are all zero, while each element (i, j) is equal to the number of connections that exist between player i and player j. In our analysis of private equity club deals, a connection between two players is registered every time they form a consortium together.

To calculate the centrality measures described above and the metrics for the entire network of private equity club deals, we decided to use the software UCINET. UCINET (used in the version 6.0) is a software developed by Borgatti, Everett and Freeman (2002), specifically for the social network analysis.

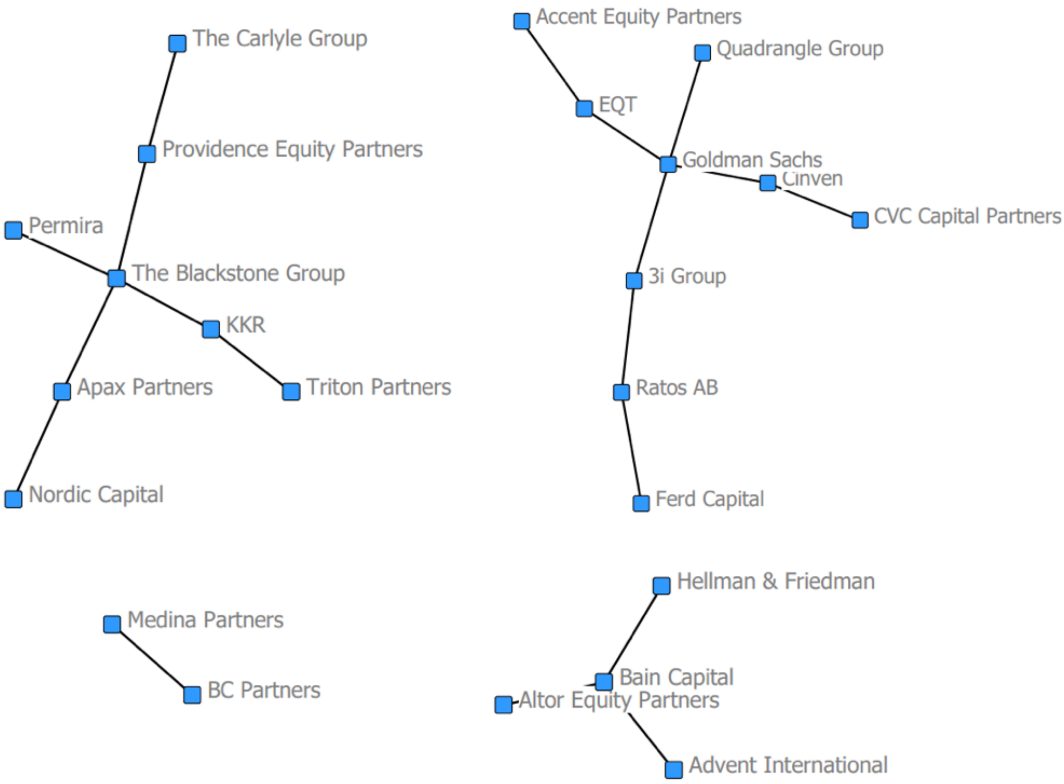
We will now describe the key findings of our analysis of the network of private equity firms arising from consortium formation in the Nordic countries

3.1. Graph Representation

First of all, to better understand how the network is structured, we can rely on a graphical representation of it. The picture below illustrates the entire network under analysis. From the picture, it is possible to see how the majority of the relationships are concentrated among the few groups of firms. The thickness of the line linking any two funds is directly proportional to the number of repeated relationships between the two players. From this particular configuration of the lines, we can already spot a small world of relationships distributed across three main independent sub-networks.

It is also possible to see that the social network structure in this region is not fully connected some funds have not had any relationship between other connected funds over the period analysed.

Exhibit 1. Graphical Representation of the Entire Network
This relationship diagram was obtained using UNICET 6.0 and show at a graphical level how the network of relationships, formed by Private Equity funds when enters in club deals, looks like



3.2. Evidence from the Centrality Measures

Table 9 illustrates the summary statistics for the three centrality measures in our analysis. In order to make meaningful comments on the prominence of single private equity firms in the network, Table 10 illustrates the different centrality measures for each of the players. For space reasons, in Table 10 we did not include all the 23 firms but we selected only the 10 with the largest value for the Degree Centrality measure. The table is sorted firstly by Degree Centrality, secondly by Betweenness Centrality and thirdly by Eigenvector Centrality.

Closeness Centrality can be only calculated for fully connected networks. As we already pointed out when commenting about the graphical representation the network of relationship in our subsample analysis is not fully connected, therefore the closeness centrality measure was excluded from the analysis. This is different from the analysis in our main thesis where the closeness centrality was included.

First of all, we can comment on the overall centrality of the network. The index centrality measures we calculate is equal to 11.7%. The number per se indicates that the network is not organized around a single player (as in a star graph which has a centralization 100%) nor as a circle graph (centralization of 0%). This value of 11.7% can be compared with the centralization values for other kinds of networks in the literature. Castilla (2003) obtained a network centralisation index of 8.46% in its network analysis of Venture Capital firm in Silicon Valley between 1985 and 1998. In the study of the co-investment network of Sovereign Wealth Funds, Gianfrate and Merlin (2016) reported a network centralisation index of less than 10% for the period 1984-2014. Finally, in the analysis of the collaborative network between US Chemicals company, Ahuja (2000) observed an average network centralization index of 18.5% for the period 1981-1991.

Degree Centrality Table 9 summarizes the Centrality Degree Statistics. The total degree centrality (sum of the degree centrality of every firm) is 38, which means that exist 138 direct ties among the nodes of the network. The mean degree centrality is 1.65, indicating that on average each private equity firm in the network experienced an alliance with approximately other 2 different players, for the period under analysis. The maximum number of ties is 4, which is held by The Blackstone Group and the private equity arm of Goldman Sachs, and corresponds to a normalized degree centrality of 18.2%, meaning that this particular private equity firm had experience of club deal with nearly 18.2% of all the other possible players in the sample. Having such a high number of relationships has certainly helped these two firms to increase its social capital and to establish itself as a reputable partner in case of consortium investing.

Betweenness Centrality Table 10 and Table 9 illustrates the Betweenness Centrality values and summary statistics for the firms in our sample.

First of all, a slightly modification of the ranking of the firms, compared to Degree Centrality can be observed. The player with the highest Betweenness Centrality measures, and therefore the highest brokerage power in the network, is the private equity arm of Goldman Sachs. This high brokerage power result might be due to the nature of this particular player, being the private equity arm of one of the leading global investment bank. Besides Goldman Sachs, the next five PE firms that scored the highest in term of Betweenness Centrality are also the ones with the highest value of degree centrality, and they are The Blackstone Group, 3i Group, Cinven and EQT. An interesting thing we can notice is how, Bain capital, which was the third players with the highest number of ties in the sample (degree centrality), now is ranked only tenth, according to Betweenness Centrality. This means that, despite having many ties, it tends not to lies in the shortest path connecting other dyads, and so it is less important for the resources (information) flow, compared to other funds.

This result is important as it clearly indicates that the brokerage power of a firm in the network does not strictly depend on the number of ties it has.

Overall we can observe a very high standard deviation, indicating that only a small group of private equity firms have a high brokerage power while the majority are less important for the efficient flow of resources inside the network. In fact, approximately 60% (14 out of 23) of the players in the network has a Betweenness Centrality of zero, meaning that those players never lie in the shortest path connecting each dyad. Graphically, those players stand at the far ends of the network, and they are in a way excluded from the network of efficient information flow, as can be seen from the graphical representation.

These observations provide the first evidence to the fact that only the small group of private equity firm mentioned above, have to be considered the most central and prominent ones in the network. Being able to develop a tie with these funds (participate in a consortium with them), is considered beneficial for a player as it offers the possibility to quickly access the entire network and increase its social capital.

Eigenvector Centrality The measure of Eigenvector Centrality allows us to answer the question about the level of prestige of a private equity firm in the network. As explained before, this measures takes into account not only the number of connections but also the quality of these connections (being connected with other well connected players). Values and summary statistics for the Eigenvector Centrality are reported in Table 10 and Table 9. The most prestigious private equity firm in this subsample analysis (in the Bonacich (1987) sense) is again the private equity arm of Goldman

Sachs (with a measure of 0.89), which was also the player with the highest number of first degree connections (highest Degree Centrality) and with the highest brokerage power (Betweenness Centrality). The high standard deviation for this measure, indicates again that only a very limited number of players have connections with other prominent funds, thus giving an evidence of the existence of a small world of relationships between the most prominent (from a social network point o view) private equity firms.

4. Conclusion

In the main thesis, we collected data for 1562 transactions completed by 225 private equity firms between 2000 and 2017. Among them, nearly 27% represented a club deal. The main purpose of this paper was to understand the structure of the network of relationships between different private equity firms. After assessing this structure and the prominence of the players in it using the tools of the social network analysis, we exploited the logit model as a tool to test our hypotheses and we reached interesting conclusions.

In this paper we performed two subsample analyses referring to the determinants of likelihood of private equity consortium formation and one subsample analysis to further investigate how the network of relationships between private equity firms which performed club deals in the Nordic countries looks like.

The first subsample analysis, dedicated to the probability of consortium formation in two the Public to Private and Private to Private transactions, we were able to further asses deal-flow motivation of consortium formation which we found relevant in both the two subsample. In particular, we found that our model, which tries to predict the conditional probability of consortium formation, is much more powerful in a private transaction context compared to a public one. This results may be explained by the fact that the network of relationship matters more when the Private Equity consortium try to bid for a private form rather than a publicly traded one.

In the second subsample analysis, where we tested our model across quartiles of different deal size. The results we got we were able to confirm the findings obtained in the main thesis which supports the deal-flow motivation of consortium formation, in addition to the financial one. Another interesting finding of this subsample analysis is that our model works better in the context of smaller size transactions compared to larger ones. This is indeed interesting since it confirms the results obtained in the first subsample analysis. In fact, in the first subsample analysis we found that our model works better in the context of Private to Private transaction and in the second subsample analysis we found that the model works better in the context of smaller deals and Private to Private transaction are more frequent in smaller size deals. In fact, the % of Private to Private transactions is 83% in Q1, 79% in Q2, 75% in Q3 and 62% in Q4.

In the third subsample analysis we were able to describe the network of relationships among private equity firms that performed a club deal in the Nordic countries. The results obtained from from this analysis are in line with the one obtained in where all the countries were considered (main thesis). In particular, we were able to show how the network of relationship is characterized by few prominent players. These players have a high brokerage power inside the network (betweenness centrality) and have a high number of high quality relationship. In addition to this we can also observe that many of the most prominent players, from a social network standpoint, in this subsample analysis are also the most prominent players in the network formed when considering the entire dataset.

In conclusion, we believe that these subsample analyses were useful for confirming and increasing the robustness the results of our main thesis. Moreover, thanks to the third subsample analysis we were able to map the network of relationships in the Nordics, which add values to the social network literature.

However, we can outline some limitation of our paper. First of all, as in every empirical analysis in the literature, sample characteristics and data quality still affect our analysis. Firstly, our database starts from 2000 and ignore all the relationships that private equity firms had already developed in the past. Secondly, our sample is strongly US-biased and we lack information about deals and firms, particularly in Asia and China. These two facts may lead to a misrepresentation of the importance of some funds in the network and to ignore consortiums established with Asian peers.

An interesting area of exploration for further research would be an investigation of the effect of the network centrality measures on the performance of different private equity firms. However, this is highly dependent on whether accurate data for performance at the firm level (not each fund of the firm) can be obtained. In addition to this, an interesting area of research would be to replicate the analysis of the social network of relationships, also for other investors in the market. In particular, we believe that hedge funds and university endowment funds represent two unexplored areas, from the point of view of social network analysis.

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6. Appendix

6.1. Tables

Table 1. Sample by Year

This table reports the number of transactions per year in the sample period of 2000 to 2017. Private equity transactions are classified by year of completion. Data are reported for the full sample, and for the club deal and sole sponsored subgroups.

	All Deals	Club Deals		Sole PE Deals	
Year	N.of Deals	N. Of Deals	% Year	N. Of Deals	% Year
2000	30	11	37%	19	63%
2001	23	12	52%	11	48%
2002	34	8	24%	26	76%
2003	57	27	47%	30	53%
2004	79	23	29%	56	71%
2005	113	35	31%	78	69%
2006	152	50	33%	102	67%
2007	193	59	31%	134	69%
2008	100	34	34%	66	66%
2009	21	7	33%	14	67%
2010	82	23	28%	59	72%
2011	91	23	25%	68	75%
2012	86	19	22%	67	78%
2013	92	11	12%	81	88%
2014	110	24	22%	86	78%
2015	97	13	13%	84	87%
2016	82	23	28%	59	72%
2017	120	21	17%	99	83%
2000-2017	**1562**	**423**	**27%**	**1139**	**73%**

Table 2. Target Industry

This table reports the number of transactions per Industry in the sample period of 2000 to 2017. The classification is based on the US *Standard Industrial Classification* (SIC 2 Digit Code). Data are reported for the full sample, and for the club deal and sole sponsored subgroups.

	All Deals		Club Deals		Sole PE Deals	
Industry Categories (two digits SIC Codes)	N.of Deals	% Total	N. Of Deals	% Total	N. Of Deals	% Total
Agriculture, Forestry, Fishing (01-09)	8	0.5%	1	0.2%	7	0.6%
Mining (10-14)	28	1.8%	11	2.6%	17	1.5%
Construction (15-17)	17	1.1%	1	0.2%	16	1.4%
Manifacturing (20-39)	484	31.0%	102	24.1%	382	33.5%
Transportation, Communications, Electric, Gas and Sanitary service (40-49)	195	12.5%	67	15.8%	128	11.2%
Wholesale Trade (50-51)	55	3.5%	13	3.1%	42	3.7%
Retail Trade (52-59)	141	9.0%	41	9.7%	100	8.8%
Finance, Insurance (60-67)	168	10.8%	57	13.5%	111	9.7%
Services (70-89)	461	29.5%	128	30.3%	333	29.2%
Public Administration (91-97)	5	0.3%	2	0.5%	3	0.3%
Total	**1562**	**100.00%**	**423**	**100.00%**	**1139**	**100.00%**

Table 3. Target Geography

This table reports the number of transactions per geography in the sample period of 2000 to 2017. Data are reported for the full sample, and for the club deal and sole sponsored subgroups.

	All Deals		Club Deals		Sole PE Deals	
Geographic Area	N.of Deals	% Total	N. Of Deals	Percent	N. Of Deals	Percent
North America	732	46.9%	208	49.2%	524	46.0%
LATAM	15	1.0%	2	0.5%	13	1.1%
Continental Europe	308	19.7%	78	18.4%	230	20.2%
Northern Europe	75	4.8%	17	4.0%	58	5.1%
Southern Europe	103	6.6%	36	8.5%	67	5.9%
UK and Ireland	234	15.0%	50	11.8%	184	16.2%
China	4	0.3%	2	0.5%	2	0.2%
Asia (ex China)	38	2.4%	12	2.8%	26	2.3%
Australia and New Zeland	21	1.3%	6	1.4%	15	1.3%
Middle East, North Africa and Turkey	22	1.4%	7	1.7%	15	1.3%
Africa	10	0.6%	5	1.2%	5	0.4%
Total	**1562**	**100%**	**423**	**100%**	**1139**	**100%**

Table 4. Deal Size

This table reports the descriptive statistics for the size of the transaction in our sample for the period of 2000 to 2017. The size of the transaction is measured with the enterprise value of the deal. Data are reported for the full sample, and for the club deal and sole sponsored subgroups.

Deal Size Descriptive Statistics	All Deals	Club Deals	Sole PE
Average	1,533	2,219	1,278
Minimum	315	336	315
Maximum	59,588	59,588	29,972
Stand. Dev.	2,728	4,176	1,871
1st Quartile	584	663	554
Median	850	1,072	806
3rd Quartile	1,500	2,274	1,300
Mode	500	900	500
Kurtosis	162.1	93.5	94.1
Skewness	10.2	8.2	8.3
Observations	1,562	423	1,139

Table 5. Transaction Characteristics

This table reports the descriptive statistics for some of the transaction characteristics in our sample for the period 2000 to 2017. In particular, the table illustrates the presence in our sample of Management Buyout, Public to Private Transactions, the presence of co-investors and the indicator for the geographic concentration. Data are reported for the full sample, and for the club deal and sole sponsored subgroups.

Transaction Characteristics	All Deals	Club Deals	Sole PE
Management Buyout			
Average (%)	6.0%	5.67%	6.06%
Observations	1,562	423	1,139
Public Takeover			
Average (%)	34.3%	41.1%	31.7%
Observations	1,562	423	1,139
Co-Investment			
Average (%)	14.0%	16%	13.2%
Observation	1,562	423	1,139
Geographic Concentration			
Average	88.6%	96.0%	85.9%
Observations	1,562	423	1,139

Table 6. Funds Under Management

This table reports the average and the total funds under management of the private equity firms in our sample per year for the period 2000 to 2017. Data are in $m.

Year	Average	Total
2000	2,196	318,462
2001	2,616	408,027
2002	2,657	443,776
2003	2,791	485,670
2004	2,932	533,582
2005	3,526	673,450
2006	4,527	914,506
2007	5,550	1,137,817
2008	6,154	1,273,865
2009	6,362	1,323,325
2010	6,142	1,283,632
2011	6,340	1,331,491
2012	6,808	1,443,238
2013	7,473	1,584,301
2014	7,705	1,656,594
2015	7,844	1,670,711
2016	7,614	1,560,913
2017	7,202	1,454,762

Table 7. Geographic Presence of Private Equity Firms

This table reports the geographic presence of the private equity firm in our sample. For each geographic region we indicated the number of players with at least an investment office. We ten took compared this value with the total number of private equity firm in our sample.

Geographic Area	N. players with an office	% of Total PE firms
North America	156	69%
LATAM	16	7%
Continental Europe	58	26%
Northern Europe	13	6%
Southern Europe	30	13%
UK and Ireland	83	37%
China	56	25%
Asia (ex China)	47	21%
Australia and New Zeland	11	5%
Middle East, North Africa and Turkey	11	5%
Africa	4	2%

Table 8. Characteristics of Private Equity Firms

This table reports the descriptive statistics for the private equity firms in our sample. In particular, it illustrates the descriptive statistics for funds under management, age and global presence.

	Average	Minimum	Maximum	Stand. Dev.	Median	Mode	Observations
Funds under Management	5,082	84	40,245	7,433	2,436	1,500	225
Age	16	2	76	10	14	9	225
Global Presence	2	1	11	2	1	1	225

Table 9. Summary Statistics of the Social Network Measures

This table reports the descriptive statistics of the social network measures for the private equity firms in our Nordic countries subsample. In particular, it illustrates the descriptive statistics for Degree Centrality, Betweenness Centrality, Eigenvector Centrality,

	Average	Minimum	Maximum	Stand. Dev.	Median	Mode	Observations
Degree Centrality	1.652	1	4	0.935	1.00	1.00	23
Betweenness Centrality	4.130	0	23	6.145	0.00	0.00	23
Eigenvector Centrality	0.164	0	0.892	0.250	0.00	0.00	23

Table 10. Centrality Rankings

For each centrality measure this table reports the ten most prominent private equity firms in our Nordic countries subsample. The aim of this table is to illustrate the modification of the ranking depending on what network centrality measure is considered.

Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
Goldman Sachs	4	Goldman Sachs	23	Goldman Sachs	0.892
The Blackstone Group	4	The Blackstone Group	18	3i Group	0.546
Bain Capital	3	3i Group	12	Cinven	0.509
3i Group	2	Cinven	7	EQT	0.509
Apax Partners	2	EQT	7	Quadrangle Group	0.405
Cinven	2	Ratos AB	7	Ratos AB	0.311
EQT	2	KKR	6	CVC Capital Partners	0.231
KKR	2	Providence Equity Partners	6	Accent Equity Partners	0.231
Providence Equity Partners	2	Apax Partners	6	Ferd Capital	0.141
Ratos AB	2	Bain Capital	3	The Blackstone Group	0.000

Table 11. Descriptive Statistics for the Variables Used in the Regressions

The table show a summary of the descriptive statistics for all the variable that will be used in our models, both in the univariate and multivariate logistic regressions.

	Descriptive Statistics								
	Obs	Mean	Median	Std. Dev	Min	Max	Range	Skewness	Kurtosis
Log (Deal Value)	1562	6.92	6.75	0.76	5.75	11.00	5.24	1.26	5.10
Management Buyout Dummy	1562	0.06	0.00	0.24	0.00	1.00	1.00	3.72	14.86
Co-Investment Dummy	1562	0.14	0.00	0.35	0.00	1.00	1.00	2.08	5.33
Public to Private Dummy	1562	0.34	0.00	0.47	0.00	1.00	1.00	0.66	1.44
Geographic Concentration	1562	0.89	1.00	0.32	0.00	1.00	1.00	-2.43	6.90
Pre 2006 Dummy	1562	0.31	0.00	0.46	0.00	1.00	1.00	0.81	1.66
Agriculture Forestry Fishing Dummy	1562	0.01	0.00	0.07	0.00	1.00	1.00	13.87	193.26
Mining Dummy	1562	0.02	0.00	0.13	0.00	1.00	1.00	7.27	53.80
Construction Dummy	1562	0.01	0.00	0.10	0.00	1.00	1.00	9.43	89.89
Manufacturing Dummy	1562	0.31	0.00	0.46	0.00	1.00	1.00	0.82	1.68
Transportation et al. Dummy	1562	0.12	0.00	0.33	0.00	1.00	1.00	2.27	6.15
Wholesale Trade Dummy	1562	0.04	0.00	0.18	0.00	1.00	1.00	5.04	26.44
Retail Trade Dummy	1562	0.09	0.00	0.29	0.00	1.00	1.00	2.86	9.18
Finance and Insurance Dummy	1562	0.11	0.00	0.31	0.00	1.00	1.00	2.53	7.42
Log (Lead Investor Size)	1561	9.48	9.55	1.10	5.17	11.23	6.06	-0.68	3.41
Degree Centrality	1562	1.16	0.70	1.14	0.10	3.70	3.60	0.93	2.50
Betweenness Centrality	1562	5.88	3.83	6.43	0.00	21.47	21.47	0.99	2.64
Eigenvector Centrality	1562	0.19	0.11	0.20	0.00	0.65	0.65	1.05	2.84
Closeness Centrality	1562	0.33	0.33	0.05	0.10	0.40	0.30	-0.73	3.92

Table 12. Multivariate Logit Models for the Public to Private and Private to Private Subsample Analysis

The table reports the logistic regression analysis for the probability of consortium formation for the subsample of Public to Private transaction (left hand side of the table) and Private to Private transactions (right hand side of the table). From pane (1) to (4) we insert one at a time the network centrality measures. For each model we include the year fixed effect. At the end of the table we compute the relevant diagnostics.

	Dependent Variable: Club Deal Dummy							
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Independent Variables	Public To Private				Private to Private			
Transaction Characteristics								
Deal Size (LN)	0.4588437***	0.4703518***	0.4574111***	0.4719814***	0.6482153***	0.6512823***	0.6513064***	0.6546184***
	(0.121502)	(0.120620)	(0.121560)	(0.120500)	(0.123069)	(0.122846)	(0.122804)	(0.122133)
Geographic Concentration	0.5273859	0.5133003	0.5564602	0.5546525	1.684902***	1.699361***	1.703488***	1.732018***
	(0.429899)	(0.429916)	(0.429089)	(0.429327)	(0.365646)	(0.366551)	(0.364612)	(0.364142)
Relevant Industries								
Manufacturing	-0.5041424**	-0.4891177*	- 0.4939303**	- 0.48238111*	- 0.4150703**	- 0.4320874**	-0.4067383**	- 0.4018503**
	(0.258021)	(0.257719)	(0.257257)	(0.256141)	(0.190504)	(0.190226)	(0.190164)	(0.188575)
Transportation et al.	0.2381073	0.2392581	0.2650348	0.2339089	0.197452	0.1690973	0.2272599	0.2114815
	(0.341596)	(0.340446)	(0.340255)	(0.341885)	(0.232379)	(0.232250)	(0.232133)	(0.230666)
Financials and Insurance	-0.1788548	-0.1397495	-0.1660788	-0.0799666	0.5355098**	0.5570775**	0.5184012**	0.6016157**
	(0.319908)	(0.318565)	(0.318812)	(0.316700)	(0.262421)	(0.261141)	(0.262331)	(0.261017)
Control Investor Size								
Lead Investor Size (LN)	-0.30223**	-0.2915029**	-0.2370333*	- 0.2954901**	- 0.5192021***	- 0.4623465***	-0.4783805***	- 0.3807917***
	(0.134521)	(0.132210)	(0.128189)	(0.146798)	(0.106305)	(0.102584)	(0.102888)	(0.121521)
Network Measures								
Degree Centrality	39.80523***				42.17526***			
	(11.482510)				(9.704162)			
Betweenness Centrality		0.0700254***				0.0627397***		
		(0.019921)				(0.016199)		
Eigenvector Centrality			1.910553***				2.195245***	
			(0.623109)				(0.537863)	
Closeness Centrality				8.838412***				4.52507*
				(3.198444)				(2.417147)
Diagnostics								
Observations	534	534	534	534	1028	1028	1028	1028
McFadden R2	7.03%	7.10%	6.54%	6.29%	9.85%	9.47%	9.62%	8.35%
Adj.McFadden R2	4.57%	4.64%	4.09%	3.84%	8.46%	8.08%	8.23%	6.96%
Log Likelihood	-266.81479	-266.61525	-268.21415	-268.93192	-458.7469	-460.70289	-459.90408	-466.37448
LR Statistics	40.34***	40.74***	37.54***	36.10***	100.27***	96.36***	97.95***	85.01***
AIC	547.6296	547.2305	550.4283	551.8638	931.4938	935.4058	933.8082	946.749
BIC	577.59	577.19	580.39	581.83	966.04	969.95	968.36	981.30

(Standard Error); * Significant at better than the 10% level; ** Significant at better than the 5% level; *** Significant at better than the 1% level

Table 13. Multivariate Logit Models for the Deal Size Subsample Analysis (Q1, Q2)

The table reports the logistic regression analysis for the probability of consortium formation for the deal size subsample analysis (Q1, Q2). From panel (1) to (4) we insert one at a time the network centrality measures. For each model we include the year fixed effect. At the end of the table we compute the relevant diagnostics.

	Dependent Variable: Club Deal Dummy							
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Independent Variables	First Quartile				Second Quartile			
Transaction Characteristics								
Deal Size (LN)	-0.9169189	-0.9745245	-0.8456394	-0.9695075	1.11566	1.153825	1.153825	1.242947
	(1.059150)	(1.051489)	(1.057794)	(1.036489)	(1.192792)	(1.187226)	(1.187226)	(1.183760)
Public-to-Private	0.1425908	0.1581821	0.1379682	0.1257758	-0.0019743	0.0018612	0.0018612	0.0281441
Transaction Dummy	(0.317092)	(0.312472)	(0.317755)	(0.309761)	(0.294885)	(0.294229)	(0.294229)	(0.293811)
Geographic Concentration	2.053731***	1.907983**	2.142368***	2.138016***	1.360738**	1.401081***	1.401081*	1.458804**
	(0.758623)	(0.751809)	(0.761711)	(0.752702)	(0.633595)	(0.633528)	(0.633528)	(0.635170)
Relevant Industries								
Manufacturing	-0.2924262	-0.3250243	-0.2811764	- 0.2576271*	-0.2390207	- 0.234363**	-0.234363	-0.2351758
	(0.337213)	(0.335440)	(0.336272)	(0.329193)	(0.306560)	(0.305709)	(0.305709)	(0.304258)
Transportation et al.	0.0371564	0.0108937	0.1150968	0.1813715	0.3842591	0.380536	0.380536	0.3735752
	(0.421165)	(0.415576)	(0.422323)	(0.404591)	(0.417507)	(0.417051)	(0.417051)	(0.417750)
Financials and Insurance	0.8691064*	0.8329835*	0.9090078**	0.9924764	0.4828529	0.5014322	0.5014322	0.5704177
	(0.451631)	(0.445116)	(0.451706)	(0.440721)	(0.262421)	(0.486439)	(0.486439)	(0.481298)
Control Investor Size								
Lead Investor Size (LN)	0.6971292***	0.5999644***	0.6290763***	0.4758018**	0.5914616***	0.5163458***	0.5163458***	-0.3411203*
	(0.177875)	(0.173884)	(0.168555)	(0.192146)	(0.169838)	(0.163124)	(0.163124)	(0.188956)
Network Measures								
Degree Centrality	80.61122***				29.01986*			
	(18.269050)				(17.496260)			
Betweenness Centrality		0.1173233***				1.067723		
		(0.030322)				(1.010788)		
Eigenvector Centrality			4.337359***				1.067723	
			(1.007923)				(1.010788)	
Closeness Centrality				9.120567*				-1.874913
				(4.101316)				(3.836597)
Diagnostics								
Observations	388	388	388	388	387	387	387	387
McFadden R2	12.57%	11.01%	12.20%	6.29%	6.99%	6.50%	6.50%	6.24%
Adj.McFadden R2	8.25%	6.71%	7.89%	3.72%	2.75%	2.26%	2.26%	2.00%
Log Likelihood	-143.46552	-146.00985	-144.06119	-150.94165	-154.03227	-154.83801	-154.83801	-155.2668
LR Statistics	41.24***	40.74***	37.54***	26.28***	23.15***	21.54***	21.54***	20.68***
AIC	302.93	308.02	304.12	317.88	324.0645	325.676	326.5336	326.5336
BIC	328.66	333.75	329.85	343.61	349.77	351.38	351.38	352.24

(Standard Error); * Significant at better than the 10% level; ** Significant at better than the 5% level; *** Significant at better than the 1% level

Table 14. Multivariate Logit Models for the Deal Size Subsample Analysis (Q2, Q3)

The table reports the logistic regression analysis for the probability of consortium formation for the deal size subsample analysis (Q1, Q2). From panel (1) to (4) we insert one at a time the network centrality measures. For each model we include the year fixed effect. At the end of the table we compute the relevant diagnostics.

Dependent Variable: Club Deal Dummy

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Independent Variables	Third Quartile				Fourth Quartile			
Transaction Characteristics								
Deal Size (LN)	-0.4407991	-0.5667893	-0.3594523	-0.3768179	0.6412018***	0.6455094***	0.6454273***	0.640438***
	(0.828246)	(0.826224)	(0.824886)	(0.817010)	(0.201426)	(0.201121)	(0.201543)	(0.202487)
Public-to-Private	0.1672357	0.174724	0.1499741	0.1871306	-0.1245166	-0.0996081	-0.1342338	-0.1350567
Transaction Dummy	(0.283963)	(0.281896)	(0.283586)	(0.282187)	(0.233964)	(0.232926)	(0.234384)	(0.235103)
Geographic Concentration	0.9087752*	0.9316282*	0.938635**	0.9399805**	0.9770232*	0.9870986**	0.9908984**	0.9445257*
	(0.485213)	(0.485519)	(0.482080)	(0.484077)	(0.496255)	(0.495912)	(0.495971)	(0.496190)
Relevant Industries								
Manufacturing	-0.5252429	-0.5435661*	- 0.5046693*	- 0.4780711	-0.669609*	-0.6565527**	-0.6722089**	-0.6684289**
	(0.344483)	(0.343033)	(0.343291)	(0.341462)	(0.284739)	(0.284085)	(0.284874)	(0.284814)
Transportation et al.	0.1832499	0.1620633	0.2150939	0.302144	0.1098072	0.1026662	0.1371385	0.0866654
	(0.428202)	(0.426430)	(0.424801)	(0.421633)	(0.344864)	(0.344941)	(0.344823)	(0.348029)
Financials and Insurance	1.077179***	1.013258***	1.048084***	1.149733***	-0.5888001*	-0.5337174	-0.6064023*	-0.4736593
	(0.389508)	(0.381925)	(0.318812)	(0.395808)	(0.360511)	(0.357652)	(0.361573)	(0.360422)
Control Investor Size								
Lead Investor Size (LN)	-0.30223*	-0.2338497	-0.2886928*	- 0.3178898*	-0.2495454	-0.1590199	-0.2423587	-0.3528839*
	(0.134521)	(0.178755)	(0.181573)	(0.210423)	(0.173549)	(0.165395)	(0.168127)	(0.190732)
Network Measures								
Degree Centrality	53.50782***				24.21979**			
	(15.621280)				(12.476220)			
Betweenness Centrality		0.0718738***				0.0279506		
		(0.025394)				(0.021587)		
Eigenvector Centrality			2.789136***				1.379373**	
			(0.868362)				(0.680355)	
Closeness Centrality				10.70183**				8.772618**
				(4.316473)				(3.712619)
Diagnostics								
Observations	371	371	371	371	385	385	385	385
McFadden R2	8.36%	7.20%	7.95%	6.78%	6.72%	6.23%	6.80%	8.35%
Adj.McFadden R2	2.62%	3.03%	3.78%	2.61%	3.49%	3.00%	3.57%	3.95%
Log Likelihood	-143.46552	-156.479	-155.21947	-157.19761	-203.01819	-204.08969	-202.84301	-202.00378
LR Statistics	28.18***	24.29***	26.81***	22.86***	29.26***	27.12***	29.61***	31.29***
AIC	325.0722	328.958	326.4389	330.3952	422.0364	424.1794	421.686	420.0076
BIC	328.34	354.37	351.85	355.81	447.71	449.85	447.36	445.68

(Standard Error); * Significant at better than the 10% level; ** Significant at better than the 5% level; *** Significant at better than the 1% level

Table 15. Bivariate Pearson Correlations

The table reports the bivariate correlation for the variable used in the regression.

	Correlations										
	1	2	3	4	5	6	7	8	9	10	11
1 Log (Deal Size)	1										
2 Public to Private Dummy	0.2582**	1									
3 Geographic Concentration	0.0524*	0.0805**	1								
4 Manufacturing	-0.0527*	-0.1160**	-0.0080	1							
5 Transportation et al.	0.0333	-0.0604*	-0.0474	-0.2531**	1						
6 Financials and Insurance	0.0752**	0.0238	-0.0576*	-0.2326**	-0.1311**	1					
7 Log (Lead Investor Size)	0.1920**	0.045	0.0301	-0.0610*	-0.0304	0.015	1				
8 Norm. Degree Centrality	0.2143**	0.0756**	0.0785**	-0.0194	0.0293	0.0135	0.6240**	1			
9 Norm. Betweenness Centrality	0.1992**	0.0552*	0.0825**	-0.0061	0.0477	-0.0084	0.5942***	0.9354**	1		
10 Eigenvector Centrality	0.2141**	0.0896**	0.0625**	-0.0250	0.0103	0.0236	0.6014**	0.9752**	0.8488**	1	
11 Closeness Centrality	0.2043**	0.0754**	0.0412	-0.0126	0.0368	-0.0612*	0.6741**	0.8379**	0.8035**	0.8056**	1

* Significant at better than the 5% level ; ** Significant at better than the 1% level

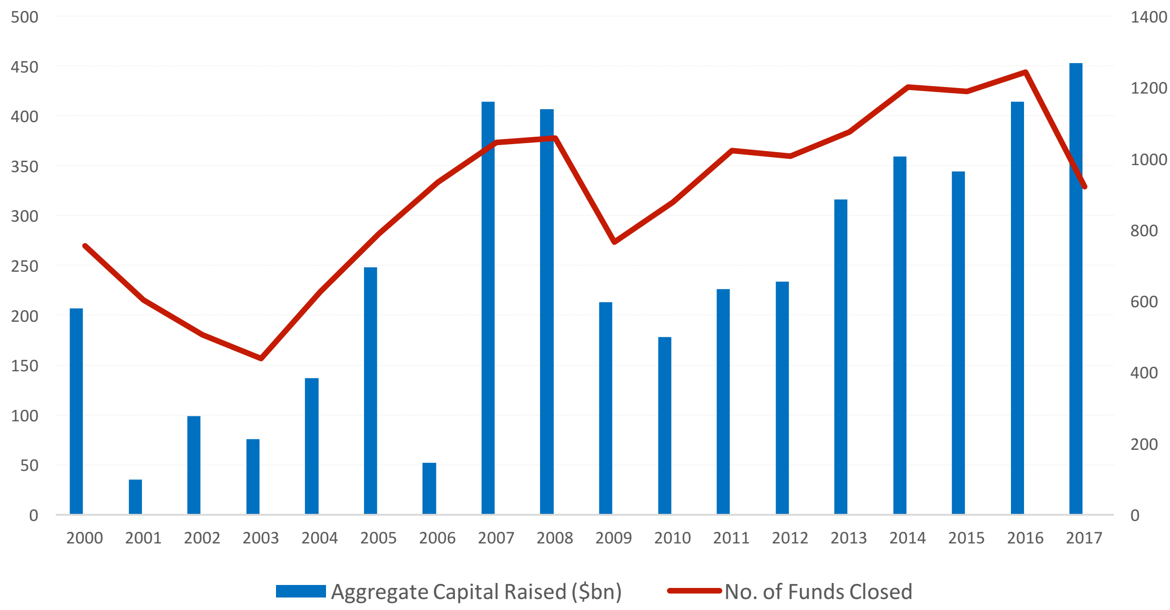
Table 16. Variance Inflation Factor and Tolerance Coefficients

This table illustrates the Variance Inflation Factor (VIF) and Tolerance coefficients used to investigate potential multicollinearity problems, in pane (4) to (7). All the VIF coefficient are smaller than 2, indicating no multicollinearity problem

	(4)		(5)		(6)		(7)	
	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance
Deal Size (LN)	1.14	0.881	1.13	0.882	1.14	0.881	1.13	0.883
Public to Private Dummy	1.1	0.906	1.1	0.908	1.1	0.905	1.1	0.906
Home Bias Dummy	1.02	0.979	1.02	0.978	1.02	0.982	1.02	0.984
Manufacturing	1.19	0.840	1.19	0.839	1.19	0.842	1.19	0.841
Transportation et al.	1.14	0.875	1.15	0.872	1.14	0.878	1.14	0.875
Financials and Insurance	1.12	0.895	1.12	0.896	1.12	0.895	1.12	0.890
Lead Investor Size (LN)	1.67	0.599	1.58	0.631	1.59	0.628	1.88	0.533
Norm. Degree Centrality	1.68	0.594						
Norm. Betweenness Centrality			1.59	0.629				
Eigenvector Centrality					1.6	0.623		
Closeness Centrality							1.89	0.530

6.2. Figures

Exhibit 1. Annual Global Private Equity Fundraising, 2000-2017



Private Equity Centrality and Club Deal Formation: Evidence from a Social Network Analysis

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Abstract

In this paper, we investigate the structure of the network of relationships established between private equity firms when they form acquisition consortiums. We collected information on 1562 private equity transactions, including both sole-sponsored and club deals, across the period 2000-2017. We analyse the consortiums within a social network framework, investigating the prominence and centrality of private equity firms inside the network. In particular, we show how this network is characterized by a low level of cohesion and the importance of the brokerage role played by central funds for information and resources transmission. We investigate the likelihood of consortium formation, and we find evidence for the "information and knowledge sharing" motivation, in addition to the financial motivation, already tested in the literature. Specifically, the social network centrality measures proved to have a significant and positive effect on the probability of consortium formation. Our results hold true also after controlling for the size of the private equity firm in the network, meaning that the prominence of a fund in the network is not a mere proxy for its size.

To my parents, my sister and my brother.

To my grandmothers, grandfathers

and all my closest relatives.

1. Introduction

There is little doubt that the private equity industry has been playing a vital role for thousands of companies around the world, both for private and public ones. 2017 was a record year for the private equity industry, with a $453bn in fundraising by 921 funds, making it the largest amount of capital ever raised in any year, as illustrated in Exhibit 1.[1] Moreover, as an asset class, the private equity industry accounted for 60% of all private capital raised in 2017. Therefore, given the size and the economic importance of this industry, it represents an interesting area of research.

Private equity club deals are consortium in which two or more private equity funds acquire together a target company. This kind of deals are not uncommon in the industry, in 2017 they represented 17% of all the private equity transaction, as reported in Table 1. The number of announced club deals reached a peak in 2006, and in the same year, the US Department of Justice started an investigation into the potentially anticompetitive behaviour of such transactions.

The majority of the criticisms to club deals in private equity are related to the claim that the consortiums' participants only cooperate in order to lower the purchasing price (anticompetitive behaviour). Other opponents claim that this kind of deals further increases the governance problems in the acquired firms, due to coordination problems and "clash of egos" between members of the consortium (Lockett, Meuleman and Wright, 2011). On the other hand, supporters of this form of investment, claims that club deals enhance the transferability of knowledge, skills, and expertise between investors, both ex-ante, in the process of selecting the target prior to the actual investment takes place, and ex-post in term of operational improvement of the acquired company.

Various aspects of club deals have been studied in the past. The anticompetitive hypothesis, together with other motivations for club deal formation, and the effect of club deals on acquisition pricing, have been analysed mainly by Officer, Ozbas and Sensoy (2010) and by Boone and Mulherin (2011).

So far, little focus has been given in the literature to the relationships between private equity firms arising from club deals. In particular, as noted for other industries,

[1] Preqin's Data

the network of repeated relationships, represents a valuable, albeit intangible, asset for the network participants.

The purpose of this paper is indeed the study of this network of relationships arising when multiple private equity firms build consortiums. With the tools of social network analysis, we aim to study the characteristics and the structure of the whole network of relationships and consider the role played by the single players in it.

In the private equity industry, the most used way to individuate the most prominent firms is to rank them in term of size. In fact, one of the most popular commercial database, also used by Officer, Ozbas and Sensoy (2010), is Private Equity International (PEI 300) which ranks the firms based on capital raised over the five-year period. In our study, we will propose alternative rankings based on the prominence and centrality of the private equity firms inside the network and the strategic roles played by them. This paper is the first one in the related literature to provide a description of this network. In particular, we were able to analyse the prominence of the private equity firms from a network centrality prospective.

In Section 4 of this paper, we were able to show how the social network centrality measures, calculated and discussed the previous sections, have a positive and significant effect on the conditional probability of consortium formation. It is important to notice that these findings hold true even after controlling for the size of the private equity firms inside the network. We, therefore, found evidence of the important role played by social capital (besides financial capital) also for the private equity industry.

The rest of this paper is organized as follows. In Section 2, after a brief paragraph which deals with some definitions and terminology of private equity industry, we analyse the existing literature, which addressed similar questions in the past. In particular, we review the theories behind the social network analysis and its applications in the private equity and venture capital industry. In Section 3, we introduce the sample and the measures of the social network analysis. We then illustrate the main features of these measures and the interpretation of their values, which represents the first key finding of this paper. In Section 4, we build a model for the probability of consortium formation. In particular, we investigate the role of the centrality measures, calculated in the previous section, on the conditional probability of consortium formation. In Section 5, we conclude the paper, commenting on the results, explaining the limitation of our analysis and areas for further research.

2. Terminology and Literature Review

2.1. Definitions and Terminology

In the literature, it is possible to find a wide range of definitions for “private equity”. For the purpose of our paper we will rely on the definition of Caselli (2010, p.4) according to which “… private equity is the provision of capital and management expertise given to companies to create value and, consequently, generate big capital gains after the deal”.

In the context of terminology, another important clarification should be done about venture capital. According to the American terminology, venture capital represents a subcategory of private equity dedicated to the financing of new companies, while according to the European definition private equity and venture capital represent two separate clusters, with the latter specialised in the early stage of the life cycle of a company (Caselli, 2010). For the purpose of this paper, we will abide with the European definition, we will exclude venture capital investments or any other type of early stage funding. Furthermore, as described later in Section 3, our definition of private equity will not include real estate, infrastructure, funds of funds and any kind of debt investment strategies (distressed, convertible, and others).

Finally, the last important definition is the club deal one. For the purpose of this paper we will use the words club deal and consortium interchangeably, to indicate an acquisition completed by two or more private equity funds (Fraser-Sampson, 2010).

2.2. Review of the literature

The main focus of our thesis is related to the formation of private equity consortiums and the network of relationships that arise from it. The topic of consortium investing is part of the broader research field of the syndication of Private Equity and Venture Capital investments. As mentioned by Lockett, Meuleman and Wright (2011) private equity club deals have been poorly discussed in the literature compared to other forms of investment syndication as in the venture capital industry. Therefore, we believe that the topic of club deals together with the social network analysis of their relationships represent a relevant and innovative area of research.

For this paper, after a brief introduction in which we describe some examples of the use of social network analysis in finance, we decided to divide the review of the literature into two different sections. The first one is focused on investment syndication and club deals networks among private equity and venture capital firms, while the second one will outline the main theories related to social network analysis and the concept of social capital.

2.2.1. Social Networks Analysis in Finance

In addition to the findings for the venture capital and private equity industry which will be outlined in the next paragraphs, the importance of relationships and social network structure has been investigated in many fields of corporate finance as well as investment management.

From a corporate finance point of view, in equity and debt capital markets, Ljungqvist, Marston, and Wilhelm (2009) have demonstrated the significance of the network position (eigenvector centrality) of a bank on the likelihood of being selected as a co-arranger in the case of equity or debt issuances. In the context of M&A advisory activity to private equity firms, Siming (2014) showed that the social network of relationships, arising from the changes of career of investment bankers becoming private equity professionals, has a positive correlation on the likelihood of being selected as advisor in a private equity buy-side or sell-side M&A deal.

In the field of Investment Management, Cohen, Frazzini, and Malloy (2008) showed the importance of the social network, arising from a shared education background, on the information flow between senior officers of listed companies and portfolio managers of mutual funds. Finally, in the context of funds performance, Rossi *et al.* (2015) found that the centrality of a pension fund inside its network (network determined by pension funds sharing the same consultant and/or the same manager) is positively associated with the fund risk-adjusted performance.

2.2.2. Social Networks and Venture Capital

In the context of empirical research, the majority of the literature on club deal formation and investment syndication has been focused mainly on early stage venture capital, while very few studies have a focus on late stage private equity transactions and leverage buyout investments (Locket, Meuleman, and Wright, 2011). As a consequence, also the studies related to the structure of the social networks, resulting from investment syndication, have been mainly concentrated on early stage VC investments.

The literature related to VC investment syndication identifies various reasons that may lead a firm to syndicate its investments. First of all, the traditional finance perspective identifies the portfolio diversification as one of the key drivers in the decision to syndicate. Moreover, as reported by Kaplan and Stromberg (2004), investment syndication is among the instruments used by investors to mitigate the information asymmetry and incentive issues when investing in early-stage firm characterized by high growth potential and high risk. Another important motive of VC syndication is related to resources sharing. This aspect, firstly analysed by Bygrave (1987), shows how syndication is used as a tool to build a network of relationships with other VC firms in order to get access to better information, sector or geographical expertise, and incremental high quality deal flow.

Bygrave (1987) represents probably first study that analyses the syndication pattern in venture capital investments from a resource-based and network perspective and not only as a portfolio diversification strategy. Lerner (1994) further expands the literature on resource-based perspective of VC syndication. Using a very specific sample of biotechnology firms in the US, the author shows a tendency of VCs to syndicate their first round investment only with other prominent and well experienced and connected VCs while only in later rounds of financing the information asymmetry is reduced and a broader range of VCs get invited to participated to the financing. Among the potential reasons for syndicating, Lerner (1994) identifies also the window dressing issue, meaning that poorly performing funds try to enter in relationship with other experienced and better performing VCs to avoid lagging behind their peers.

Hochberg, Ljungqvist and Lu (2007) extensively analyse the social network structure arising from venture capital syndication and study how the position of a VC inside the network affects its performance. Analysing a US based dataset that comprise 3,469 VC funds managed by 1,974 VC firms which targeted more than 16 thousand portfolio companies, the authors describe the social network structure arising from the syndication using the network measures of Degree Centrality, Betweenness Centrality and Eigenvector Centrality. Hochberg, Ljungqvist and Lu (2007) demonstrated that these network centrality measures have a positive and statistically significant effect on both VC funds profitability and performance persistence as well as on the survival probability of portfolio companies. In particular, the study found that a

one-standard-deviation increase in network centrality measures mentioned above increases the exit rates of the investment by around 2.5 percentage points.
The study also demonstrated that the economic effect of the network measures is relevant even after controlling for the experience of the single VC firm, meaning that the position of a VC inside the network is not a mere proxy for experience.

Sorenson and Stuart (2001) using a sample of US based VC firms, studied how social networks, arising from venture capital investment syndication, facilitate the information diffusion across both geographic and industry specific boundaries. This study on the geographical reach of venture capital investment finds that VC investors characterized by a high centrality position in the network are the ones that are more capable to expand the geographical boundaries and overcome the informational constraints.

The majority of the venture capital investments is managed by more than one VC collectively (Trapido, 2009). Therefore, venture capital firms rely heavily on the resources coming from the network of their peers not only to improve the deal flow but also in term of adding value to portfolio companies. Again, using a sample of US based VC firms Trapido (2009) extensively describes the evolution of syndication network of VCs firm and demonstrated the importance of partner stability to avoid unfavourable outcome in the portfolio companies (measured by hazard rate of company failure).
Further evidence of the positive contribution of network centrality on performance of VC firms has been found by Seppä and Jääskeläinen (2002). More specifically, the authors show that measure of degree centrality and eigenvector centrality of VC firms are positively related to the IPO performance of their portfolio companies (used as a measure of the performance of the VC firm).

The majority of the literature related to Venture Capital investment syndication is focused on US market. This is mainly due to the longer history of Venture Capital activity in the United States, compared to Europe or Asia, and certainly to the size of the market in the United States. More than $84bn were invested in 2017 in the US VC industry across more than eleven thousand deals.[2]

Outside the focus of the literature on the US venture capital industry, Manigart *et al.* (2006) represents the first study that examines the motives of Venture Capital syndication in Europe. The authors employed a questionnaire-based methodology to

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[2] Preqin's data.

investigate the motives of VC syndication in 6 different European countries (UK, Sweden, France Germany, Belgium and the Netherlands). In contrast with the US literature, in which syndication motives are mainly driven mainly by the need of resources access and improved deal flow, the study finds that investment syndication in European VC industry is mainly driven by financial consideration, meaning that syndication is used as a way to build better diversified portfolios.

To conclude, Du (2008) analyses the determinants of the likelihood of investment syndication in the US venture capital industry. The study uses a logit model to analyse which are the most relevant determinants of the likelihood of VC syndication. The author finds evidence that the heterogeneity in the Network Centrality measure (which is calculated as the standard deviation of Degree Centrality and Eigenvector Centrality) is negatively associated with syndication formation, meaning that VCs with a central position in the network tend to invest together, further strengthening their relationship.

2.2.3. Social Networks and Private Equity

The literature on private equity club deals formation and the social networks arising from such relationships is much more limited compared to the one related to venture capital.

The determinants of club deal formation in Private Equity have been analysed by Officer, Ozbas and Sensoy (2010) and by Boone and Mulherin (2011). The two papers, both focused on leverage buyout transactions (public to private takeovers), analyse broadly whether Private Equity consortiums (club deals) facilitate the collusion bidding and whether the prices and premiums paid by a consortium are lower compared to the one of sole-sponsored deal. In both studies, the authors begin their analysis by building an empirical model for the determinants of club deal formation. In their study, Boone and Mulherin (2011) find that the size of the target has a positive and significant effect on the likelihood of consortium formation. Book leverage of the target (assumed by the author as a measure of risk of the target firm) is a significant determinant of consortium formation. However, the sign of the latter coefficient is negative, going against the VC literature about portfolio diversification motive, according to which a riskier firm is more likely that will be bought out by a consortium rather than a sole investor (Smith and Smith, 2000).

Officer, Ozbas and Sensoy (2010), build a similar model to analyse the determinants of club formation.[3] The study finds that the size of the transaction has a positive and significant impact on the probability of club formation, while the effect of the risk (measured by both beta and 12-month return volatility of the target firm an) is not significant. Finally, is worth mentioning that both the two studies use a dummy variable to control if the deal was concluded before 2006. Indeed, 2006 represents the year in which the US Department of Justice announced an investigation into the potentially anticompetitive behaviour of club deals in private equity transactions (Jackson, 2008).

The previous two papers mainly analyse the motives of consortium formation between private equity firm from a financial perspective, not considering the networks that these repeated relationships create. The social network perspective is instead considered by the studies of Meuleman *et al.* (2009) and of Huyghebaert and Priem (2016). Using a sample of management buyout transactions in UK between 1993 and 2006, Meuleman *et al.* (2009) find evidence that the network centrality of a PE firm (measured with Degree Centrality) has a positive and significant effect on the likelihood of consortium formation. Moreover, the study finds evidence that better networked investors have the ability to moderate the agency costs arising from the syndication of the investment.

Using a sample of European private equity transactions between 1999 and 2009, Huyghebaert and Priem (2015) investigate how lead private equity funds select their co-investors when deciding to form an investment consortium. The study provides evidence that the measures of network centrality (such as Degree Centrality, Eigenvector Centrality, Betweenness Centrality, and Closeness Centrality) have a significant effect on the choice of which partner to select in a buyout syndication.

2.2.4. Social Network Theories

The main goal of this thesis is to investigate how the social network of private equity firms looks like, and which are the funds that occupy a central and prominent position from a social network point of view. In this context, it is essential to review the relevant

[3] The logit and probit models that analyse the likelihood of club deal formation is described but not reported in the paper.

theories related to social capital, that explain how partnership choices help to create and sustain network of relationships.

Social Capital is not uniformly defined in the literature, however, one of the most effective formulations is the one provided by Bourdieu and Wacquant (1992, p.119), according to which social capital is

"*…the sum of the resources, actual or virtual, that accrue to an individual or a group by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition"*

According to Colemann (1988)'s view of social capital, repeated relationships among the same group of players, increase the level of closure of the network, and this is beneficial as it facilitates trustworthy cooperation and diminishes the incentives for opportunistic behaviour. Therefore, according to this theory, the higher the level of closure of a network, the larger is the amount of social capital available for the participants of this network. In the context of club deals, this means that private equity firms may seek to build relationships with similar players within their close network, avoiding "new" potential partners in order to reduce the likelihood of opportunistic behaviour and minimize coordination costs.

A completely opposite approach to social capital is given by Burt (1992) Structural Hole theory. According to the Structural Hole theory, information flow in cohesive networks tends to be redundant and does not provide much value to the players. Sparse and well diversified networks, on the contrary, are beneficial to social capital because each player acts as a broker towards non-redundant source of information. Holding a brokerage position inside the network is therefore beneficial as it allows to get access to a large amount of social capital available in the network. Again, in the context of club deals, Burt (1992) theory suggests that private equity firms are more likely to build relationship with "diverse" players with complementary skills especially in term of geography, industry or process.

The literature does not provide a definite answer on which of the two theories finds more evidence in practice, and very often the two theories appear to be complementary rather than opposite. This is exactly the "paradox of embeddedness" expressed by of Uzzi (1997), which states that players inside a network have constantly to find a balance between safety (strengthening trustworthy relationships with players in the close network), and adaptability (building new relationship to access complementary resources).

3. Sample Description and Social Network Analysis

The main purpose of this research thesis is to investigate the structure of the network created by private equity firms when forming consortium. In particular, we will use the tool of the social network analysis to show how the network looks like, which firms hold a centrality position, which are the most prominent ones, which have a function of gatekeeper or broker of connections and investigate whether there is evidence of a “small world” of relationships. Moreover, a further set of research question aims to investigate the determinants of club deals formation. In particular, along with other variables already tested in the literature, we want to test if and which of the network centrality measures of private equity firms are significant determinants of club deal formation. The exact research questions are illustrated in Section 4.

3.1. Forming the Sample

3.1.1. Data and sample construction

Data was collected using several sources and databases. Private equity transactions data were collected from Zephyr. Zephyr is the database of Bureau van Dijk which contains a comprehensive set of information about M&A, IPO, Private Equity and Venture Capital transactions. For each deal, Zephyr provides all the details about the transaction, the players involved, a commentary of the deal and a link to the official press release of both the bidder and the target. It is important to notice that when reporting a transaction, Zephyr always discloses the private equity firm that completed the transaction but rarely specifies which specific funds of the private equity firm was involved. Therefore, like many other analyses on club deals (Officer, Ozbas and Sensoy, 2010) in the literature, our study focuses on private equity firms and not their funds.

Private equity features like age and funds under management were collected via Thomson One Banker. It is important to remark that each database has its own drawbacks and biases. In our case, for example, Thomson One Banker did not report any data for some private equity firms, while for others the data about the fund raised were unreliable (e.g. zero values). To minimize this issue, the commercial database Palico was used to check the cases of missing or unreliable data related to private equity firms.

Our study relies on a unique dataset (hand-collected in part) which includes information on global Private Equity transactions completed in the period 2000-2017, in which the deal value (enterprise value) is greater than $300 million. Using this query, we obtain a sample of 2,533 transactions reported in the Zephyr universe. Since the scope of this thesis is focusing on corporate private equity transaction, we decided to exclude the following transaction classified by Zephyr under Private Equity:[4]

- Private equity Real Estate Transaction
- Private equity Infrastructure Transaction
- Secondaries deals
- Debt to Equity Swap, Restructuring transactions and other bankruptcies procedures[5]

In addition to the previous selection criteria, we cross-matched data from Thomson One Banker in order to get information about funds' features. As a consequence, some of the transactions reported by Zephyr were excluded as Thomson One Banker lacked the information on some players.

In the context of club deals, original press releases, official press news, and the deal comments all reported by Zephyr allowed us to identify the lead financial sponsor of the deal, or the financial sponsor that originated the consortium. Most of the times Zephyr reported who was the lead financial sponsor in the consortium, other times it reports the percentage of ownership in the target. In the latter case, the sponsor with the majority or the highest percentage of ownership was considered the lead investor in the club. Transactions, where the lead sponsor could not be identified, were excluded from the sample. This represents the same procedures used by Huyghebaert and Priem (2016), to identify the lead private equity firm in buyout syndicates.

Overall, the majority of the missed information concerns Asia and China, as the disclosure on single deals as well as on funds' features was low. As a result, as we will see later, our database is strongly US-biased.

[4] Real estate and Infrastructure deals were excluded by filtering for the relevant SIC code, while the others categories were manually excluded using the information provided by Zephyr in the commentary as well as in the official press release, when available.
[5] We exclude any transaction in which the end result consisted in debt holders taking control of the company.

3.1.2. Sample Descriptive Statistics

As a result of all the abovementioned eliminations, our sample is composed of 1562 transactions, performed by 225 private equity firms. Tables describing the sample are available in Appendix.

Table 1 reports the distribution of the sample of 1562 transactions over time. Private equity deals are classified by the year of completion. For the full sample, the number of transactions per year generally rises over time from 2000 to 2007. After a strong decrease during the years subsequent to the financial crisis, the activity picks up again from 2013 onwards. The greatest number of deals, both sole sponsored (134) deals and club deals (59), were completed in 2007.[6] Table 1 also indicates that club deal represents 27% of all the sample. It is possible to compare this rate of 27% for our time period 2000-2017 with other previous studies on Club Deal.[7] Axelson *et al.* (2007) reported a consortium rate of 31% in the period 1985-2006, Officer, Ozbas and Sensoy (2010) of 35% for the period 1984-2007, Demiroglu and James (2010) also 35% for the period 1997-2007 and finally, Boone and Mulherin (2011) of 44% for the period 2003-2007.

As stated before, in our sample of 1562 private equity transactions 423 of them were club deals. For these transactions, it is possible to calculate some statistics for the size (number of players) of the consortium. The minimum size as for the definition of consortium, is logically two players, while the maximum number of players is 5, which occurs 6 times in the sample. The average value for the size of the consortium is 2.27, which indicates that the large majority of club deals are constituted of two players. In fact, 336 club deal transaction out of 423, or 79 percent, are constituted by two private equity firms.

Using US *Standard Industrial Classification* (two digit SIC codes), we can spot ten different industries, reported in Table 2 together with the number and percentage of investments in each industry. Our sample provides evidence that the large number of club deals happens in Services (30%) followed by Manufacturing (24%), Transportation, Communications, Electric, Gas and Sanitary service (16%) and finally in Finance and Insurance (14%). In the second set of research questions, we will

[6] Most likely the deals completed in 2007 were announced in 2006 or earlier.
[7] All the studies mentioned focused on LBOs, while our study analyses club deals both in public and private transactions

analyse which of the industries plays a significant discriminatory role in the probability of club deal formation.

As we mentioned before, our sample is biased towards US. In fact, from Table 3 we can see that the majority of both sole sponsored (46%) and club deal (49%) targets are located North America, followed by Continental Europe and UK & Ireland. The geographic location of the target and the global presence of the private equity firm (investment office locations) were used to build our *Geographic Concentration* dummy variable.

Table 4 reports the descriptive statistics of the size of the deals (Enterprise Value of the transaction provided by Zephyr) in our sample. Consistent with the financial motivation of club deal formation we can see that club deal targets are significantly larger than sole sponsored targets. For the full sample, the mean target value is $1.53bn and the median target value is $0.85bn. The target values for sole sponsored deals are below average, the mean value is $1.28bn and the median is $0.81bn. By contrast, the target size for club deals are above the sample average, the mean value is $2.22bn and the median value is $1.07bn. As average values are higher than median ones, we observe a positive skewness in the distributions of the two subsample driven by big outliers. To minimize the effect of outliers we took a logarithmic transformation of size in our subsequent analysis on the probability of consortium formation.

Now we will outline some of the characteristics of the private equity firms in the sample. Table 6 reports the average funds under management by year and the total funds under management in the industry. We can clearly see that both the statistics showed a strong growth over the period considered, underlying the importance that the corporate private equity industry developed over time. The average funds under management growth at a rate of 6.8% over the period and the total funds in the industry growth at a rate of 8.8%, suggesting also an increase of players in the private equity industry. From Table 8, which summarize some characteristics of the players in the sample, we can observe that the distribution of the Age and the Funds under Management is positively skewed with a substantial degree of variation[8]. The average age is slightly more than 16 years. The oldest player in the sample was on average 76

[8] The metrics in the table were calculated by first taking the average of each individual PE firm for the years they were investing, then using these averages to calculate the relevant statistics.

years old while the youngest had just started with only an average of 2 years of experience.

Thomson One banker also provided the geographic footprint of each private equity firm. Table 7 summarize, among the players in the sample, how many private equity firms have an office in that specific geographic area. We can observe that the large majority of our players in the sample has at least an office in North America (69%), followed in importance by UK&Ireland (37%) and Continental Europe (26%). This fact confirms again the bias of our sample towards US and Europe, as well as the importance of cities like New York or London for the process of raising funds for PE firms. We can see from Table 8 that the average PE firm in the sample had a presence in at least 2 of the geographic areas indicated in the previous table. Out of 225 players in the sample, 126 of them (56%) have offices only in one geographic area. On the other hand, only one firm (The Carlyle Group) have at least an office in every geographic location analysed. As already mentioned above, this information about the geographic footprint of PE firms will be matched with the information on the location of the target in order to create the *Geographic Concentration* dummy variable.

3.2. Social Network Analysis

To map the relationships among Private Equity firms involved in Club Deals, we use the tools and framework of the Social Network Analysis. From a methodological standpoint, the Social Network Analysis (SNA) is a is an interdisciplinary methodology that studies the relationship, patterns and their implications among social entities. The peculiarity of SNA, compared to traditional data analysis tools, is that it provides a theoretical approach to explore the interactions of actors in their specific field, rather than sampling them independently (Hanneman and Riddle, 2005). The objective is to try to empirically derive the social structure of a group of players based on their observed relationships.

SNA is able to offer a theoretical framework to investigate the interactions of actors in a system and to test theories around collective behaviour and social interaction among players (Wasserman and Faust, 1994). The building blocks of social network analysis are the individual actors within the network (called *nodes*) and the relationships between them (called *ties* or *connections*). The theoretical background, on which Social Network Analysis is based, includes a wide range of data analysis disciplines such as mathematics, statistics, matrix algebra and graph theory.

In the following section, we will explain which variables are used to describe the network of relationships arising from private equity club deals.

3.2.1. Centrality Measures

Centrality has been defined by Wasserman and Faust (1994) as "the extent to which a central actor is connected with others in a specified network". In Social Network Analysis centrality metrics allow to identify which are the most important players, in our case private equity firms, inside a network. Therefore, they allow to capture how well connected a particular private equity firm is in the market.

According to Wellman (1983), network centrality allows the player which have a central role to access diverse strategic resources and also play a facilitating role in the integration of knowledge and technology of other participants.

Centrality is a multi-dimensional concept, meaning that there could be multiple reasons for a player to be important inside a network. As a consequence, there exist multiple centrality measures. Among them, we decided to investigate the three centrality measures proposed by Freeman (1979) which are Degree Centrality, the Betweenness Centrality, and Closeness Centrality and the one proposed by Bonacich (1987) which is the Eigenvector Centrality. As explained later, each centrality measure captures a slightly different aspect the economic function played by a single private equity firm in the network. Compared to other social network measures and indicators, that give information about the entire network, Centrality measures are actor-specific, meaning that are calculated for each node in the network.

3.2.2. Degree Centrality

The Degree Centrality is defined as the number of vertices adjacent to a given vertex in a symmetric graph (Freeman, 1979). Degree Centrality measures the number of direct ties (first degree relationships) that a player has in its peer network. The underlying concept is that the more ties a firm has, the more opportunity for resources exchange has, and so the more centrally located and influential it is within its network. In our context, private equity firms that have many ties with other competitors (completed many club deals together with other players in the network) may hold an advantage position, since they could have access to a broader range of expertise, contacts, capital and improved deal flow (Hochberg, Ljungqvist and Lu, 2007).

Graphically, this measure can be seen as the number of nodes the PE firm under analysis is directly connected to. This measure only depends from the first degree of separation from other players in the network, therefore it is not influenced by the overall network position of the actor.

One of the drawbacks of Degree Centrality is that it is a function of the network size. Over the period under analysis, the size of the network varies as new PE firms enter in the market while others stop existing. A way to address this issue is normalizing each degree centrality measure by dividing it by the maximum possible number of connection *n-1.*[9]

From a computational point of view, defining $\delta\ (i,j)$ as an indicator that nodes i and j are connected, the degree centrality for a given player i in the network will be

$$Degree\ Centrality_i = \sum_{j \neq i} \delta(i,j)$$

3.2.3. Betweenness Centrality

Betweenness centrality, firstly introduced by Freeman (1979), measures how crucial a player is in connecting other nodes to each other in the network. In our study, it quantifies the frequency with which a particular private equity firm lies along the shortest path between any two other nodes of the network.

Betweenness is a centrality measure that is able to capture the brokerage power of an actor with respect to the whole network. In fact, an actor with a high betweenness centrality measure represents a cut-point (“mandatory bridge”) along the shortest path connecting two other players in the market (Newman, 2005). Therefore, it might be able to control and direct the flow of information, resources, and opportunities, acting as a “gatekeeper” inside the network.

According to Tsai (2001), actors that occupy a central position in the network, in the betweenness sense, manage to have access to diverse strategic resources and information thanks to their intermediating roles between other players. Like closeness centrality, also Betweenness Centrality depends both on direct and indirect

[9] Where *n* is the number of nodes (players) in the network analysed.

connections, and it captures the centrality of each node with respect to the entire network.

From a computation standpoint, we define $G_i\ (k,j)$ as the number of shortest paths between node k and node j passing through player i. We also define $G\ (k,j)$ as the total number of shortest paths that links node k and node j. Betweenness centrality for player i, is then calculated as

$$\text{Betweenness centrality}_i = \sum_{j \neq i \neq k} \frac{G_i\ (k,j)/G(k,j)}{(n-1)(n-2)/2}$$

The normalized measure, which will be used in the second set of research questions, is obtained dividing the betweenness centrality by the maximum possible measure in the network, expressed as a percentage.

3.2.4. Eigenvector Centrality (Bonacich Centrality)

The Eigenvector Centrality is a measure of prestige of an actor inside the network. Differently from the other centrality measures, the Eigenvector Centrality measures the status of a player in the network depending not only on the number of connections but also on the “quality” of these ties. This centrality measure, introduced by Bonacich (1987), uses an iterative process which weights the centrality of each player by the centrality of its connections. According to this metric, the importance of a player inside the network depends, iteratively, from the importance of the player’s neighbours.

In our study of private equity club deals network, it thus measures the extent to which a private equity firm is connected to other well-connected peers (Hochberg, Ljungqvist and Lu, 2007). In a co-investment context, as the one of club deals, high-status investors are likely to receive more invitation to join club deals because of the legitimacy they confer to the other investors involved in a deal.

As developed by Bonacich (1987) Eigenvector Centrality is calculated as follow. Let R be the matrix of relationships which is also called Sociomatrix or Adjacency Matrix in the social network analysis. The (i,j) element of the Adjacency Matrix, is R_{ij} and it is equal to the number of ties that exist between players i and j , and equal to zero otherwise. The Adjacency Matrix is symmetric and the elements of the main diagonal of the matrix R are all zero. The Eigenvector Centrality for the player i (ev_i) is given by the following expression

$$\lambda\, ev_i = \sum_j R_{ij}\, ev_j$$

where λ is a constant required so that the equations have a non-trivial (non zero) solution. In matrix notation we have

$$\lambda\, ev = R\, ev$$

where ev is an eigenvector of R, and λ is its associated eigenvalue (Bonacich, 1987).[10] The centrality metrics for all the players in the network will be the elements of the principal eigenvector ev.

3.2.5. Closeness Centrality

A second measure of the prominence of a player in the network is the *Closeness Centrality* measure. Closeness Centrality measures how close a vertex is located to all the others in the network. This measure can be only calculated for fully connected networks, and being a local measure, it is computed for every player.

Closeness Centrality measure the strength of both direct (first degree) and indirect connections, therefore, differently from degree centrality, it is influenced by the position of the player with respect to the whole network. A high value for the Closeness Centrality is associated with an efficient use of information and resources available in the network. In fact, short distances among nodes implies shorter time to reach any other player in the network and ultimately lower transaction costs. Intuitively, the player with the highest closeness centrality (lowest total distance to all other nodes) is the one that relies less on intermediaries to build relationships with other nodes in the network.

[10] Usually, the largest eigenvalue is the preferred one (Bonacich (1987)).

From a computation standpoint, closeness centrality is computed as the inverse of farness, where farness is defined as the sum of the shortest distance between a vertex and every other vertex in the network. Defining $d\ (i, j)$ the number of steps in the shortest path between node i and j, the closeness centrality for a given player i in the network will be

$$Closeness\ Centrality_i = \frac{n-1}{\sum_{j \neq i} d(i,j)}$$

3.2.6. Centrality of the entire network

Besides the measures of centrality calculated above, for each single player in the network, it is possible also to calculate a measure for the centralization of the whole network. The measure of network centralization indicates the extent to which a single actor dominates the entire network (Ahuja, 2000). High value for the centralization index indicates a network in which all the connections activity happens with one central player, and there is less connection activity between other firms. An example of a maximum centralized network is the star graph. On the other hand, if all nodes in the network have approximately the same number of connections the centralization index will display a low value (circle graph).

3.2.7. Structural Holes and Effective Size

Another important measure that can be calculated for each player in the network is the *effective size* developed by Burt (1992) as part of the Structural Hole theory. As firstly defined by Burt (1992, p.18), a structural hole is "…a relationship of non-redundancy between two contacts". Contacts are defined "redundant" when "…they lead to the same actors in the network and therefore they provide the same information benefit" (Burt, 1992, p.17). Structural hole acts as the only bridging connection between two otherwise disconnected networks. As a consequence of this bridging ability, a player that have many non-redundant connections (structural hole position) has a high brokerage power. According to this theory, networks characterized by a sparse structure are more efficient and provide more information benefits compared to the ones with dense structure. In fact, in a sparse network, each player act as a bridge towards a non-redundant source of information.

One of the measures of structural hole developed by Burt (1992) is *Effective Size.* Effective size is the number of non redundant contacts that a player has in the network. Being a measure of brokerage role of a player inside the network, the results of this statistic will be compared to the ones obtained with the Betweenness Centrality. The *Effective Size* of the network of player i is calculated as follow

$$Effective\ Size_i = \sum_j \left[1 - \sum_q p_{iq}\, m_{jq}\right] \qquad with\ q \neq i, j$$

where $\boldsymbol{p_{iq}}$ is the ratio between the interactions of i with q and by the sum of all the relations of i and $\boldsymbol{m_{jq}}$ is the ratio between the interactions of j with q and the strongest relation of j with anyone else.

3.2.8. Cohesiveness: Cliques, Density and Geodesic Distance Measures

Other three measures that do not belong to the set of the centrality measures but help to describe the structure and evaluate the cohesiveness of the whole network are Cliques, Density, and Geodesic Distance.

Clique is defined as a maximally connected sub-graph containing three vertices or more. Within a clique, all nodes are connected to every other node. Networks characterized few large cliques that contain a lot of players are considered cohesive, while a large number of cliques but containing few nodes is an index of low cohesiveness of the network.

Network Density is defined as the ratio between the number of actual connection with the number of potential connection in the network. A low level for this density measures indicates low cohesiveness of the network.

A further important measure, useful to better understand the whole structure of the network arising from private equity club deals, is the geodesic distance measure. Geodesic distance is defined as the shortest distance (optimal path) between any two nodes of the network. The highest the geodesic distance connecting the dyads, the lowest is the cohesion of the network, as it will be composed mostly by indirect relationships. In the next session, we will calculate all these metrics along with a graphical representation in order to gain an understanding of the structure of the network under analysis.

3.3. Empirical Evidence from the Social Network Analysis

To calculate all the previously mentioned metrics that allow to describe the structure of the social network and the prominence of the single players in it, it was essential to build the Adjacency Matrix or Sociomatrix. In graph theory, a Sociomatrix is a square diagonal matrix that is used to represent a finite graph, and in our study, it represents the matrix of relationships between investors. The rows and columns of this matrix are the 225 Private Equity Firms of our sample described above. In the 225x225 matrix, the elements of the main diagonal are all zero, while each element (i, j) is equal to the number of connections that exist between player i and player j. In our analysis of private equity club deals, a connection between two players is registered every time they form a consortium together.

To calculate the centrality measures described above and the metrics for the entire network of private equity club deals, we decided to use the software UCINET. UCINET (used in the version 6.0) is a software developed by Borgatti, Everett and Freeman (2002), specifically for the social network analysis.

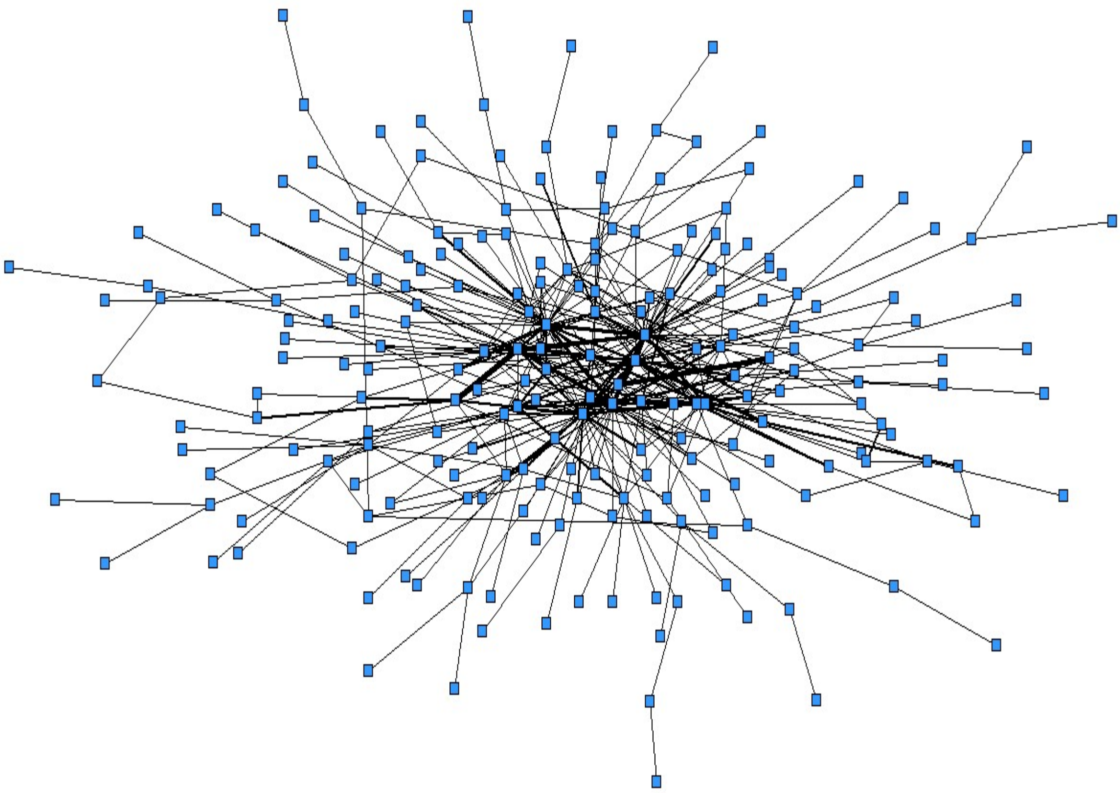
We will now describe the key findings of our analysis of the network of private equity firms arising from consortium formation.

3.3.1. Graph Representation

First of all, to better understand how the network is structured, we can rely on a graphical representation of it. Exhibit 2 illustrates the entire network under analysis. Due to the high number of players in the full network (225), the labels and the graph may result quite unclear and we decided not to plot them. However, from the picture, it is still possible to see how the majority of the relationships are concentrated among the few most central players. The thickness of the line linking any two funds is directly proportional to the number of repeated relationships between the two players. From this particular configuration of the lines, we can already spot a small world of relationships between the most central players.

For illustrative purpose only, and to better visualize a network of consortium relationships between Private Equity firms, we drew the network for the most central players. The result is presented in Exhibit 3. We select only the private equity firms with a degree centrality above 5% (21 players in total), and we plotted the network for their relationships. Also from this graph, it is possible to have a sense of the role played by some of the most prominent funds such as The Blackstone Group, KKR and the private equity arm of Goldman Sachs.

Exhibit 2. Graphical Representation of the Entire Network



3.3.2. Evidence from the Centrality Measures

Table 9 illustrates the summary statistics for the four centrality measures in our analysis and for the structural hole effective size of a player's network. In order to make meaningful comments on the prominence of single private equity firms in the network, Table 10 illustrates the centrality measures for each of the players. For space reasons, in Table 10 we did not include all the 225 firms but we selected only the 60 with the largest value for the Betweenness Centrality measure. The table is sorted firstly by Betweenness Centrality, secondly by Eigenvector Centrality and lastly by Closeness Centrality.

First of all, we can comment on the overall centrality of the network. The index centrality measures we calculate is equal to 20.5%. The number per se indicates that the network is not organized around a single player (as in a star graph which has a centralization 100%) nor as a circle graph (centralization of 0%). This value of 10.5% can be compared with the centralization values for other kinds of networks in the literature. Castilla (2003) obtained a network centralisation index of 8.46% in its network analysis of Venture Capital firm in Silicon Valley between 1985 and 1998. In the study of the co-investment network of Sovereign Wealth Funds, Gianfrate and Merlin (2016) reported a network centralisation index of less than 10% for the period 1984-2014. Finally, in the analysis of the collaborative network between US Chemicals company, Ahuja (2000) observed an average network centralization index of 18.5% for the period 1981-1991.

Degree Centrality Table 9 summarizes the Centrality Degree Statistics. The total degree centrality (sum of the degree centrality of every firm) is 1055, which means that exist 1055 direct ties among the nodes of the network. The mean degree centrality is 4.69, indicating that on average each private equity firm in the network experienced an alliance with approximately other five different players, for the period under analysis. The high value for the standard deviation (9.09) clearly indicates that a small subgroup of actors in the network are significantly more prominent than others. The maximum number of ties is 66, which is held by The Blackstone Group, and corresponds to a normalized degree centrality of 29%, meaning that this particular private equity firm had experience of club deal with nearly 30% of all the other possible players in the sample. Having such a high number of relationships has certainly helped The Blackstone Group to increase its social capital and to establish itself as a reputable partner in case of consortium investing. Beside The Blackstone Group, only other three firms in the network (Goldman Sachs, KKR, TPG Capital) had ties with more than fifty other players, underlying their prominence in the network. In particular, we have the private equity arm of Goldman Sachs with 56 ties, KKR with 51 ties and finally TPG Capital also with 51 ties. In term of degree centrality, and therefore number of connections developed through the years, the first European based fund, ranked 7th in the sample, is CVC Capital Partners with a total of 25 ties. The chart in Exhibit 4 illustrates the frequency (percentage) distribution of degree centrality in our sample. From the chart, we see that the large majority (82%) of private equity firms in the sample has only experienced a partnership with less than 5 different other players, and 43% of them formed a consortium with only one different PE firm in the sample.

Betweenness Centrality Table 11 and Table 9 illustrates the Betweenness Centrality values and summary statistics for the firms in our sample.
First of all, an important modification of the ranking of the firms, compared to Degree Centrality can be observed. The player with the highest Betweenness Centrality measures, and therefore the highest brokerage power in the network, is the private equity arm of Goldman Sachs. This high brokerage power result might be due to the nature of this particular player, being the private equity arm of one of the leading global investment bank. Besides Goldman Sachs, the next five PE firms that scored the highest in term of Betweenness Centrality are also the ones with the highest value of degree centrality, and they are The Carlyle Group, TPG Capital, The Blackstone Group, KKR and Bain Capital. However, we can notice how The Blackstone Group, which was the players with the highest number of ties in the sample, now is ranked only fourth, according to Betweenness Centrality. This means that, despite having many ties, it tends not to lies in the shortest path connecting other dyads, and so it is less important for the resources (information) flow, compared to other funds.

It is important to notice that two European based funds, CVC Capital Partners and BC Partners, showed a particularly high value for Betweenness Centrality (ranking seventh and eighth), this may be an indicator of the high brokerage power of this two European funds, and their importance for accessing deals, and country-specific capabilities, in European countries. Particularly for the private equity firm BC Partner, it is important to notice how it ranked only 19th in term of Degree centrality with only 12 ties, while eighth in term of Betweenness Centrality. This result is important as it clearly indicates that the brokerage power of a firm in the network does not strictly depend on the number of ties it has. Further evidence of this statement is given by the firm Cerberus Capital Management. It is ranked 28th in term of degree centrality with only 8 ties, while it is ranked 10th in term brokerage power, indicating the importance of the bridges it created between other private equity firms.

Overall we can observe a very high standard deviation, indicating that only a small group of private equity firms have a high brokerage power while the majority are less important for the efficient flow of resources inside the network. In fact, half (113 out of 226) of the players in the network has a Betweenness Centrality of zero, meaning that those players never lie in the shortest path connecting each dyad. Graphically, those players stand at the far ends of the network, and they are in a way excluded from the network of efficient information flow, as can be seen from Exhibit 2. Exhibit 5 illustrates the frequency distribution for the Normalized Betweenness Centrality, which is obtained dividing the betweenness centrality by the maximum possible measure in the network.

These observations provide the first evidence to the fact that only the small group of private equity firm mentioned above, have to be considered the most central and prominent ones in the network. Being able to develop a tie with these funds (participate in a consortium with them), is considered beneficial for a player as it offers the possibility to quickly access the entire network and increase its social capital.

As explained above, the effective size developed by Burt (1992) in the Structural Hole theory, is an alternative measure of the brokerage power of a player in a network. The results we get with the Structural Hole effective size are in line with the result we got for the Betweenness Centrality. In fact, the highest number of non redundant connections is recorded for the private equity arm of Goldman Sachs, strengthening the evidence of its brokerage power in the network.

Eigenvector Centrality The measure of Eigenvector Centrality allows us to answer the question about the level of prestige of a private equity firm in the network. As explained before, this measures takes into account not only the number of connections but also the quality of these connections. Values and summary statistics for the Eigenvector Centrality are reported in Table 9,10 and 11. Despite a slight modification of the ranking, the results for this measure follow closely the ones for the Degree Centrality. The most prestigious private equity firm (in the Bonacich (1987) sense) is the Blackstone Group (with a measure of 0.64), which was also the player with the highest number of first degree connections (highest Degree Centrality). Following in the ranking of prestige, we found KKR, the private equity arm of Goldman Sachs, Bain Capital and TPG Capital. Exhibit 6 illustrates the distribution of Eigenvector Centrality, and it is possible to see how the large majority of players have a nil value for this measure. This, together with the high standard deviation for this measure, indicates that only a very limited number of players have connections with other prominent funds, thus giving an evidence of the existence of a small world of relationships between the most prestigious private equity firms.

Closeness Centrality From the values and the summary statistics of Closeness Centrality we can see a modification of the rank compared to the Degree Centrality. As previously explained, the high values for Closeness Centrality are a proxy for an efficient use of the network. In our analysis, the highest value of this measure is held by The Carlyle Group, which was ranked only fifth in term of degree centrality. This means that The Carlyle Group, despite having a lower number (47) of first degree connections compared to other more connected firms, it is the player that is closest, in a social network sense, to all the other private equity firms in the dataset, making the most efficient use of its relationships. From Exhibit 7, it is possible to see that the distribution of this measure is not skewed as the previous centrality measures. This indicates that the number of steps to reach any other node in the network (farness) is evenly distributed in the sample.

3.3.3 Evidence for the Cohesiveness of the Whole Network

The density of the whole network under analysis is only 4.2%. Recalling the definition of density, this means that of all the possible connections that an actor can establish, on average only 4.2% of them are actually established.

Another way to examine the cohesiveness of the network is by looking at the cliques. A clique is defined as a maximally connected sub-graph containing three vertices or more. Table 12 reports the number of cliques for each size (number of players involved). There are 108 cliques in total. The largest cliques contain only 6 players and account for 7% of the total, while 87% of the total cliques contain 4 or fewer players. This high number of cliques with few players in them is a clear indicator of the low level of cohesion of the network, confirming the comment we made about the density.

The final measure we include in our analysis to have an idea of the cohesion of the network arising from private equity club deals is the Geodesic Distance measure. Table 13 shows for each possible value of geodesic distance in the network, the proportion of dyads connected by that distance. The most frequent geodesic distance connecting any two nodes is 3 (35%), meaning that they are only mutually reachable by the intervention of 3 intermediary firms. Only 2% of all the possible dyads in the network have a direct relationship (geodesic distance of 1). The longest geodesic distance is 9, which represents the most indirect relationship in the network. This result show that the network is made mostly by indirect ties and it further confirms the evidence of low cohesiveness of the network.

4. Determinants of Private Equity Consortium Formation

The second set of research questions are answered through the construction of a logistic regression model on 1562 private equity deals (both sole sponsored and club deals) from 2000 to 2017. In this analysis, we want to build a model for the probability of consortium formation in private equity deals.

The dependent variable of our analysis is the binary variable indicating the presence of a club deal in the sample, equal to one if the acquisition is made by a consortium private equity firms and zero otherwise.

Beside testing target's and fund's specific variables already analysed by the relevant literature, our focus will be on the significance and economic effect of the different network centrality measures on the probability of consortium formation. In particular, our main research questions will be:

1) Is there a positive and significant correlation between holding a central position in the network and the probability of consortium formation between private equity firms?

2) Among the different measures of network centrality, which are the ones with the largest economic effect on the conditional probability of consortium formation? Which are the ones that lead to the construction of a better model?

4.1. Methodology

Since dependent variable of our interest is a binary outcome ($y = 1$ if there is a Club Deal, 0 otherwise) in order to investigate the determinants of club deals formation and test our hypothesis we decide to employ a Logit Model. In particular, we wish to evaluate the impact of our independent variables ($\boldsymbol{x}$) on the probability of Club Deal formation, and to do so , we model $Pr(y = 1|x)$ as a function of $\boldsymbol{x}$.
Since $0 < Pr(y = 1|x) < 1$ a suitable functional form for $Pr(y = 1|x)$ is any cumulative distribution function evaluated at a linear combination of $\boldsymbol{x}$.

$$Pr(y = 1|x) = F(x'\beta)$$

In the case of the Logit model we have that the cumulative distribution function is the Logistic distribution with with zero mean and variance $\pi^2/3$:

$$F(x'\beta) \equiv \Lambda(x'\beta) \equiv exp(x'\beta) / [1 + exp(x'\beta)]$$

Being $F(x'\beta)$ a cumulative distribution function, the binary model can be motivated as a latent regression model:

$$y^* = x'\beta + \varepsilon \text{ and } y = 1[y^* > 1]$$

where y^* is the latent continuous random variable and ε is a zero mean random variable that is independent from $\boldsymbol{x}$ and with $\varepsilon \sim F$, where F is the Logistic cumulative distribution function. Logit models are also called index models as they restrict the way that the probability depends on x as it depends on $\boldsymbol{x}$ only through the index of $\boldsymbol{x}$.
In a logit model the estimation of the parameters is carried out via Maximum Likelihood Estimation. As common when dealing with a multi-year panel, we include in the Logit model the Year fixed effects. This should help to capture the different level of activity of the Private Equity market across the years of the sample.

The β coefficients presented in the univariate and multivariate regressions (Tables 15 and 16) cannot be interpreted as a marginal effect, as it is done in an OLS setting, as within the Logit model, the relationship between the dependent and independent variables is not linear in nature.

However, in the Logit model, it is possible to work out the marginal effect by using the chain rule of derivation. The marginal effect of x at observation i are estimated by Logit model as:

$$(\partial_x F_i)_{logit} = f_{logit,i} b_{logit} = \Lambda\left(x_i' \, b_{logit}\right)\left[1 - \Lambda\left(x_i' \, b_{logit}\right)\right] b_{logit}$$

This can be easily implemented with Stata using the post-estimation command *margins* with the option *dydx (varlist)*. We calculated the marginal effects for the main models in Table 18 in Appendix. Marginal effects can be described as a change in outcome (in our case probability of club deal) as a function of the change in the independent variable, holding all other variables in the model constant.

As an alternative to marginal effects, another way to present the results of a binary model (as the Logit model) is to use the odds ratio derived from the logistic regression. However, for the purpose of this thesis, we decided to use marginal effects as we believe they represent a better and more meaningful metrics to describe the results.

A further issue in the context of logit analysis is the lack of a measure analogous to the R^2 statistic as in the Ordinary Least Square Setting. Various alternatives for the goodness-of-fit measures have been developed in the literature. For the purpose of this paper, we will employ the McFadden Pseudo R^2 developed by McFadden (1973) as follow

$$McFadden\ Pseudo\ R^2 = 1 - \frac{L(\beta)}{L(\bar{y})}$$

where $L(\beta)$ is the value of the maximized log-likelihood for the model and $L(\bar{y})$ is the value of the log-likelihood evaluated for the model with only the intercept and no covariates (null model).

As in the traditional OLS setting, also the McFadden Pseudo R^2 always increases as the number of predictors increase. To make the measure more meaningful, is it possible to adjust the McFadden Pseudo R^2 to take into account the number of independent variables in the model (model complexity). Defining k the number of independent variables in the model, the adjusted measure is the following

$$Adjusted\ McFadden\ Pseudo\ R^2 = 1 - \frac{(L(\beta) - k - 1)}{(L(\bar{y}) - 1)}$$

Another way to compare the plausibility of two logit model and taking into account the model complexity is to consider the Bayesian Information Criterion (BIC) and Akaike Information Criterion. For two information measures the smaller the value the better the fit of the model under consideration, and are calculated as follow

$$AIC = -2L(\beta) + 2p$$
$$BIC = -2L(\beta) + \ln(n)\, p$$

where p is the number of predictor in the model and n the number of observations.

4.2. Explanatory Variables Description

Besides testing the significance of the four network centrality measures outlined in the first part of this thesis, which represents the main goal of this research, we will also study the role transaction-specific and firm-specific factors tested in the literature and briefly described below. In case of club deal in the sample, all the variables related to the private equity firms (network centrality measures and funds under management), are calculated for the lead investor of the club, as described in the sample selection. The descriptive statistics of all the variables used in our models can be found in Table 14.

Target Size

To measure the size of the target when the acquisition took place we decided to use the total Enterprise Value ($m) of the transaction, including both debt and equity arrangements, reported by Zephyr database. In the club deal literature, it is possible to find examples of target size measured only considering the equity value, as did by Officer, Ozbas and Sensoy (2010) or considering the total enterprise value of the transaction (debt plus equity value) as did by Meuleman *et al.* (2009). Since our sample is constituted both by public and private targets, the equity value of the transaction isn't always disclosed, therefore we decided to use the total enterprise value.

Private equity funds are usually constrained for investing more than a certain percentage of their total committed capital in a single investment (Axelson, Stromberg

and Weisbach, 2007), therefore we would expect target size to be a significant determinant of club deal formation.
As already mentioned in the sample descriptive statistics (Table 4), the distribution of this variable in the sample is positively skewed, with the presence of big outliers both for sole sponsored deals and club deals. For this reason, in the logitstic regression, we used the natural log of this variable.

Management Buyout Dummy

Dummy variable equal to one if the transaction is a Management Buyout, and zero otherwise. This Classification was based on definition of Management buyout (and management buy-in) given by Zephyr database. The database classifies a transaction as a management buyout when all or some of the existing management of the company (or an external management team in the case of management buy-in) buy at least 50% of the company from its existing owners, together with the help of one or more private equity firms. On average management buyout deals represent nearly 6.0% of the total deals. This percentage decrease to 5.7% among club deals and increase to 6.1% in sole sponsored deals, as reported in Table 5. From the statistics, we can already see that management buyout deals are evenly distributed between the two subsample, and therefore we already expect a low significance for this variable.

Public to Private Dummy

Dummy variable equal to one if the transaction is a takeover of a public traded company and zero otherwise. The majority of previous studies related to consortiums of private equity firm was focused only on public takeovers. In our study, we decided to have a wider scope and include also private company acquisitions and acquisition of divisions of private companies. In our sample, public takeovers account for 34% of the overall number of deals. This percentage is significantly higher for club deals where public takeover accounts for 41% of the deals, while it is lower (32%) for sole sponsored private equity transactions, as reported in Table 5. Therefore, we expect this variable to have a discriminatory power in the probability of club deal formation.

Co-Investment Dummy

This dummy variable is equal to 1 if the deal is participated by co-investment (different from private equity firm) and zero otherwise. We decided to include this dummy

variable to test if the presence of co-investors (typically Pension Funds, SWFs, Endowments, Family Offices) has a positive and significant effect on the likelihood of club deal formation. In fact, the presence of a co-investor, which can be a limited partner of multiple private equity funds, may facilitate the formation of a consortium acting as a bridge and catalyst of relationships between multiple funds.
In our sample, 14% of the total deal was characterized by equity co-investments. This percentage is slightly higher for club deals where the percentage is 16%, as reported in Table 5.

Geographic Concentration

Dummy variable equal to 1 if at least one of the private equity firm in the consortium (or the sole sponsor in case of) has an office in the same geographic location where the target is incorporated. This variable tries to capture the tendency international of private equity firm to partner with local players in order to gain access to local expertise and incremental investment opportunities. The average value of this variable is 96% for club deals while 86% for sole sponsored deals as reported in Table 5. We would expect a positive and significant coefficient for this variable, confirming the resource motivation for building consortiums.

Pre 2006 Dummy

We tested the significance of the Pre 2006 Dummy variable which is equal to 1 if the deal was completed before 2006 and o otherwise. This variable, already tested by Officer, Ozbas and Sensoy (2010) and by Boone and Mulherin (2011), is used to control for any difference in the probability of consortium formation prior 2006, which is when the US Department of Justice started an investigation into the possible collusive effects of private equity Club Deals.

Target Industry Dummies

Each target company has been grouped in the ten different industries reported in Table 2 and ten different industry dummy variables were created accordingly. The industries have been identified using the two digits US Standard Industrial Classification (two-digit SIC codes), and the relevant descriptive statistic can be found in Table 2. For any model to be correctly specified and avoid perfect multicollinearity problem only nine of the ten industry dummy variables will be used in the model.

Investor Size

This variable measures the size of each private equity firm in our sample, by considering the amount of funds under management ($m). The amount of funds under management were not directly provided by Thomson One Banker. In fact, the database only provides the characteristics (name of the fund, investment focus, year, committed capital) of the funds raised by each private equity firms through the years. Using the same procedure of Hochberg, Lindsey and Westerfield (2011), we computed the funds under management for each private equity firm as the sum of the total capital committed to its currently active funds, where a fund is considered to be active for ten years since its initial raising. The descriptive statistics for this variable are summarized in Table 6 and Table 8. As reported in Table 8 the distribution of this variable positively skewed, with the presence of big outliers. For this reason, we considered the natural log of this variable when running the logistic regressions.

4.3. Results

4.3.1. Univariate Logistic Regressions

We first run univariate logistic regression models for all the variables described in the previous paragraph on the dependent Club Deal dummy variable in order to understand if whether it is meaningful to insert all the variable in the final model. In particular, we examined the explanatory power, sign and robustness of each variable. The coefficients (and their significance level), z-stats, and McFadden Pseudo R^2 of the univariate regressions are reported in Table 15.

A clear positive relationship between Deal Value and the dependent dummy variable was observed. In particular, the model yields a coefficient of +0.565, with a McFadden Pseudo R^2 of 3.3%, making it the most relevant variable in the model.[11]
The coefficient is statistically significant at more than 1% level (z-stat at +7.63) confirming the “financial motive” for club deal formation as analysed by Meuleman *et al.* (2009) and Officer, Ozbas and Sensoy (2010) for the Private Equity industry and by Manigart *et al.* (2006) for the venture capital industry.

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[11] The decision to use the McFadden Pseudo R^2 has been discussed in the Methodology session (4.1).

As far as the industry dummies are concerned the univariate logit model yielded results that are in line with the industry descriptive statistics. A positive and significant coefficient has been found for Transportation et al. dummy +0.4 (z-stat 2.43) and for Finance and Insurance dummy +0.37 (z-stat 2.11).[12] Despite the low level of pseudo R^2 (0.72% and 0.24%, respectively), the results indicate that these represent the two industry where club deal happens with the higher probability in the sample. On the other hand, a negative and significant coefficient -0.46 (z-stat -3.56) has been found for the Manufacturing dummy, indicating the negative relationship between consortium formation and the manufacturing industry.[13] No other industry dummy coefficients have been found significant at the usual confidence level. According to these results about the industry classification, we decided to insert in the final multivariate models only the dummy related to Transportation et al., Finance and Insurance and Manufacturing.

We found a positive and statistically significant relationship, +0.41 (z-stat 3.48) between our dependent variable and the Public to Private Transaction dummy, indicating a higher probability of club deal formation in the case of public takeover transactions rather that private acquisitions or carve-out transactions.

The univariate regression on the Geographic Concentration dummy variable yields a coefficient that is positive and statistically significant, +1.36 (z-stat 3.48), with a considerable Pseudo R^2 for the model (2.05%). This contributes to support the thesis of “incremented deal flow” as a reason for club deal formation, as international private equity firms, tend to form alliances with local players to gain access to specific deals in the region of expertise of local players.

We did not find any statistical evidence for the relationship between management buyout dummy and club deals, the coefficient of -0.01 and z-stat too low (-0.29) to reject the null hypothesis at any level of confidence.

Surprisingly, no statistical evidence has been found on the expected positive correlation of Club Deal and presence of co-investors (typically Pension Funds, SWFs, Endowments, Family Offices). The sign of the coefficient is positive, as we expected, however, the coefficient is not statistically significant. Therefore, in this case, we reject

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[12] The original SIC code include also Real Estate, however, in the sample selection we decided to exclude this Industry in order to focus only on Corporate Private equity and not on Real Estate Private Equity.

[13] According to the US SIC classification, the manufacturing industry comprises a wide range of sub industries such as Food&Beverage, Tobacco, Chemicals, and Industrials.

the hypothesis, that co-investors might play a catalyst role in consortium formation between Private Equity firms.

As already pointed out by Officer, Ozbas and Sensoy (2010) and by Boone and Mulherin (2011), we find a positive and statistically significant coefficient between our dependent variable and the dummy variable pre-2006, indicating that the likelihood of consortium formation was higher prior 2006, year in which the US Department of Justice launched an investigation into the possible collusive effects of private equity club deals.[14] In the multivariate models, in which we employ Year fixed effect, this variable was not included in order to avoid a one-way causation problem.

Finally, we find positive and statistically significant evidence between the dependent Club Deal dummy variable and all the different variables that describe the centrality of the private equity firms inside the network. Degree, Betweenness, Eigenvector and Closeness Centrality, all yield a positive coefficient as we would have expected, indicating that better networked players are more likely to form a consortium. Although the Pseudo R^2 of each univariate regression is not very high, the coefficients are all statistically significant at a more than 1% confidence level. In the next session, we will identify which of these network centrality metrics (which are all highly correlated with each other) has the largest economic effect on the likelihood of consortium formation.

In addition to this, we also run a univariate logit model between the dependent variable and the Size of the lead private equity firm. The coefficient -0.1 (z-stat -1.9), is negative and statistically significant, indicating that private equity firms with more funds under management are less likely to form a consortium when they decide to acquire a company. This result confirms again the “financial motive” for club deal formation, indicating that capital constrained firms are more likely to engage in club deals.

4.3.2. Multivariate Models for Consortium Formation

Table 16 presents the results of the multivariate logit models that try to predict the conditional probability of consortium formation among private equity firms when

[14] For running this regression, the Year fixed effect was not used otherwise the model would have had a one-way causation problem.

pursuing acquisitions. As mentioned above, for all these models we included Year fixed effect to capture the size of the PE market across the years.

In the first model, we start by inserting the relevant variables referring to the characteristics of the transaction. The first model yields a positive and significant coefficient for the size of the deal and for the geographic expertise indicator.

In particular, the positive and significant coefficient for the size supports the "financial motive" for organizing a club deal. It is important to note that this does not involve endogeneity issues as already demonstrated by Meuleman *et al.* (2009), who use a number of instrumental variables to check this potential problem related to the size of the transaction.

On the other hand, the positive sign and the significance of the coefficient of the geographic concentration contribute to support the "resource based" theory of syndication (Bygrave,1987; Lerner, 1994), with international players that seek to build relationships with local ones in the countries where the target is located. Despite having the same sign as in the univariate regression the coefficient of the dummy variable indicating a public takeover transaction is no longer significant.

In the second model, we added the dummy variable for the relevant industries identified in the previous paragraph. Overall, the signs of the coefficients stay the same, however, the positive relationship between the dependent variable and the Transportation and Utilities industry is no longer significant at any confidence level. Considering the Adjusted McFadden R^2, it increases by 0.7 percentage point between regression (1) and (2). Despite the low level of R^2 (5.43%), from these two models we can conclude that transaction-specific characteristics and target's industry proved to be good determinants of private equity consortium formation.

In the third model, we add to the logarithm of the size of the lead investor in the transaction (in the case of no club deal the figure refers to the size of sole sponsor in the deal), measured by the funds under management, as explained in the variables description session. The rationale to add this variable is twofold. First of all, it helps to test the "financial motive" motivation for forming a consortium. In fact, as mentioned before, we would expect that larger funds will be less likely to syndicate or form a club as they would have enough capital themselves to conclude the acquisition. The second reason to add the variable, as expressed by Hochberg, Ljungqvist, and Lu (2007), is that it is used as a control variable for the Network Centrality measures used later. In fact, it is important to control that our measures of network centrality are not a mere proxy for the size of the private equity firm, but they are relevant indicators of the importance of the position of a player inside their network of relationships. The sign of this coefficient is negative as we would have expected, confirming the abovementioned financial motivation for club bidding. Adding this variable does not increase much the explanatory power of the model, the adjusted pseudo R^2 shows a really tiny increase. However, for the reasons explained above, we believe it is important to take into account this variable in our model.

From regression (4) to (7) we include the four metrics that measure the centrality position of a player inside the network, representing the most interesting findings of this thesis. We decided to include the centrality variables one at a time to mitigate potential problems of multicollinearity, as explained Hochberg, Ljungqvist, and Lu (2007). In fact, from the Pearson Correlation Matrix in Table 17, we can see that the network centrality measures are highly correlated with each other.

The first thing we can notice is that the Likelihood-Ratio Chi Squared Test indicates that all the coefficients included in the models are jointly significant at a more than 1% level. In fact, in the context of logistic regression, the Likelihood-Ratio Chi Squared Test for the entire model is used as a global test of parameters (test the null hypothesis that all the coefficients are zero against the alternative one that at least one is different from zero).[15] Overall, we can see that every coefficient related to the four metrics of network centrality is significant at more than 1% level. All the coefficients display a positive sign, meaning that, in general, holding a central position in the network (independently of the different possible meanings of centrality) have a significant and positive association with the likelihood of forming consortiums.

This outcome strongly supports the deal-flow motivation of consortium formation, in addition to the financial one. In fact, it suggests that private equity firms may have used club deals to strength existent relationships or developing new ones with their competitors in order to increase their deal flow, investment opportunities, as well as the exchange of information and sector or geographical capabilities (Huyghebaert and Priem 2016).

As already expressed in the methodology, the logit model is not linear. If we want to have information about the magnitude of the economic effect of these network

[15] Equivalent to the F-test in the OLS setting.

centrality coefficients on the likelihood of consortium formation, we should run the model again with the calculation of the Average Marginal Effects (AMEs). Results of the AMEs for models (4) to (7) are reported in Table 18.

Of the four network measures, Degree Centrality has the largest economic effect, followed by Betweenness Centrality and closely by Eigenvector Centrality. To illustrate, a one-standard-deviation increase for the first three measure is associated with a 5.9-8.4 percentage point increase in the probability of club deal formation, from the 27.08% sample average, holding other variables constant at their mean values.[16] From these results we can see how the conditional probability of forming a club is mostly influenced by the overall number of previous relationships that an actor in the network has (Degree Centrality), and on a second level by the ability of a player of acting as a broker inside the network (Betweenness Centrality).

Also having high-quality connections, or in other words having many connections with others well-connected players in the network (Eigenvector Centrality), revealed to be a significant and important determinants of the probability of club bidding, however, its magnitude effect (5.9 pp increase in probability for a one standard deviation increase) is lower compared to the magnitude effect of the two abovementioned metrics (respectively 8.4 pp for Degree Centrality and 6.3 for Betweenness Centrality).

These results, obtained for the private equity industry, are in line with the evidence obtained by Gianfrate (2016) for the Sovereign Wealth Found Industry. In fact, the authors show that the Betweenness Centrality measure, which indicates the ability of a player to act as a broker in the network, plays the most important role on the conditional probability of co-investment (compared to other centrality measures).

The economic effect of Closeness Centrality is very little (0.9 pp increase in probability for a one standard deviation increase). Recalling the definition of Closeness Centrality given in Section 3, this means that the conditional probability of forming a club is little influenced by the player being “close” to others players in the network (short path to reach any other players in the network), and the other measures of centrality definitely plays a more crucial role on the likelihood of consortium formation.

Besides the magnitude of the economic effect of the coefficients, from the original Logit model with year fixed effects (Table 16), we can gain an understanding

[16] $(dy/dx)_i * std.dev_i$

of the overall significance of the model and the explanatory powers of the different network centrality measures in regressions (4) to (7).

If we look at the McFadden R^2, we clearly see that the explanatory powers of the models increase when inserting the centrality measures, going from 6.7% to more than 8.5% on average. The regression model that reports the highest increase in Adjusted McFadden R^2, and thus with the highest explanatory power is the one that includes the Degree Centrality measure (Adj. McFadden R^2 increase by 1.97 pp from (3) to (4)), closely followed by the one that includes Betweenness Centrality measure (Adj. McFadden R^2 increase by 1.74 pp from (3) to (5)).

Therefore, from the analysis of the goodness of fit measures, we can confirm that, among all the centrality measures, the number of connections (Degree Centrality), as well as the ability to act as a broker (Betweenness Centrality) represent the most relevant determinants of the probability of consortium formation between private equity firms, confirming the results obtained when analysing the average marginal effects.

As already reported in the section regarding the Goodness of Fit measure, we decided to include at the end of each regression model also the *Akaike Information Criterion* (AIC) and the *Bayesian Information Criterion* (BIC), and to plot the *Receiver Operating Characteristic* (ROC) *curve* in order to identify the best model among the ones containing a Network Centrality metrics (from (4) to (7)). For the two Information Measures, AIC and BIC, the smaller the value of the statistic the better the fit of the model. Again, looking at the statistics reported under each model, we reach the same conclusion that we obtain when analysing the McFadden R^2, that is, the models containing the Degree Centrality and Betweenness Centrality are the preferred ones. The same conclusion can be derived by looking at the area under the ROC Curve for the models (4) to (7), plotted in Exhibit 8, in which the higher the area under the curve the better explanatory power the model has.

4.4. Diagnostic Checking and Controls

In the following sections, we check the regression diagnostics for our logit model and discuss usual problems in similar applications.

4.4.1. Linearity Analysis

In the logistic regression model, one of the assumption is that the logit of the outcome variable is a linear combination of the independent variables.
One way to check that the model is correctly specified in our case is the use of the Goodness of Link Test developed by Pregibon (1980).[17] After running the base logit model, this test rebuilds the model, using as predictors, the linear predicted value and linear predicted value squared, obtained from the original logit model. If the model is correctly specified, the coefficient of the linear predicted value should be statistically significant while the coefficient of the linear predicted value squared should not be significant.[18] We run this Link Test after models (4) to (7) and the results we get indicates that the Logit model is correctly specified.

4.4.2. Homoscedasticity Analysis

To see if the models suffer from a heteroscedasticity problem we run our final models (panels (4) to (7)) with the heteroscedasticity-consistent (HR) standard errors (Huber-White standard errors). The results of this new models are reported in Table 17. From the outputs, we can see that, despite the fact that the standard errors for all the variables slightly increased, no important changes in the overall significance or sign of the variables in models occurred. Hence, we can conclude that heteroscedasticity does not represent a big problem in our original models.

[17] Pregibon, D. (1980). "Goodness of link tests for generalized linear models". Journal of the Royal Statistical Society. Series C, 29(C): 15-24.
[18] Logistic Regression Diagnostics. UCLA: Statistical Consulting Group.

4.4.3. Multicollinearity Analysis

We can state that there is no relevant multicollinearity problem because the values reported in the bivariate Pearson correlation matrix (Table 17) are rather small. The only noteworthy correlations are the ones among the centrality measures. However, we already decided to add this measure one at a time to investigate which definition of centrality was the most determinant for the probability of club deal formation and avoid any multicollinearity problem. Furthermore, high correlation (slightly above 60% on average) can be detected between the centrality measures and the Log of the Size of the lead investor. However, this seems reasonable as we used the latter as a control variable for the centrality measures, to make sure that the position of a player inside the network was not a mere proxy of its size (funds under management). No other correlations are higher than 30%.

Also looking at VIF and Tolerance coefficients reported in Table 20 we reach the same conclusions. No variable has a high VIF factor or low Tolerance. In fact, all the VIF coefficient are smaller than 2, indicating no multicollinearity problem.

4.4.4. Endogeneity Analysis

We do not believe that our models suffer from an endogeneity problem for the following main reasons. First of all, all our network centrality metrics have been calculated only from the socio-matrix, thus only from the club deal sample (423) and is subsequently regressed on the whole set of observations (1561). Secondly, apart from Degree Centrality measure, which strictly depends on the number of club deals that a firm had participated to, all the other metrics depend from the structure of the network among the actors as a whole, and not only by the number of club deals they participated. In fact, in our dataset, we can see how many players, despite having a lower value for degree centrality, are assigned a high value for the other measures of centrality (Betweenness, Eigenvector and Closeness). Thirdly, we decided to implement the Smith and Blundell (1986) test of exogeneity, in order to investigate the possibility of our centrality measures not being exogenous. [19] This test requires the identification of

[19] The exogeneity test and the related Stata command *Probexog*, have been developed only for Probit models. However, we believe it is sensible to insert this analysis also for our Logit models, as we did not find any significant difference in the results when running our models using Probit instead of Logit model.

an Instrumental Variable for the suspected endogenous variable. We decided to use the variable *Age of the Private Equity Firm* as an instrument for the centrality metrics in our model. Looking at the outcome of the test in Table 21, we can see that for the models (4) to (7) we cannot reject the null hypothesis of the test (that the suspected variables are exogenous), meaning that the models are appropriately specified and that the centrality measures under analysis are not endogenous in the models.[20]

[20] Baum (1999, p.1): "Under the null hypothesis, the models are appropriately specified with all explanatory variables as exogenous. Under the alternative hypothesis, the suspected endogenous variables are expressed as linear projections of a set of instruments, and the residuals from those first-stage regressions are added to the model. Under the null hypothesis, these residuals should have no explanatory power".

5. Conclusion

In this paper, we collected data for 1562 transactions completed by 225 private equity firms between 2000 and 2017. Among them, nearly 27% represented a club deal. The main purpose of this paper was to understand the structure of the network of relationships between different private equity firms. After assessing this structure and the prominence of the players in it using the tools of the social network analysis, we exploited the logit model as a tool to test our hypotheses and we reached interesting conclusions.

Our first finding is related to the low cohesiveness and relatively high centralization for the entire network of private equity firms. In particular, we were able to see that the network is made mostly by indirect ties, and only 2% of all the possible dyads in the network have a direct relationship. Moreover, the relatively high centralization of the network, together with the high standard deviation for all the centrality measures indicates that the network is dominated by few central players, suggesting the existence of a “small world” of relationships.

Our second finding from the social network analysis is related to the different definitions of centrality. For each network centrality measure, we are able to observe a modification of the ranking for the most prominent players. An interesting finding, is related to the brokerage power of some private equity firms inside the network. In particular, we found that some players, despite having a lower number of connections, act as a broker of relationships between many players, increasing the resources exchange in the network. This evidence was confirmed both by the Betweenness Centrality measures and by the Structural Hole Theory.

From the second set of research questions, we were able to confirm the financial motivation for consortium formation. In particular, we found that the size of the target has a positive and significant effect on the likelihood of club deal formation. Moreover, we find evidence that larger private equity funds are less likely to build consortiums, as they will be less capital constrained compared to smaller players.

The key finding of this paper lies on the positive and significant coefficients of the centrality measures on the probability of consortium formation. In particular, we found that the Degree Centrality and Betweenness Centrality have the largest economic effect on the likelihood of club deal formation. This finding supports the idea that private equity consortiums are established not merely for capital constrain motivation or portfolio diversification (financial motivations) but also to increase the social capital and ensure future deal flow.

In conclusion, we believe that this paper gives a contribution to the current literature on club deals in private equity. On the one hand, it confirms some results found by previous researches. On the other hand, it offers many aspects of novelty, especially related to the description of the network of relationships, rarely described in the literature for the private equity industry.

However, sample characteristics and data quality still affect our analysis. Firstly, our database starts from 2000 and ignore all the relationships that private equity firms had already developed in the past. Secondly, our sample is strongly US-biased and we lack information about deals and firms, particularly in Asia and China. These two facts may lead to a misrepresentation of the importance of some funds in the network and to ignore consortiums established with Asian peers.

Finally, we should be aware that also possible misspecifications of our model might affect our analysis. Despite having implemented many of the relevant variables already tested by the previous literature, a large number of variables may have been omitted from the analysis. This is due to the fact that our database is mainly constituted of acquisitions of private companies, for which we do not have any reliable disclosure of accounting metrics. However, we tried to limit this problem of omitted variables using year fixed effects in most of our regressions.

An interesting area of exploration for further research would be an investigation of the effect of the network centrality measures on the performance of different private equity firms. However, this is highly dependent on whether accurate data for performance at the firm level (not each fund of the firm) can be obtained. Another interesting developement would be to investigate the effect of the centrality measures calculated in this paper on the pricing of leverage buyout transactions. Finally, an interesting area of research would be to replicate the analysis of the social network of relationships, made in Section 3 of this paper, also for other investors in the market. In particular, we believe that hedge funds and university endowment funds represent two unexplored areas, from the point of view of social network analysis.

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7. Appendix

7.1. Tables

Table 1. Sample by Year

This table reports the number of transactions per year in the sample period of 2000 to 2017. Private equity transactions are classified by year of completion. Data are reported for the full sample, and for the club deal and sole sponsored subgroups.

	All Deals	Club Deals		Sole PE Deals	
Year	N.of Deals	N. Of Deals	% Year	N. Of Deals	% Year
2000	30	11	37%	19	63%
2001	23	12	52%	11	48%
2002	34	8	24%	26	76%
2003	57	27	47%	30	53%
2004	79	23	29%	56	71%
2005	113	35	31%	78	69%
2006	152	50	33%	102	67%
2007	193	59	31%	134	69%
2008	100	34	34%	66	66%
2009	21	7	33%	14	67%
2010	82	23	28%	59	72%
2011	91	23	25%	68	75%
2012	86	19	22%	67	78%
2013	92	11	12%	81	88%
2014	110	24	22%	86	78%
2015	97	13	13%	84	87%
2016	82	23	28%	59	72%
2017	120	21	17%	99	83%
2000-2017	**1562**	**423**	**27%**	**1139**	**73%**

Table 2. Target Industry

This table reports the number of transactions per Industry in the sample period of 2000 to 2017. The classification is based on the US *Standard Industrial Classification* (SIC 2 Digit Code). Data are reported for the full sample, and for the club deal and sole sponsored subgroups.

	All Deals		Club Deals		Sole PE Deals	
Industry Categories (two digits SIC Codes)	N.of Deals	% Total	N. Of Deals	% Total	N. Of Deals	% Total
Agriculture, Forestry, Fishing (01-09)	8	0.5%	1	0.2%	7	0.6%
Mining (10-14)	28	1.8%	11	2.6%	17	1.5%
Construction (15-17)	17	1.1%	1	0.2%	16	1.4%
Manifacturing (20-39)	484	31.0%	102	24.1%	382	33.5%
Transportation, Communications, Electric, Gas and Sanitary service (40-49)	195	12.5%	67	15.8%	128	11.2%
Wholesale Trade (50-51)	55	3.5%	13	3.1%	42	3.7%
Retail Trade (52-59)	141	9.0%	41	9.7%	100	8.8%
Finance, Insurance (60-67)	168	10.8%	57	13.5%	111	9.7%
Services (70-89)	461	29.5%	128	30.3%	333	29.2%
Public Administration (91-97)	5	0.3%	2	0.5%	3	0.3%
Total	**1562**	**100.00%**	**423**	**100.00%**	**1139**	**100.00%**

Table 3. Target Geography

This table reports the number of transactions per geography in the sample period of 2000 to 2017. Data are reported for the full sample, and for the club deal and sole sponsored subgroups.

	All Deals		Club Deals		Sole PE Deals	
Geographic Area	N.of Deals	% Total	N. Of Deals	Percent	N. Of Deals	Percent
North America	732	46.9%	208	49.2%	524	46.0%
LATAM	15	1.0%	2	0.5%	13	1.1%
Continental Europe	308	19.7%	78	18.4%	230	20.2%
Northern Europe	75	4.8%	17	4.0%	58	5.1%
Southern Europe	103	6.6%	36	8.5%	67	5.9%
UK and Ireland	234	15.0%	50	11.8%	184	16.2%
China	4	0.3%	2	0.5%	2	0.2%
Asia (ex China)	38	2.4%	12	2.8%	26	2.3%
Australia and New Zeland	21	1.3%	6	1.4%	15	1.3%
Middle East, North Africa and Turkey	22	1.4%	7	1.7%	15	1.3%
Africa	10	0.6%	5	1.2%	5	0.4%
Total	**1562**	**100%**	**423**	**100%**	**1139**	**100%**

Table 4. Deal Size

This table reports the descriptive statistics for the size of the transaction in our sample for the period of 2000 to 2017. The size of the transaction is measured with the enterprise value of the deal. Data are reported for the full sample, and for the club deal and sole sponsored subgroups.

Deal Size Descriptive Statistics	All Deals	Club Deals	Sole PE
Average	1,533	2,219	1,278
Minimum	315	336	315
Maximum	59,588	59,588	29,972
Stand. Dev.	2,728	4,176	1,871
1st Quartile	584	663	554
Median	850	1,072	806
3rd Quartile	1,500	2,274	1,300
Mode	500	900	500
Kurtosis	162.1	93.5	94.1
Skewness	10.2	8.2	8.3
Observations	1,562	423	1,139

Table 5. Transaction Characteristics

This table reports the descriptive statistics for some of the transaction characteristics in our sample for the period 2000 to 2017. In particular, the table illustrates the presence in our sample of Management Buyout, Public to Private Transactions, the presence of co-investors and the indicator for the geographic concentration. Data are reported for the full sample, and for the club deal and sole sponsored subgroups.

Transaction Characteristics	All Deals	Club Deals	Sole PE
Management Buyout			
Average (%)	6.0%	5.67%	6.06%
Observations	1,562	423	1,139
Public Takeover			
Average (%)	34.3%	41.1%	31.7%
Observations	1,562	423	1,139
Co-Investment			
Average (%)	14.0%	16%	13.2%
Observation	1,562	423	1,139
Geographic Concentration			
Average	88.6%	96.0%	85.9%
Observations	1,562	423	1,139

Table 6. Funds Under Management

This table reports the average and the total funds under management of the private equity firms in our sample per year for the period 2000 to 2017. Data are in $m.

Year	Average	Total
2000	2,196	318,462
2001	2,616	408,027
2002	2,657	443,776
2003	2,791	485,670
2004	2,932	533,582
2005	3,526	673,450
2006	4,527	914,506
2007	5,550	1,137,817
2008	6,154	1,273,865
2009	6,362	1,323,325
2010	6,142	1,283,632
2011	6,340	1,331,491
2012	6,808	1,443,238
2013	7,473	1,584,301
2014	7,705	1,656,594
2015	7,844	1,670,711
2016	7,614	1,560,913
2017	7,202	1,454,762

Table 7. Geographic Presence of Private Equity Firms

This table reports the geographic presence of the private equity firm in our sample. For each geographic region we indicated the number of players with at least an investment office. We ten took compared this value with the total number of private equity firm in our sample.

Geographic Area	N. players with an office	% of Total PE firms
North America	156	69%
LATAM	16	7%
Continental Europe	58	26%
Northern Europe	13	6%
Southern Europe	30	13%
UK and Ireland	83	37%
China	56	25%
Asia (ex China)	47	21%
Australia and New Zeland	11	5%
Middle East, North Africa and Turkey	11	5%
Africa	4	2%

Table 8. Characteristics of Private Equity Firms

This table reports the descriptive statistics for the private equity firms in our sample. In particular, it illustrates the descriptive statistics for funds under management, age and global presence.

	Average	Minimum	Maximum	Stand. Dev.	Median	Mode	Observations
Funds under Management	5,082	84	40,245	7,433	2,436	1,500	225
Age	16	2	76	10	14	9	225
Global Presence	2	1	11	2	1	1	225

Table 9. Summary Statistics of the Social Network Measures

This table reports the descriptive statistics of the social network measures for the private equity firms in our sample. In particular, it illustrates the descriptive statistics for Degree Centrality, Betweenness Centrality, Eigenvector Centrality, Closeness Centrality and Structural Holes Effective Size.

	Average	Minimum	Maximum	Stand. Dev.	Median	Mode	Observations
Degree Centrality	4.69	1	66	9.09	2.00	1.00	225
Betweenness Centrality	274	0	5459	735	2.00	0.00	225
Eigenvector Centrality	0.038	0	0.649	0.086	0.013	0.00	225
Closeness Centrality	0.265	0.1	0.398	0.054	0.271	0.286	225
Structural Holes Effective Size	3.39	1	35.84	5.29	1.99	1.00	225

Table 10. Centrality Rankings

For each centrality measure this table reports the ten most prominent private equity firms in our sample. The aim of this table is to illustrate the modification of the ranking depending on what network centrality measure is considered.

Degree Centrality		Betweenness Centrality		Eigenvector Centrality		Closeness Centrality	
The Blackstone Group	66	Goldman Sachs	5459	The Blackstone Group	0.65	The Carlyle Group	0.40
Goldman Sachs	56	The Carlyle Group	4967	KKR	0.52	The Blackstone Group	0.40
KKR	51	TPG Capital	4174	Goldman Sachs	0.45	Goldman Sachs	0.39
TPG Capital	51	The Blackstone Group	4114	Bain Capital	0.45	TPG Capital	0.39
The Carlyle Group	47	KKR	3153	TPG Capital	0.44	KKR	0.38
Bain Capital	42	Bain Capital	2855	The Carlyle Group	0.32	Bain Capital	0.37
CVC Capital Partners	25	CVC Capital Partners	2117	Providence Equity Partners	0.27	Providence Equity Partners	0.36
Providence Equity Partners	25	BC Partners	1597	Hellman & Friedman	0.26	CVC Capital Partners	0.36
Advent International	21	J.P. Morgan	1484	Advent International	0.23	Permira	0.35
Apax Partners	21	Cerberus Capital Management	1440	Thomas H Lee Partners	0.22	J.P. Morgan	0.35

Table 11. Social Network Measure for Private Equity Firms in the Sample

This table reports the centrality measures for a subsample of private equity firms. In particular, we selected for this table only the players with a Degree Centrality larger than 3. The table is sorted firstly by Betweenness Centrality and then in accordance with the other columns.

Name of Private Equity Firm	Betweenness Centrality	Eigenvector Centrality	Closeness Centrality	Degree Centrality
Goldman Sachs	5459	0.700	577.0	56.0
The Carlyle Group	4967	0.485	568.0	47.0
TPG Capital	4174	0.683	576.0	51.0
The Blackstone Group	4114	1.000	572.0	66.0
KKR	3153	0.808	589.0	51.0
Bain Capital	2855	0.697	618.0	42.0
CVC Capital Partners	2117	0.293	637.0	25.0
BC Partners	1597	0.075	701.0	12.0
J.P. Morgan	1484	0.157	643.0	15.0
Cerberus Capital Management	1440	0.081	714.0	8.0
Partners Group	1346	0.022	773.0	8.0
Silver Lake	1319	0.259	661.0	16.0
Cinven	1195	0.172	645.0	19.0
Apax Partners	1136	0.329	656.0	21.0
Apollo Global Management	1136	0.173	647.0	17.0
Permira	1134	0.290	640.0	20.0
Ardian	1069	0.079	718.0	11.0
Advent International	973	0.361	677.0	21.0
3i Group	887	0.121	696.0	11.0
Providence Equity Partners	699	0.412	622.0	25.0
EQT	666	0.029	785.0	4.0
Actis Capital	647	0.020	779.0	3.0
Aquiline Capital	645	0.028	787.0	2.0
Clayton Dubilier & Rice	637	0.094	720.0	8.0
Morgan Stanley	573	0.133	682.0	10.0
Golden Gate Private Equity	528	0.029	825.0	4.0
Eurazeo	498	0.071	685.0	8.0
Stone Point Capital	484	0.071	729.0	6.0
First Reserve Corporation	476	0.045	773.0	6.0
Parcom Capital	472	0.012	834.0	3.0
Electra Private Equity	464	0.017	814.0	5.0
Fortress Investment Group	461	0.003	906.0	3.0
APriori Capital Partners	450	0.183	691.0	10.0
Hillhouse Capital	436	0.007	912.0	4.0
Baring Private Equity Asia	434	0.003	900.0	4.0
Kelso & Company	433	0.059	789.0	5.0
Genstar Capital	433	0.001	1000.0	3.0
Duke Street Capital	433	0.001	986.0	3.0
Insight Venture Partners	432	0.028	831.0	2.0
Investitori Associati Sgr	432	0.003	914.0	2.0
Candover	405	0.113	708.0	9.0
Affinity Equity Partners	394	0.048	738.0	3.0
Riverstone	377	0.060	739.0	7.0
One Equity Partners	350	0.028	785.0	3.0
Thomas H Lee Partners	301	0.341	645.0	15.0
Charlesbank Capital Partners	282	0.034	781.0	3.0
Onex	258	0.034	774.0	3.0
MSD Capital	257	0.011	858.0	3.0
Citigroup	254	0.098	734.0	10.0
Vestar Capital Partners	250	0.076	728.0	6.0
Warburg Pincus	239	0.202	659.0	13.0
Madison Dearborn Partners	236	0.099	693.0	10.0
TA Associates	235	0.032	800.0	4.0
CCMP Capital	230	0.063	750.0	4.0
Leonard Green & Partners	228	0.141	751.0	8.0
Trilantic Capital Partners	228	0.003	934.0	4.0
Oak Hill Capital	220	0.011	831.0	3.0
Charterhouse	218	0.015	851.0	3.0
CITIC Capital	217	0.073	752.0	4.0
New Mountain Capital	217	0.069	753.0	3.0

Table 12. Network Cliques

This table reports the descriptive statistics for the number of cliques in the social network arising from private equity club deals, classified by the size of the clique.

Clique Size	N. Cliques	Frequency
6	8	7%
5	6	6%
4	27	25%
3	67	62%
Total	108	100%

Table 13. Geodesic Distance

This table reports the proportion of dyads connected by the geodesic distance under consideration.

Geodesic Distance	% of Dyads
1	1.78%
2	13.75%
3	34.61%
4	30.21%
5	14.42%
6	4.34%
7	0.82%
8	0.08%
9	0.004%

Table 14. Descriptive Statistics for the Variables Used in the Regressions

The table show a summary of the descriptive statistics for all the variable that will be used in our models, both in the univariate and multivariate logistic regressions.

	Descriptive Statistics								
	Obs	Mean	Median	Std. Dev	Min	Max	Range	Skewness	Kurtosis
Log (Deal Value)	1562	6.92	6.75	0.76	5.75	11.00	5.24	1.26	5.10
Management Buyout Dummy	1562	0.06	0.00	0.24	0.00	1.00	1.00	3.72	14.86
Co-Investment Dummy	1562	0.14	0.00	0.35	0.00	1.00	1.00	2.08	5.33
Public to Private Dummy	1562	0.34	0.00	0.47	0.00	1.00	1.00	0.66	1.44
Geographic Concentration	1562	0.89	1.00	0.32	0.00	1.00	1.00	-2.43	6.90
Pre 2006 Dummy	1562	0.31	0.00	0.46	0.00	1.00	1.00	0.81	1.66
Agriculture Forestry Fishing Dummy	1562	0.01	0.00	0.07	0.00	1.00	1.00	13.87	193.26
Mining Dummy	1562	0.02	0.00	0.13	0.00	1.00	1.00	7.27	53.80
Construction Dummy	1562	0.01	0.00	0.10	0.00	1.00	1.00	9.43	89.89
Manufacturing Dummy	1562	0.31	0.00	0.46	0.00	1.00	1.00	0.82	1.68
Transportation et al. Dummy	1562	0.12	0.00	0.33	0.00	1.00	1.00	2.27	6.15
Wholesale Trade Dummy	1562	0.04	0.00	0.18	0.00	1.00	1.00	5.04	26.44
Retail Trade Dummy	1562	0.09	0.00	0.29	0.00	1.00	1.00	2.86	9.18
Finance and Insurance Dummy	1562	0.11	0.00	0.31	0.00	1.00	1.00	2.53	7.42
Log (Lead Investor Size)	1561	9.48	9.55	1.10	5.17	11.23	6.06	-0.68	3.41
Degree Centrality	1562	1.16	0.70	1.14	0.10	3.70	3.60	0.93	2.50
Betweenness Centrality	1562	5.88	3.83	6.43	0.00	21.47	21.47	0.99	2.64
Eigenvector Centrality	1562	0.19	0.11	0.20	0.00	0.65	0.65	1.05	2.84
Closeness Centrality	1562	0.33	0.33	0.05	0.10	0.40	0.30	-0.73	3.92

Table 15. Univariate Logit Models Results

The table reports the results of the univariate logistic regression models of all the variables of this paper on the dependent club deal dummy variable.

	Coefficient	Z-stat	P-value	McFadden R^2
Log (Deal Value)	0.5654328***	7.63	0.000	3.28%
Management Buyout Dummy	-0.070	-0.29	0.776	0.00%
Co-Investment Dummy	0.233	1.47	0.141	0.12%
Public to Private Dummy	0.409451***	3.48	0.000	0.66%
Geographic Concentration	1.369034***	5.23	0.000	2.05%
Pre 2006 Dummy	0.4939993***	4.14	0.000	0.93%
Agriculture Forestry Fishing Dummy	-0.959	-0.9	0.370	0.06%
Mining Dummy	0.567	1.45	0.148	0.11%
Construction Dummy	-1.794	-1.74	0.102	0.28%
Manufacturing Dummy	-0.4625257***	-3.56	0.000	0.72%
Transportation et al. Dummy	0.3964268**	2.43	0.015	0.31%
Wholesale Trade Dummy	-0.189	-0.58	0.559	0.02%
Retail Trade Dummy	0.109	0.56	0.576	0.02%
Finance and Insurance Dummy	0.3662582**	2.11	0.035	0.24%
Log (Lead Investor Size)	-0.0971381*	-1.9	0.057	0.20%
Norm. Degree Centrality	0.2461289***	5.09	0.000	1.40%
Norm. Betweenness Centrality	0.0417258***	4.89	0.000	1.29%
Eigenvector Centrality	1.327476***	4.81	0.000	1.25%
Closeness Centrality	3.013102***	2.67	0.008	0.40%

(Standard Error); * Significant at better than the 10% level; ** Significant at better than the 5% level; *** Significant at better than the 1% level

Table 16. Multivariate Logit Models for the Probability of Consortium Formation

The table reports the logistic regression analysis for the probability of consortium formation. In panel (1) we employed the independent variables related to the transaction characteristics. In panel (2) we insert the relevant dummy variables for the target industry. In panel (3) we insert our control variable for the size of the lead investor. From pane (4) to (7) we insert one at a time the network centrality measures. For each model we include the year fixed effect. At the end of the table we compute the relevant diagnostics.

	Dependent Variable: Club Deal Dummy						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Transaction Characteristics							
Log (Deal Size)	0.555***	0.539***	0.584***	0.555***	0.560***	0.556***	0.568***
	(0.080)	(0.081)	(0.084)	(0.085)	(0.084)	(0.085)	(0.084)
Public to Private Dummy	0.146	0.115	0.108	0.065	0.086	0.057	0.078
	(0.128)	(0.131)	(0.131)	(0.133)	(0.132)	(0.133)	(0.132)
Geographic Concentration	1.243***	1.292***	1.314***	1.271***	1.274***	1.293***	1.316***
	(0.267)	(0.269)	(0.271)	(0.272)	(0.272)	(0.271)	(0.271)
Relevant Industries Dummies							
Manufacturing		- 0.411***	- 0.411***	- 0.442***	- 0.448***	-0.433***	- 0.419***
		(0.149)	(0.149)	(0.151)	(0.151)	(0.151)	(0.150)
Transportation et al.		0.231	0.233	0.202	0.180	0.232	0.213
		(0.187)	(0.187)	(0.189)	(0.189)	(0.189)	(0.188)
Financials and Insurance		0.312*	0.298*	0.263	0.294*	0.258	0.352*
		(0.196)	(0.197)	(0.200)	(0.199)	(0.199)	(0.198)
Control for Investor Size							
Log (Lead Investor Size)			- 0.125*	- 0.443***	- 0.403***	-0.392***	- 0.350***
			(0.069)	(0.083)	(0.080)	(0.079)	(0.093)
Network Measures							
Norm. Degree Centrality				0.419***			
				(0.073)			
Norm. Betweenness Centrality					0.067***		
					(0.012)		
Eigenvector Centrality						2.114***	
						(0.402)	
Closeness Centrality							6.092***
							(1.916)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diagnostics							
Observations	1562	1562	1562	1562	1562	1562	1562
McFadden R2	5.43%	6.47%	6.73%	8.70%	8,47%	8.37%	7.35%
Adj.McFadden R2	5.07%	5.75%	5.77%	7.74%	7.51%	7.42%	6.39%
Log Likelihood	-796.939	-788.248	-785.016	-768.431	-770.344	-771.136	-779.766
LR Statistics	91.59***	108.97***	113.21***	146.38***	142.55***	140.98***	123.71***
AIC	1599.878	1588.495	1586.032	1552.863	1556.687	1558.272	1575.532
BIC	1615.94	1620.62	1628.86	1595.69	1599.52	1601.10	1618.36

(Standard Error); * Significant at better than the 10% level; ** Significant at better than the 5% level; *** Significant at better than the 1% level

Table 17. Bivariate Pearson Correlations

The table reports the bivariate correlation for the variable used in the regression.

		Correlations										
		1	2	3	4	5	6	7	8	9	10	11
1	Log (Deal Size)	1										
2	Public to Private Dummy	0.2582**	1									
3	Geographic Concentration	0.0524*	0.0805**	1								
4	Manufacturing	-0.0527*	-0.1160**	-0.0080	1							
5	Transportation et al.	0.0333	-0.0604*	-0.0474	-0.2531**	1						
6	Financials and Insurance	0.0752**	0.0238	-0.0576*	-0.2326**	-0.1311**	1					
7	Log (Lead Investor Size)	0.1920**	0.045	0.0301	-0.0610*	-0.0304	0.015	1				
8	Norm. Degree Centrality	0.2143**	0.0756**	0.0785**	-0.0194	0.0293	0.0135	0.6240**	1			
9	Norm. Betweenness Centrality	0.1992**	0.0552*	0.0825**	-0.0061	0.0477	-0.0084	0.5942***	0.9354**	1		
10	Eigenvector Centrality	0.2141**	0.0896**	0.0625**	-0.0250	0.0103	0.0236	0.6014**	0.9752**	0.8488**	1	
11	Closeness Centrality	0.2043**	0.0754**	0.0412	-0.0126	0.0368	-0.0612*	0.6741**	0.8379**	0.8035**	0.8056**	1

* Significant at better than the 5% level ; ** Significant at better than the 1% level

Table 18. Multivariate Logit Models with Average Marginal Effects

This table reports the Average Marginal Effects for the panel (4) to (7), used to measure magnitude of the economic effect of each variable. In particular, in the last section the table we illustrate the change in the probability of consortium formation for a one-standard deviation increase of the network centrality measures. For each model we include the year fixed effect.

	(4) AME	(5) AME	(6) AME	(7) AME
Transaction Characteristics				
Log (Deal Size)	0.095***	0.082***	0.078**	0.0162859*
	(0.029)	(0.031)	(0.031)	(0.009)
Public to Private Dummy	0.011	0.013	0.008	0.002
	(0.023)	(0.021)	(0.019)	(0.004)
Geographic Concentration	0.218***	0.188**	0.183**	0.0378*
	(0.078)	(0.080)	(0.081)	(0.024)
Relevant Industries Dummies				
Manufacturing	- 0.076*	- 0.066*	-0.061*	-0.012
	(0.039)	(0.038)	(0.037)	(0.009)
Transportation et al.	0.035	0.027	0.033	0.006
	(0.034)	(0.029)	(0.030)	(0.007)
Financials and Insurance	0.045	0.043	0.036	0.010
	(0.037)	(0.034)	(0.032)	(0.008)
Control Variables				
Log (Lead Investor Size)	- 0.076**	- 0.059*	- 0.055*	-0.01
	(0.038)	(0.035)	(0.034)	(0.008)
Network Measures				
Norm. Degree Centrality	0.072**			
	(0.034)			
Norm. Betweenness Centrality		0.0098*		
		(0.005)		
Eigenvector Centrality			0.298*	
			(0.173)	
Closeness Centrality				0.175
				(0.131)
Year Fixed Eeffect	Yes	Yes	Yes	Yes
Change in the probability of consortium formation for a one standard deviation increase for the relvant centrality measure				
Norm. Degree Centrality	0.082			
Norm. Betweenness Centrality		0.063		
Eigenvector Centrality			0.059	
Closeness Centrality				0.009

(Standard Error); * Significant at better than the 10% level; ** Significant at better than the 5% level; *** Significant at better than the 1% level

Table 19. Multivariate Logit Models with Heteroscedasticity Consistent Standard Errors

This table reports the logistic regression models for panel (4) to (7), using the Huber-White Heteroscedasticity consistent standard errors, showed in parenthesis. We can see that the significance of the coefficients does not change significantly from the original models.

	(4-HR)	(5-HR)	(6-HR)	(7-HR)
Transaction Characteristics				
Log (Deal Size)	0.555***	0.556***	0.556***	0.568***
	(0.074)	(0.076)	(0.072)	(0.073)
Public to Private Dummy	0.065	0.086	0.567	0.078
	(0.148)	(0.146)	(0.150)	(0.151)
Geographic Concentration	1.271***	1.274***	1.294***	1.316***
	(0.249)	(0.248)	(0.249)	(0.249)
Relevant Industries Dummies				
Manufacturing	- 0.442***	- 0.448***	-0.433***	- 0.419***
	(0.142)	(0.145)	(0.139)	(0.144)
Transportation et al.	0.202	0.180	0.232	0.213
	(0.181)	(0.185)	(0.180)	(0.186)
Financials and Insurance	0.263	0.295	0.258	0.352
	(0.273)	(0.279)	(0.270)	(0.274)
Control Variables				
Log (Lead Investor Size)	- 0.443***	- 0.403***	- 0.392***	- 0.350***
	(0.085)	(0.098)	(0.080)	(0.094)
Network Measures				
Norm. Degree Centrality	41.923***			
	(6.538)			
Norm. Betweenness Centrality		0.067***		
		(0.013)		
Eigenvector Centrality			2.114***	
			(0.406)	
Closeness Centrality				6.092***
				(1.676)
Year Fixed Effect	Yes	Yes	Yes	Yes
Diagnostics				
Observations	1562	1562	1562	1562
McFadden R2	8.70%	8,47%	8.37%	7.35%
Adj.McFadden R2	7.62%	7.39%	7.30%	6.27%
Log Likelihood	-768.43142	-770.34367	-771.13603	-779.76579
LR Statistics	146.38***	142.55***	140.98***	123.71***
AIC	1552.863	1556.687	1558.272	1575.532
BIC	1595.69	1599.52	1601.10	1618.36

(Standard Error); * Significant at better than the 10% level; ** Significant at better than the 5% level; *** Significant at better than the 1% level

Table 20. Variance Inflation Factor and Tolerance Coefficients

This table illustrates the Variance Inflation Factor (VIF) and Tolerance coefficients used to investigate potential multicollinearity problems, in pane (4) to (7). All the VIF coefficient are smaller than 2, indicating no multicollinearity problem

	(4)		(5)		(6)		(7)	
	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance
Deal Size (LN)	1.14	0.881	1.13	0.882	1.14	0.881	1.13	0.883
Public to Private Dummy	1.1	0.906	1.1	0.908	1.1	0.905	1.1	0.906
Home Bias Dummy	1.02	0.979	1.02	0.978	1.02	0.982	1.02	0.984
Manufacturing	1.19	0.840	1.19	0.839	1.19	0.842	1.19	0.841
Transportation et al.	1.14	0.875	1.15	0.872	1.14	0.878	1.14	0.875
Financials and Insurance	1.12	0.895	1.12	0.896	1.12	0.895	1.12	0.890
Lead Investor Size (LN)	1.67	0.599	1.58	0.631	1.59	0.628	1.88	0.533
Norm. Degree Centrality	1.68	0.594						
Norm. Betweenness Centrality			1.59	0.629				
Eigenvector Centrality					1.6	0.623		
Closeness Centrality							1.89	0.530

Table 21. Smith-Blundell Test of Exogeneity

The table reports the results of the Smith-Blundell test which investigates whether the centrality measures are endogenous in the panels (4) to (7). Looking at the p-values, we are not able to reject the null hypothesis, meaning that the models are correctly specified, and that the centrality measures under analysis are not endogenous in the models.

	(4)	(5)	(6)	(7)
Smith-Blundell statistics	0.0334	1.0334	2.0334	3.0334
P-value	(0.8549)	(0.8549)	(0.8549)	(0.8549)

7.2. Figures

Exhibit 1. Annual Global Private Equity Fundraising, 2000-2017

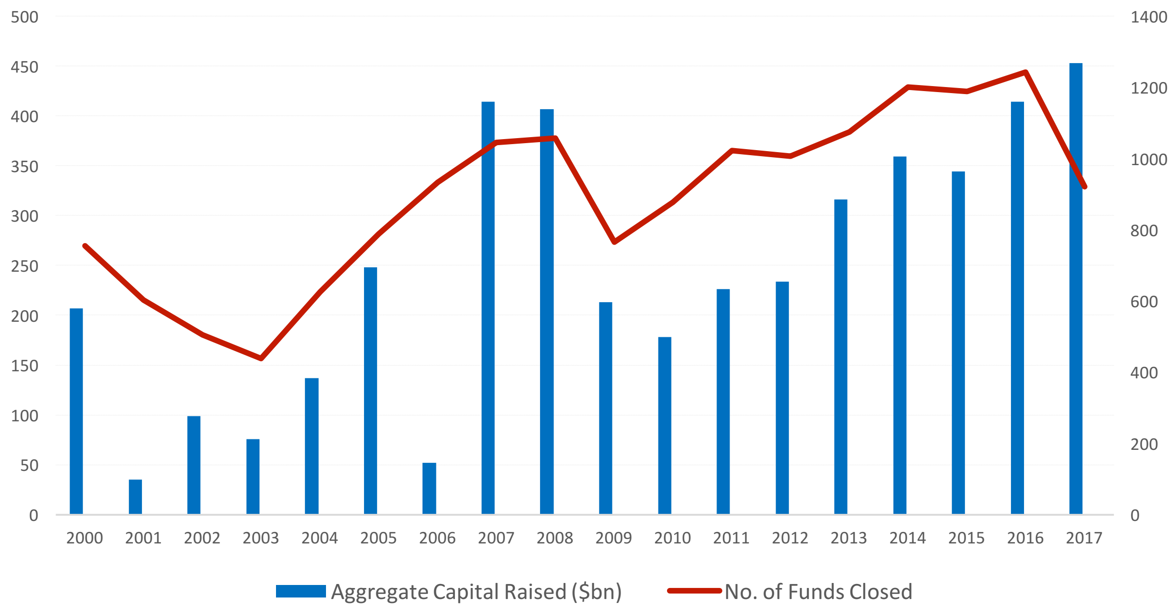

Exhibit 2. Graphical Representation of the Entire Network

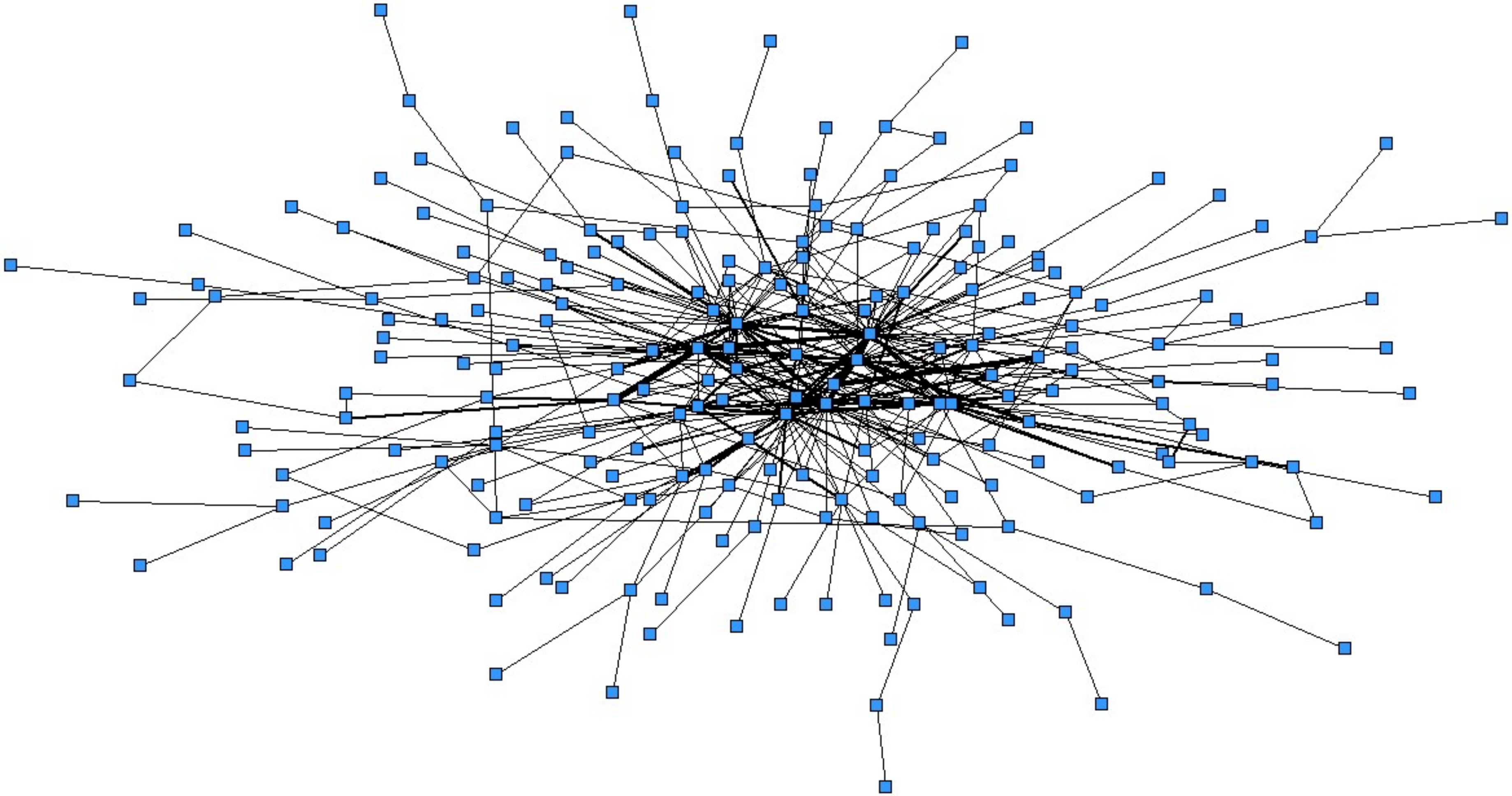

Exhibit 3. Graphical Representation of a Subgroup of the Entire Network

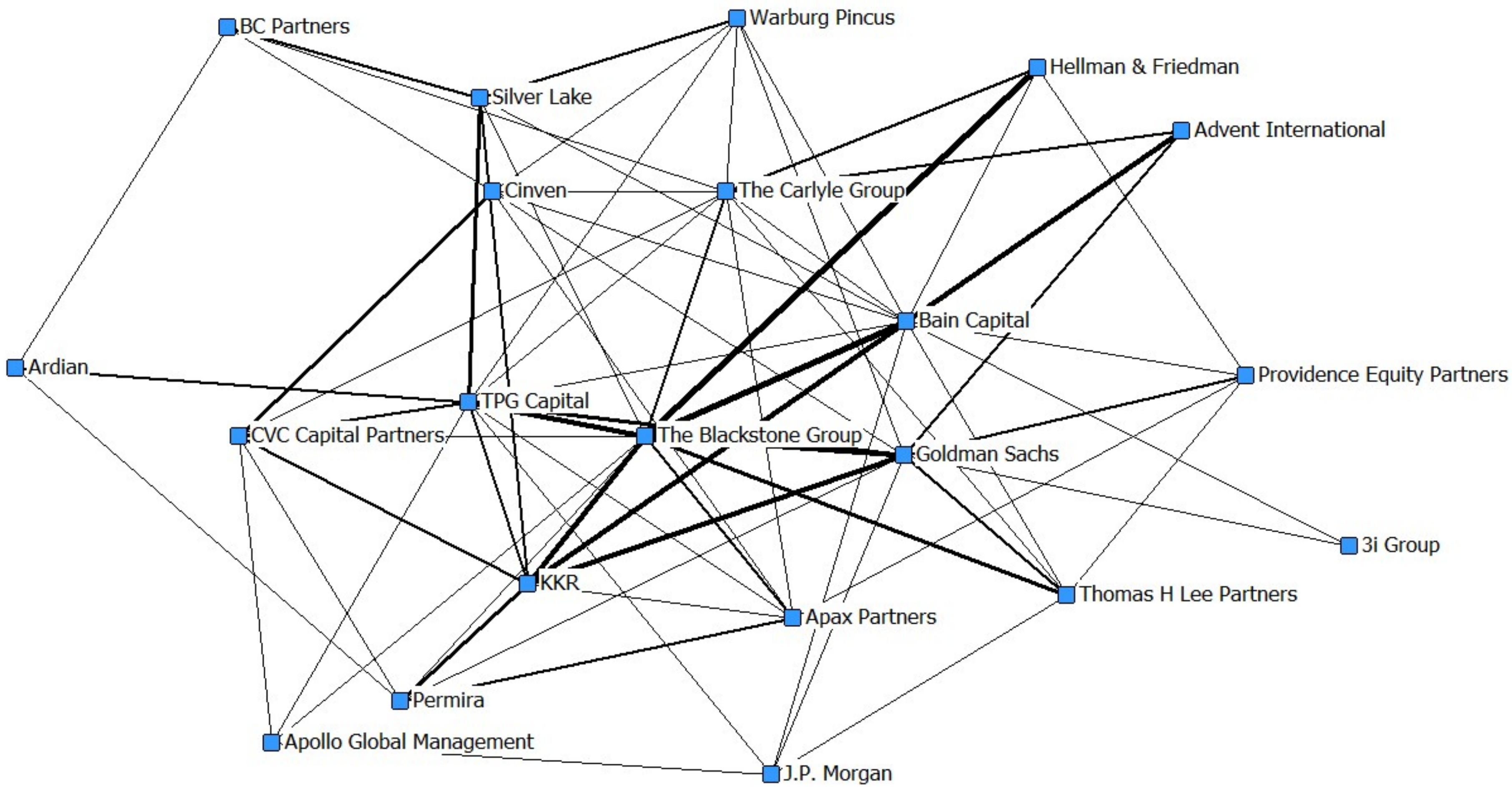

Exhibit 4. Degree Centrality Distribution

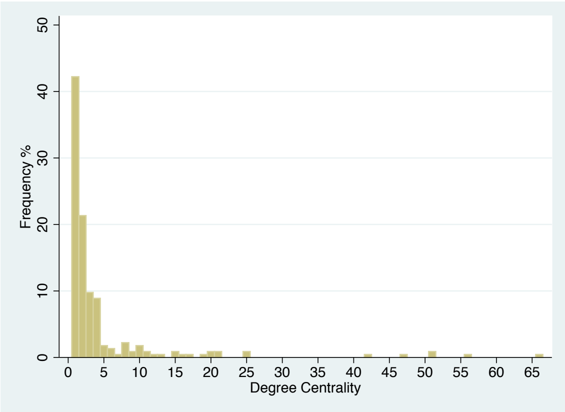

Exhibit 5. Normalized Betweenness Centrality Distribution

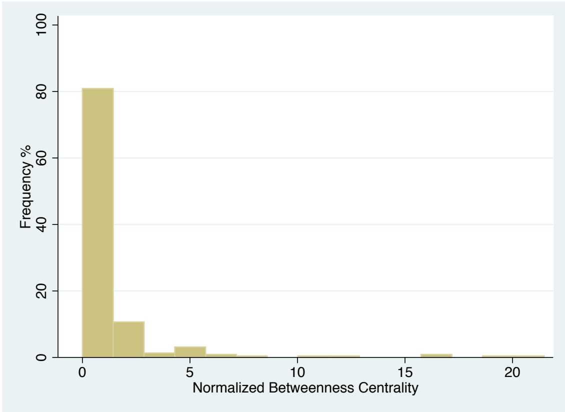

Exhibit 6. Eigenvector Centrality Distribution

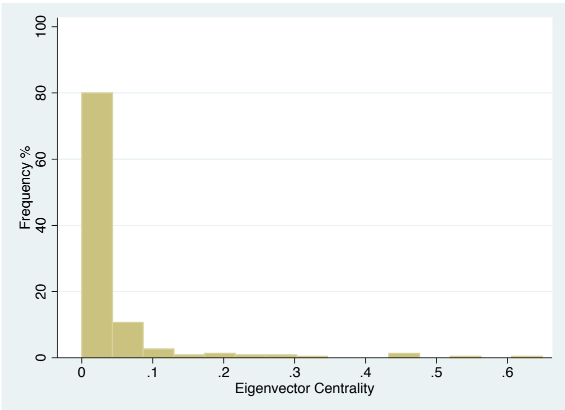

Exhibit 7. Closeness Centrality Distribution

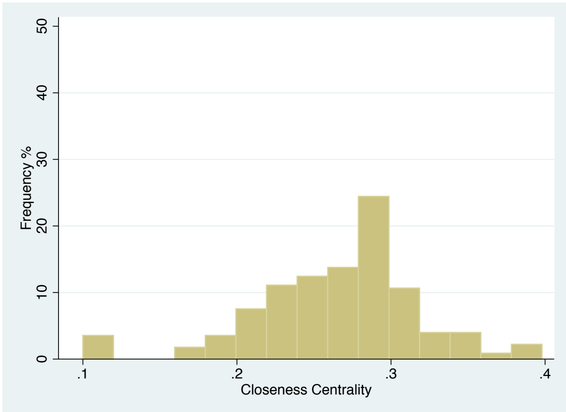

Exhibit 8 - Area under the ROC Curve for the Models Containing the Network Centrality Measures