Unlocking the Power of Relationships: Limited Partner Networks and Performance in Private Equity

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Abstract

This paper analyzes the relationship between performance and the organizational structure of Limited Partners (LPs) using Network Theory. The results show an annual return difference of 5-6 percentage points between the top and bottom quartile LPs when investing in Venture Capital (VC) funds. We find that these results are primarily driven by preferential access of top quartile LPs to top-privileged VC general partnerships (GPs). Additionally, we understand that the centrality measures capture those LPs who are loyal and serve as quality signalizers for top-performing GPs. Our findings present a novel approach to segmenting LPs in the venture capital market. For Buyout (BO) funds these findings do not hold.

Keywords: Private Equity, Limited partners, Investor heterogeneity, Networks

JEL Classification: G11; G23; G24; D85

1 Introduction

In various markets, it is customary for investors to establish connections and cultivate networks among themselves. In Private Equity (PE), this is no different. Lerner et al. (2008) mentions that endowments use their networks to optimize their investments, and this is one of the components of the success of their returns. In the theory proposed by Hochberg et al. (2014), limited partners (LPs) reinvesting in venture capital (VC) funds play a vital role as signalers by conveying the quality of the GP amidst informational asymmetry. Da Rin and Phalippou (2017) shows that small-sized LPs (those with a low volume of investments in PE and capacity to conduct due diligence) place great importance on the commitment of other LPs in the same investment when making investment decisions. Recently, Goyal et al. (2021) suggests that LPs follow their peers in reinvestments with the same GP manager.

The literature shows how networks among LPs are important and may assist them in making investment decisions. On the other hand, within the structure of these networks, there are LPs

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with better-quality relationships, meaning they are more influential within the network compared to other LPs. This can lead to differences in investment opportunities, access to information, prestige, among other factors. The question that arises is whether LPs with better-quality-connections (top central LP) in their networks have higher returns.

This paper focuses on whether organizational differences, captured through LPs networks, can explain the heterogeneity in performance across LPs. This work contributes to the PE literature by examining performance at the LP level, focusing on organizational differences. This approach to organize/classify LPs is not restricted to the traditional administrative categories (Banks, Endowments, Pension Funds, Advisors, among others), as used in the previous articles (Lerner et al., 2007; Sensoy et al., 2014). Instead, it considers the actual investments (including all behaviors, access, reputations, prestige and others) made by LPs to arrive at the structural organization to be analyzed.

To analyze the connections between LPs (coinvestments[1]), we use Network Theory to measure the level of centrality/influence of LPs. Networks are formed by "nodes" and their connectors "edges." The "nodes" will be the LPs, and the "edges" will represent co-investments between two LPs in the same fund. Due to the different characteristics of asset classes, the sample will be separated for investments in Buyout and VC funds. We capture the centrality level of the nodes (LPs), which can generally be divided into four measures: Degree, Betweenness, Closeness, and Eigenvector. Each measure has a different characteristic and purpose. The Eigenvector measure, considered most appropriate for this paper, captures the nodes that have the most influence in the network. As the networks evolve over time with the entry and exit of LPs, leading to the reordering of relationships, we adopt a strategy of constructing a new network for each vintage year by leveraging data from the preceding 5 years (utilizing a rolling window of 5 years). This helps us mitigate endogeneity problems, common in network analysis, by using previous network data to understand current performance.

The majority of the literature in PE, particularly in venture capital, concerning networks and performance predominantly centers on relationships at the GP level. In essence, the interaction between GPs (VC firms or fund managers) can be examined through either a univariate analysis, focusing solely on their interactions (Hochberg et al., 2007), or a bivariate analysis, which considers the relationship between GPs and either investors or invested companies. However, recent research has expanded to encompass multivariate networks involving more than two economic agents in the process of network formation (Ozmel et al., 2020). Our paper diverges from the typical literature on VC networks in two ways. First, it concentrates on analyzing relationships exclusively at the LP level, as opposed to the customary examination of GPs or multi-agent interactions. Second, our analysis extends to networks involving LPs investing in BO, going beyond the confines of VC. This broader perspective facilitates a meaningful comparison between the two most important investment classes within PE.

[1]In this paper, coinvestments refer to a pair of Limited Partners (LPs) that jointly invests in the same Private Equity (PE) fund.

The data used in this paper comes from Preqin©. Information about the funds (including performance - Net IRR%), LPs, and GPs was collected with a reference date of March 2022. To construct our univariate network, we used LPs from 2,528 Buyout and VC funds between 1991 and 2015. The sample size of funds used exceeds the papers from Lerner et al. (2007), Sensoy et al. (2014), including subperiods, and Cavagnaro et al. (2019).

The findings indicate higher returns (Net IRR%) for top central LPs in VC funds. In our analysis, we classified LPs into quartiles based on their centrality measures. Notably, the 1st quartile, representing top central LPs[2], demonstrated a superior performance compared to the 4th quartile by 5.7% across the entire dataset. This excess return is similarly observed when contrasted with the 2nd and 3rd quartiles, however with a lower difference. In a more recent sub-period (from 2007 to 2015), we also identified higher returns for influential LPs (1st quartile LPs). Specifically, 3rd quartile and 4th quartile LPs exhibited lower performances, trailing behind influential LPs by 2.46% and 3.5%, respectively[3]. These later findings potentially contradicts the conclusions of Sensoy et al. (2014). The authors, based on results from a previous subperiod (1999-2006), suggested that the market matured, justifying the absence of excess returns among LPs categories. However, this conclusion relies on a administrative organizational structure used, separated by categories/classes. Since this study does not consider the administrative structure but rather an organization based on LPs' actual network, different results have been observed. These results do not hold for BO.

In addition, we investigate the reasons why top central LPs have higher returns than other investors. Lerner et al. (2007), mentions four reasons why LPs might have different performance: special access to top performing funds (GPs), risk profile, objective functions and inside information. However, like Sensoy et al. (2014), we will focus our analysis in only two reasons; evaluating if access to top PE funds and inside information (skills) can explain top central LPs higher performance.

In PE, specially in venture capital investments, access to the best performing funds is not easy. Successful GPs usually do not increase fund sizes to equalize demand generated by their success. For them, identifying consistently good investments that require substantial capital commitments can be challenging, and recruiting skilled individuals to effectively oversee the expanding portfolio is no simple task. So increasing fund size, to accommodate new LPs investments, might work against GPs as their funds might not deliver the promised returns with excess cash not deployed or pressure to make not optimal investments (Kaplan and Schoar, 2005). Another way GPs might employ to balance demand is by increasing the fees they charge. However, this usually is not the case. Hochberg et al. (2014), mentions that GPs don´t raise fees to incentivize current LPs to reinvest in their next fund and consequently signal to the market (other LPs) that they are a good fund manager. Also, Lerner and Schoar (2004) mentions GPs can screen for "deep-pocket"

[2]In this paper, we will use top central LPs, influential LPs and 1st quartile LPs interchangeably.

[3]To address concerns about outliers affecting our results, we applied winsorization to our performance measurements (Net IRR%) in all presented regressions. Additionally, we conducted Robust Regressions, and the conclusion regarding the presence of differences in performance among categories remains the same.

investors, as they might be interested in filtering those LPs that might bring long-term relationship for future re-investments. In general, LPs encounter a challenging environment when seeking access to top-performing funds.

To evaluate if access to the best GPs (and, consequently, best funds) can explain the higher performance for influential LPs, we shift our focus to GPs. Our first task was to identify who are these best performing GPs. In a novel identification strategy, compared to previous papers on performance at the LP level[4], we incorporated network analysis to identify the best GPs. Across all periods, our results reveal that 1st quartile GPs, on average, outperform other quartile GPs by 7.69%. To arrive at these results, we used a bipartite network composed of two types of nodes; GPs and LPs. The connections were the investments made by LPs in GPs (represented by the funds). These results do not hold for BO funds.

Following this analysis, we paired the most central GPs with influential LPs (1st quartile LPs). For venture capital funds, we found that influential LPs have in average 53,1% of all their investments directed towards the most privileged GPs. However, this proportion drops significantly when we analyze the low central LPs (4th quartile LPs). In this case, only 13,7% of the investments made by the 4th quartile LPs were in GPs classified in the 1st quartile. Furthermore, through probit regression analysis, we found that LPs in the 1st quartile exhibit a higher likelihood of investing in 1st quartile GPs compared to their counterparts in other quartiles.

For venture capital funds, the results show strong evidence of investment concentration of top central LPs in privileged/1st quartile and, consequently, profitable GPs, which can help explain the excess return found in more central LPs. Our results align with Lerner et al. (2022), who also found evidence of concentration in LPs investments. They observed that LPs with a strong track record in the past are more likely to access alternative vehicles (AV) that demonstrate superior performance. On the other hand, upon investigating whether the superior performance of top central LPs was attributable to their skills, we found no consistent evidence supporting this notion when utilizing the two main econometric strategies commonly employed in the literature.

We understand that centrality measures capture LPs that are both loyal and quality signalizers for successful GPs. Interestingly, we find that the superior performance of top central LPs is not necessarily linked to their prior PE experience or size (measured by the AUM). This finding suggests that another dynamic is at play, reinforcing our perspective on loyalty and serving as good signalizers of quality for GPs (more details can be found in section VI).

Overall, for venture capital investments, our findings suggest that top central LPs enjoys higher performance than other less central LPs, in general because of their access to the best venture capital partnerships. These results are consistent for most of the sub-periods analyzed, however, becoming smaller through time. These results shows how returns in VC depends largely on the match between GPs and LPs. With our results, this paper has the potential to introduce a

[4] In Section 5.1, we provide a detailed explanation of our approach and highlight the distinctions compared to existing literature.

novel LP categorization approach, focusing on influence levels rather than traditional categories classifications.

Our paper contributes to the literature that documents heterogeneity in performance among LPs (Lerner et al., 2007; Dyck and Pomorski, 2016; Andonov et al., 2018; Cavagnaro et al., 2019). Additionally, our findings support the theoretical expectations outlined by Lerner and Schoar (2004), Hochberg et al. (2014) and Maurin et al. (2023), which demonstrates high correlation between the presence of LPs and successful GPs. All these theories emphasize the importance of certain types of LPs, and our centrality measure could serve as a valuable empirical technique for identifying these significant LPs.

The remainder of the paper is organized as follows. Section II presents the data set used in the analysis and construction of the networks and Section III details the methodology used. Section IV addresses the findings on top central LPs, Section V investigates the reasons for superior performance, Section VI presents the interpretation of the LP centrality measure in VC and, finally, Section VII concludes the paper.

2 The Data and Summary Statistics

The data set was collected from the specialized alternative investments platform called Preqin©[5] . The data include PE funds with vintage years between 1991 and 2015. Information about the funds, performance, LPs, and GPs were collected with a reference date of March 2022. Funds launched after 2015 were not included to ensure that performance information was more consolidated, as some funds were still active (following a similar strategy used by Kaplan and Schoar (2005), Hochberg et al. (2007), Sensoy et al. (2014) and Harris et al. (2023)). The number of funds used in the modeling was 2,528 funds, including 1,075 VC funds and 1,453 BO funds. All funds have at least 2 LPs and performance data (Net IRR%). The funds in the sample are only Buyouts (BO) or Venture Capital (VC) types. For VC funds, all available subdivisions in the Preqin database were collected, which include *Venture (General)*, *Early Stage*, *Early Stage: Start-up*, *Early Stage: Seed*, and *Expansion / Late Stage*. There are no subdivisions for BO funds in the Preqin platform.

The analysis was segmented into three sub-periods, aligning with prior literature, to facilitate a comparison of the results. The first two sub-periods, 1991-1998 and 1999-2006, are compatible with the papers from Lerner et al. (2007) and Sensoy et al. (2014). The third sub-period, which has not been explored in the literature (given our best knowledge), covers the period from 2007 to 2015. In comparative terms, this paper has a larger sample of funds compared to Lerner et al. (2007) for the period of 1991-1998. Despite having an initial sample of 838 funds, only 341 funds had performance data, whereas our sample includes data from 436 funds. When comparing with Sensoy et al. (2014), who used 412 funds and 838 funds in the first and second sub-periods, respectively, our sample is also larger, consisting of 436 funds and 1001 funds in the first and second sub-periods, respectively (see table 1).

Since the LPs network represents our main source of variation, in table 2 we present some summary statistics. In a similar strategy as Di Maggio et al. (2019)[6], to limit noise to construct the network, we focused on LPs that would be more relevant in our context. For our networks, we restricted to LPs with 5 or more investments in private equity (PE)[7], thereby excluding less committed and focused LPs from our sample. Nevertheless, even with this criterion, the remaining LPs still accounted for over 90% of all investments when considering the entire sample.

In table 2, we classified the LPs into quartiles based on their centrality level (Eigenvector) within the network, in contrast to previous studies that categorized LPs into administrative groups such as Endowments, Advisors, Insurance Companies, Banks/Finance companies, Investment Firms,

[5]Preqin is a database for alternative investments that collects information from PE funds through: (1) public information, including FOIA (Freedom of Information Act), which requires some LPs to provide the performance of the funds they invest in; (2) Voluntary requests to LPs and GPs. According to Gompers and Kaplan (2022), approximately half of the information comes from GPs. Harris et al. (2014) conducted a comparison of major PE data information platforms. For the performances of BO funds, they find that the platforms deliver similar results for vintages after 2000. However, for VC funds, Preqin and Pitchbook show lower average returns than the other two platforms (Burgiss and Cambridge Associates). The authors suggest that this may be because top VC funds do not allow public disclosure of their performance, making it more difficult for Preqin and Pitchbook to access such data.

[6]The paper focuses on the network between brokers and institutional investors. They encountered a similar challenge to ours. To address the issue of potentially noisy data that could compromise their results, they implemented a screening process, reducing observations to 80% of the original dataset.

[7]Including both VC and BO prior investments.

and others. This implies that LPs classified in the 1st quartile possess the highest eigenvector centrality measures, while those in the 4th quartile exhibit the lowest centrality measures. For VC investments, our sample consists of 903 distinct LPs, and for BO investments, we have a total of 1155 unique LPs. The eigenvector centrality measures is standardized to unit variance (centrality measure divided by is standard deviation). In Panel A and B, reveals skewness in centrality measures across LPs. In essence, 1st quarter LPs exhibit high eigenvector levels compared to 4th quartile LPs with very low centrality levels. Further analysis of lower percentiles, as indicated in Table B, highlights that a small group of LPs exhibit high levels of eigenvector centrality measures. This pattern is observed for both LPs investing in VC and BO.

Table 3 shows the characteristics of the funds that the LP categories invest in. This analysis is at the LP level. For example, there were 6,890 investments in VC funds made by LPs classified as 1st quartiles between 1991 and 2015. The average returns (Net IRR%) of these investments in VC funds by these LPs had an average of 14.0%. In other words, each investment represents an LP (classified in a specific quartile) investing in a specific fund and subperiod.

The combination of funds and LPs resulted in 37,188 investments (for both VC and BO) between 1991 and 2015. In comparative terms, for the first subperiod between 1991 and 1998, Lerner et al. (2007) used 4,618 investments, Sensoy et al. (2014) used 3,685 investments, and this paper used 3,435 investments. For the second subperiod between 1999 and 2006, Sensoy et al. (2014) used 10,695 investments, while we used 15,592. The performance of these investments made by LPs can be examined through the average IRR for each category. Unlike other papers that used different performance metrics such as PME and fund multiple, this work only uses IRR due to greater accessibility to this information.

2.1 Network and Centrality Measures (levels of LPs influence)

The objective is to identify the level of influence of LPs through their connections using Network Theory[8]. The analysis will be at the LP level (co-investments), i.e., how they invest with each other in PE funds. This tool is widely used in areas such as logistics, ecology, and social sciences. This theory will help identify lead investors, connectors, and sporadic investors, in other words, influential LPs and their centrality levels. We use a specialized software called Gephi© to help generate the networks.

Networks are formed by nodes and their edges (connectors). In this paper, the nodes are the LPs, and the edges represent co-investments between two LPs in the same fund. The edges can be classified as directed or undirected, and in this paper, they will all be undirected. Due to the different characteristics of asset classes, the sample will be separated for investments in BO and VC funds.

[8]See Easley et al. (2010); Jackson et al. (2008); Jackson (2011) for a detailed review of network theory and analysis.

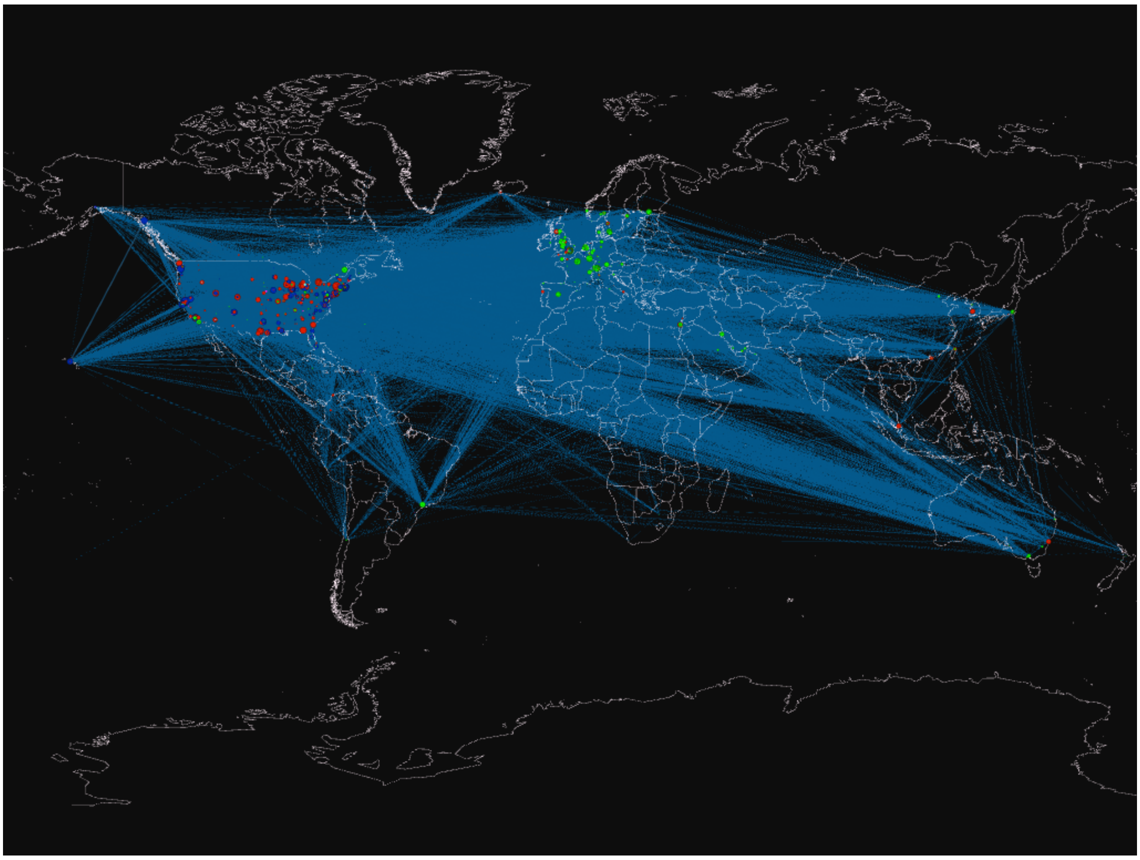

Figure 1: LPs Network
The colored dots represent the LPs (nodes), while the blue lines represent the co-investments (edges) between LPs.

Figure 1 represents the co-investments (connections) between LPs in the sample (blue lines), and you can see the locations of LPs (headquarter addresses) on the world map. The sample contains LPs from all continents, but most LPs are located in North America and Europe. Figure 1 consists of all LPs that form co-investments made in 2,528 PE funds between 1991 and 2015. The dots/circles represent the LPs, and the size (dots dimension) represents the degree (weighted degree). The degree measures the number of edges (number of co-investments) incident on a given node (LP). In other words, a large-sized dot (node) means that it's an LP that has many co-investments with other LPs. It can be observed that the North America and Europe regions have the largest LPs in terms of degree of connections.

According to Jackson et al. (2008), to analyze the centrality of vertices (LPs), it can be divided into 4 (four) measures: Degree, Betweenness, Closeness, and Neighbor Characteristics. Each measure has different characteristics and objectives. The measure of neighbor characteristics considered most appropriate for this project is Eigenvector, which captures the vertices that have the most influence in the network (Bonacich, 1972, 1987; Bonacich and Lloyd, 2001). In other words, the level of influence of a node comes from the connections it has with other influential vertices. In addition, the eigenvector measure is used in several other papers focusing information transmission (Hochberg et al., 2007; Di Maggio et al., 2019; Nanda et al., 2020).

2.1.1 Network Construction and main explanatory variable

The construction of the networks, with the objective to extract the centrality measures of the LPs, was obtained through the strategy we call ex-ante. This strategy is similar to Hochberg et al. (2007) and addresses endogeneity concerns associated with reverse causality. As the authors mentions, over the years, investors have experienced entries and exits in the market, and this generates a reordering of relationships. Therefore, to capture these dynamics, a new network will be built for each year of analysis. Since the total period covers the years from 1991 to 2015, this represents 25 years, and therefore, 25 new networks were constructed. For the construction of the new networks in a given period t, the previous 5 years of that period t will be used. For example, to analyze the ex-ante network of 2015, we used the information from the years 2010-2014. This strategy is different from Hochberg et al. (2007), which uses data including period t, and this paper does not. In this case, we understand that for period t, there might not be access to LP information or it would be very difficult to access them. Thus, period t will not be included in the construction of the ex-ante networks. This strategy is important because it considers only the information available at the time the funds start.

As outlined in section 2.0, in order to minimize noise and concentrate on LPs pertinent to the network, we also implemented a criterion for each created network, requiring LPs to have a minimum of 5 prior investments in private equity (PE) at period t. For instance, if an LP in 2010 had 3 prior investments in PE (VC and BO included), considering all the sample prior to 2010, would not be included in the network; however, if it had 5 prior investment it would be included. Despite these restrictions, our data sample still encompasses 90% of all investments from the original dataset.

3 Methodology

In this paper, we adopt the methodology proposed by Sensoy et al. (2014), including control variables, fixed effects and clusters. The difference is that we substitute the LPs categories dummies by quartile centrality dummies, our main explanatory variable . The regression model takes LPs' performance, tied to the fund's Net IRR in which they invest, as the dependent variable, along with two control variables: funds size and LPs previous experience. Below is the empirical model used:

$$LPsPerf_{iv,j} = \beta_0 + \sum_k \alpha_{1,k} DummyQuartileLP_{j,k,v} + \alpha_2 fundsize_i + \alpha_3 LPExper_{j,v} + FE + \varepsilon_{iv,j} \tag{1}$$

LPs Performance = Performance of the invested fund i (IRR %) given its vintage year v by LP j; Dummy Quartile LP = Four dummy variables identify the centrality quartile of LP for each LP-fund pair, taking the value of one for each observation consisting of an investment in fund i made by an LP j classified to a quartile k based on vintage year v, and zero otherwise. Important to highlight, these dummies are time varying as LPs can change quartile position through time (notation used to represent time varying is v, as we are interested in LPs quartile information at the time of the fund´s vintage year v). 1st Quartiles LPs are the base and will be omitted in the regressions; the main coefficient of interest in Eq.1 is α_1, which captures the relationship between LP centrality and their performance; Fund Size = variable related to fund characteristics, natural logarithm of the fund's committed value; LP Experience = variable Ln of the natural logarithm number of previous PE investment made by the LP j at the time v; $\varepsilon_{iv,j}$ = error.

For our dependent variable there are several concerns regarding outliers, specially for VC funds, that might influence the results and conclusions. To address this concern, we winsor our funds performance sample at 1% for all our regressions. However, we winsor separately for VC funds and BO funds, rather than winsor with all the funds together. This approach allows us to specifically isolate the effects of outliers within the two categories we are examining.

To capture as much residual variation as possible, especially those related to heterogeneity in PE fund or economic conditions, some control variables were included. First, we use the natural logarithm of fund size in MM$. Also, we include the natural logarithm of the total number of PE investments that a given LP made before the current investment (LP Experience). Fixed effects for fund's vintage year, LP's country of origin, the main region[9]and sector of the fund's investments, the GP's country of origin, and of interactions between fund focus[10]and fund vintage year. Last, because a particular fund can enter the equation multiple times, especially those funds with many LPs, the standard error was clustered by fund.

4 Limited partner performance and centrality measures

Table 4 shows the results of the regressions, following the methodology presented in section 4. The table considers the centrality measure obtained through the ex-ante strategy. As mentioned, it is believed that this is the best way to analyze the predictive power of the model since the centrality variable is obtained with previous (preceding) information from the vintage year of the fund.

The results for all periods (1991-2015) in VC funds, shows that 4th quartile LPs performs 5,7% less than 1st quartile LP (influential LPs). This positive comparison for influential LPs also happens when compared to 2nd and 3rd quartiles. In other words, influential LPs perform better than all other investors, when considering the whole sample. These results are driven specially by the first and last sub-periods. In the second sub-period (1999-2006), the 1st quartiles exhibited a 2.29% outperformance in comparison to the 4th quartile. These results are interesting as they diverge from the findings from Sensoy et al. (2014) during the same period. The authors employed administrative categories for LP classification and reported that no category exhibited a performance advantage. For the last sub-period (2007-2015), we still notice a difference in performance between quartiles, however, lower than the first sub-period. These results do not hold for BO funds.

[9]The region of fund investments can be classified as USA, Europe, and the Rest of the World.

[10]Only for VC funds, they can be further subdivided into focus areas like Venture (General), Early Stage, Early Stage: Start-up, Early Stage: Seed, and Expansion / Late Stage. For BO funds, there is no distinction in focus because Preqin does not provide any separation.

4.1 Some Robustness Checks

To address concerns by classifying LPs in quartiles, we substituted the main independent variable (quartile centrality Dummy) in equation 1 by the standardized eigenvector centrality measure. Below, is our new equation:

$$LPsPerf_{iv,j} = \beta_0 + \alpha_1 LPcentrality_{j,v} + \alpha_2 fundsize_i + \alpha_3 LPExperience_{j,v} + FE + \varepsilon_{iv,j} \quad (2)$$

where the dependent variable is the LP j investment performance in a fund i with vintage year v. The new independent variable is the centrality measure for LP j at vintage year time v standardized to unit variance. As equation 1, it also includes controls variables (fund size and LP experience), fixed effects and clustering strategy.

In table 5, we can see the results for equation 2. For VC funds, specifically in the first and last sub-period, the coefficients are economically relevant and significant at the 5% to 10% statistical level. In general, we can infer that higher levels of centrality results in more performance. As LPs eigenvector centrality is skewned we expect that a small group of LPs, those with higher centrality measures, will have higher results than other investors. Considering the whole sample, we find that a one standard deviation increase in LPs centrality increases performance by approximately 10% relative to its mean (using the mean return is 13,3%). For BO funds, in general, these results do not hold.

When addressing a common endogeneity problem during the construction of the centrality measure—the potential for reverse causality—where superior performance might lead to the enhancement of LPs' network centrality rather than the reverse, we do not believe this to be the case. This is because the network centrality measure (Eigenvector) was derived from data collected 5 years prior to the fund's inception. In simpler terms, the fact that past data can successfully explain LPs future fund performance suggests that networks indeed have a significant importance on performance.

To address worries that the centrality measure would be a proxy for LPs size, in table 6, we analyze the effects using three different proxies. Formally, it is equation 1 plus the new control variable. Below, this is our new specification:

$$\begin{aligned} LPsPerformance_{iv,j} =& \beta_0 + \sum_k \alpha_{1,k} DummyQuartileLP_{j,k,v} + \alpha_2 fundsize_i \\ &+ \alpha_3 LPExp._{j,v} + \alpha_4 LPSize_{j,v} + FE + \varepsilon_{iv,j} \end{aligned} \quad (3)$$

where $LPSize_{j,v}$ stands for LP j asset under management in MMU$ at time v (v stands for the vintage year of the fund i). Unfortunately, LPs' size is not observable due to the lack of historical and consistent information in the databases. However, Cavagnaro and Wang (2019) proposes two proxies, and the third was developed by us. Proxy 1 is the natural logarithm of the asset under management of LPs. This constant value is maintained throughout the analysis period (this is the only LP size proxy that is not time varying). The second proxy is time-varying. As recommended, we start by dividing each LPs AUM by the total number of investments the LP made between 1991-2015. Afterwards, we multiplied this value by the total number of investments the LP made each year. Our third proxy is also time-varying and was developed by us. First, we divide each LPs assets allocated exclusively for PE by the total number of PE investments (VC and BO combined investments) the LP made between 2013-2022. The assumption is that the asset value provided by Preqin represents the current portfolio of LPs. Since PE investments typically take about 10 years to materialize, we infer that these assets actually represent the previous investments made by the LPs. Then, for each year and LP, we multiplied this value by the total number of investments each LP made in a past 10 year window.

For VC and BO investments, the results from table 6 shows that the size of LPs does not have a significant impact on performance, nor does it affect relevantly the coefficient and significance of the main centrality variable.

To address concerns about outliers influencing our conclusions/results, all regressions utilizing performance data (Net IRR%) were winsorized at a 1% level. Therefore, the presented results already consider the performance data after winsorization. Additionally, we conducted a Robust Regression (see Table 7) and found that our overall conclusion regarding differences in categories remains consistent, albeit with smaller coefficients. In the first and last subperiods, we observe a reduction in the coefficients (when compared to the OLS regressions). Interestingly, we observe that the subperiod from 1999-2006 now displays higher significant differences in performance between the LPs quartiles. In summary, when analyzing our robust regressions, our main conclusions from the OLS regressions remain consistent, albeit with smaller coefficients (first and last subperiods), and we understand that our conclusions/results are not solely driven by outliers.

Furthermore, continuing our examination of outliers, in Figures 2 and 3, we observe the return (Net IRR%) distributions for each quartile of LPs as outlined in table 4 for VC funds spanning the period 1991-2015. Notably, in Figure 3, when comparing the distributions of 1Q LPs with those of other LPs, we can visually discern similar distributions, particularly in the right-hand tail. Upon examining the summary statistics table, we note that the kurtosis across all LP categories is similar. This suggests that our findings, predominantly centered on performance comparisons between LP categories, reveal similar distributions, particularly regarding the tails, which are important for outlier analysis. In essence, our performance comparisons among categories essentially involve comparing LPs with similar tail distributions. Therefore, if the performance disparity of 1Q LPs is attributed to a fat-tail distribution, we can verify that other quartiles LPs also exhibit similar fat-tail return distributions, consequently yielding comparable outcomes.

5 Investigating the reasons for superior performance

The evidence provided regarding performance and its relationship with the centrality of LPs may raise questions about the underlying reasons for the superior returns observed among top central

LPs compared to other investors. Lerner et al. (2007), mentions four reasons why there might be different returns between LPs.

The first is related to access to privileged GPs and their top performing funds. Also, risk profile can play a role in differentiating performance across LPs, as more risk-taking investors might enjoy higher returns than other LPs. Another reason is the objective function of LPs. For example, banks and public pension funds might diverge from the classical return maximization objective function. However, the authors mentions that this might not be the reason for superior returns, as banks usually under-perform and public pension funds have different returns when investing in or out-of-state ventures. Finally, it is possible that LPs may possess privileged/inside information during the investment decision-making process[11]. This is important in PE because not all information are public and, usually, relevant information are only available to existing investors. This can give them advantages when analyzing follow-on funds and optimize their decisions to invest in promising funds.

Like Sensoy et al. (2014), we will investigate only two reasons for these different returns; access to top funds and good investment decisions (inside information).

5.1 LPs access to top performing funds and GPs

In this section, we analyze whether the superior performance of top central LPs merely serves as a proxy for their access to top-tier funds/GPs. Lerner et al. (2007) and Sensoy et al. (2014), approach's by identifying funds that potentially restricts access to new investors. The premise relies on the findings outlined in Kaplan and Schoar (2005), revealing a concave correlation between fund size and performance. This implies that the best funds deliberately constrain their size, foregoing additional capital despite the potential to raise more. In essence, if LPs ability to generate superior returns is limited to funds with access restrictions, it may indicate that access to top funds plays a crucial role in explaining their superior returns.

In this paper, our approach to identifying access to top-performing funds differs from existing literature strategies. Instead of exclusively seeking a group of funds that restrict access, we shift our focus to understand the GPs/funds our LPs are investing. Therefore, a few questions arise if top central LPs, given their superior performance, are the investors of specific or pulverized groups of profitable GPs? Is there a more discernible correlation between privileged LPs and non-privileged LPs in terms of their investment choices?

To investigate this question, using network theory, we begin by constructing a *bipartite* network composed of two types of nodes (LPs and GPs) to identify the most central GPs. The edges (connections) were the investments made by LPs in GPs (represented by the investments into their funds). The type of edge was *undirected*. We chose this option because in PE not only does LPs selects where to invest, but GPs can also hand pick investors. This can be the case in more

[11] Sensoy et al. (2014) classifies this strategy as LPs *skill* in making decisions

central, influential, highly-demanded and top performing GPs. The construction of the networks followed the ex-ante strategy, detailed in section 3.1, considering a previous 5 year window.

To identify if GPs in the 1st quartile enjoys higher performance than other GPs, we use the equation below. As a disclaimer, this is the only time we will make an analysis at the fund level. The other tables and equations are at the LP level.

$$GPFundPerformance_{ivr} = \beta_0 + \sum_k \alpha_{1,k} Dummy1stQuartileGP_{k,v,r} + FE + \varepsilon_{ivr} \tag{4}$$

where GP fund performance is the fund i Net IRR (%) in vintage year v winsorized by 1% given its GP r. The GP centrality measure dummy returns one if the fund i with GP r is classified as 1st quartile in vintage year v, and zero otherwise. The quartiles of centrality measure (eigenvector) was extracted from ex-ante bipartite networks. For all vintage years v from 1991-2015 we constructed networks to extract the centrality measures, so we have time varying GPs dummies (we used the v notation to highlight this point in the equation, as time goes by the centrality position of the GP might change). Vintage year and funds region focus were added as fixed effects and cluster by vintage years.

In table 8, panel A for VC funds, we can identify that GPs in the 1st quartile enjoys higher performance than other GPs. The period of 1991-2015 shows a 7,69% higher return for 1st quartile when compared to other quartile GPs. For all subperiods, top quartile GPs outperforms other quartiles. These findings do not hold for BO funds. In panel B, as a robustness test, we replace the dummy variable with the directly eigenvector variable (standardized to unit variance). As observed, the earlier mentioned conclusions remain consistent, indicating that more central or privileged GPs has higher returns.

After identifying that top performing venture capital GPs are also the most influential (1st quartile GPs), we turn back our analysis at the LP level. Our objective is to understand if 1st quartile LPs enjoys superior returns because of their investments in 1st quartile GPs. To do this, we separate our analysis into two strategies; analyzing proportions and using probit models.

We start with the most simple, analyzing proportions. The idea is to understand if the better-connected GPs, which, as we know, are the most profitable, receives investments from top central LPs. When we analyze table 9 panel A for VC investments, the results show that better-connected GPs (1st quartile) receives 66,5% of the total investments (for BO is 61,4%) coming from LPs classified in the 1st quartile (most influential LPs). Meanwhile, less central LPs (4th quartile) represent only 2.9% of the total investments (for BO is 5,1%) in these more better-connected GPs (central GPs). This shows us that the most influential GPs receives the majority of its investments coming from the top central LPs, independent if we are analyzing VC or BO investments.

Another way, is to analyze the proportions of investments made by LPs. For VC funds, between 1991-2015, the results in table 10 indicates that the most influential LPs have 53.1% of all their investments directed towards the most influential GPs. However, this proportion drops significantly when we analyze the less central LPs. In this case, only 13,7% of the investments made by the less central LPs were in GPs classified in the 1st quartile. Hence, there´s strong evidence of investment concentration of influential LPs in central and, consequently, profitable GPs, which can help explain the excess return for these privileged LPs. On the other hand, it is uncommon for low-influential LPs (4th quartile) to invest in the top 1st quartile general partners (GPs). These proportions conclusions also holds for investments in BO, however, with smaller differences between quartiles.

Table 11 is a quartile analysis and matches how LPs invests in different GPs, however comparing the performance between quartiles. From panel C - columns (1), (2),(3) and (4) we can verify how investments in top quartile GPs in VC delivers higher performance than investments in other lower quartile GPs. These results, in general, do not hold for BO funds (Panel F). In summary, for VC funds, these results reinforces that superior performance for top central LPs is associated to its high centrality measure and their investments in more better-connected GPs

In our pursuit to reinforce the investment dynamics between 1st quartile LPs and privileged GPs, our second strategy involves the application of probit models. This statistical methodology enables us to assess the likelihood of 1st quartile LPs engaging in partnerships with top-tier privileged GPs. This analysis was conducted at the level of LP investments.

$$Prob(1stQGP_{iv,j,r} = 1) = \phi(\beta_0 + \sum_k \alpha_{1,k} DummyQuartileLP_{j,k,v} + Controls + FE + \varepsilon_{iv,j,r}) \quad (5)$$

The dependent variable equals to one if the investment made by LP j is in fund i with vintage year v and managed by 1st quartile GP r, zero otherwise. The Dummy Quartile LP independent variables, controls, fixed effects and clusters are similar to equation 1. As table 12 shows, 1st quartile LPs have higher probability to invest with 1st quartile GPs than other quartiles. The results are consistent for all subperiods. For BO funds, there is also some level of concentration, though it is not as pronounced as observed in venture capital.

In summary, for VC funds, we find strong evidence that the superior performance of top central LPs comes from their investments in more central GPs, who statistically outperform other less central GPs. These findings demonstrate that the top central LPs and GPs establish robust connections in VC investments. Since the most influential GPs tend to exhibit superior performance, this enables top central LPs to enjoy the benefits of higher returns. These conclusions do not hold for BO funds.

5.2 Investment decision-making skills of Limited Partners

Another reason for superior returns for top central LPs can be related to their good investment decisions. These decisions can happen in two ways; if the LP is a current investor of a specific GP or outside investor. In PE being inside or outside investor can make a big difference in access to important information when analyzing future investments. Lerner et al. (2007) proposes a few strategies to capture the quality of investment decisions. If LPs are current investors of a specific GP, the strategy to capture LPs skills is to evaluate the quality of the re-investments decisions (table 13). On the other hand, if the LPs are outside investors the strategy will be to compare performance for first-time funds against later sequence funds (table 14).

Existing literature have pointed to conflicting results when using these strategies. Lerner et al. (2007) have found superior skills for Endowments analyzing reinvestments decisions and first-time VC funds (the authors uses investments in recently established GPs), when compared to other categories of LPs. However, Sensoy et al. (2014), for the same period, did not find any superior reinvestment skills nor better investments decisions in first-time funds for any category in VC funds. Several reasons could account for these different results, but despite the controversy, we still believe that these strategies represent the best approach to date.

We start analyzing LPs reinvestment decisions. Limited partners have the potential to gain access to privileged information when investing in a specific GP, which could enhance their ability to analyze follow-on funds from the same GP[12].

Table 13 presents the results of re-investments and abandoned funds by LPs. To create the sequence of funds (current and follow-on funds), we used the same methodology presented by Harris et al. (2023). As fund selection is quite rigorous, the number of funds in the sample decreased, and so did the investments that could be analyzed. However, on the other hand, we believe that we have a more reliable basis for analyzing results. For VC funds in panel A, the results considering all periods (1991-2015) reveals no significant differences in returns between reinvested and abandoned funds of LPs. Interestingly, during the subperiod from 1999-2006, 1Q LPs exhibited poorer reinvestment decisions. However, in subsequent subperiods, their decision-making notably improved, yielding better outcomes. In general, given our quartile analysis for VC funds, we understand that top central LPs do not have consistent superior return when facing reinvestment decisions.

Table 13, even though focused on analyzing reinvestment decisions, can help consolidate even more the importance of access. In panel A, when comparing returns between 1st quartile LPs and other LPs we can identify differences in returns. For example, during 1991-2015 the reinvested funds from the 1st quartile investors had a average return of 15,6%, while Other LPs had average returns of 12,3%. When comparing abandoned funds we see a similar gap. Furthermore, even when comparing the lowest performance within the 1st quartile LPs it still surpasses the highest performance among reinvested funds for other LPs. This can be observed in all sub-periods. However, it is unquestionable that through time the access advantage for these top central LPs has declined, yet still exists.

On the other hand, in panel B of Table 13, analyzing all periods, differences in returns between reinvested and abandoned funds of LPs are observable for BO funds, albeit small. Intriguingly, abandoned funds demonstrate superior performance compared to reinvested ones, which is contrary to what we would typically expect. Furthermore, when comparing reinvested funds by 1Q LPs

[12] specially that current LPs are consistently granted preferential access to subsequent funds

and other LPs, the returns across all subperiods are similar. Thus, the significance of access, as observed in the analysis of VC funds, doesn't seem as pronounced in this context.

An alternative approach to assess LPs' skill is to examine their performance when investing in first-time funds or GPs. In essence, if 1st quartile LPs demonstrate superior performance when investing in these initial funds or GPs, it could be indicative of their skill in evaluating investment opportunities. In table 14, we can find the returns in first time and mature funds. For VC investments, the superior performance for top central LPs comes clearly from mature funds and nothing from 1st time funds. This indicates that their returns came from re-investing in established funds and not choosing wisely 1st time funds. For BO funds, we do not find any significance for LPs centrality measures in both 1st time and mature funds.

In summary, our findings regarding decision-making based on skills align with Sensoy et al. (2014) study, which similarly found no consistent/significant distinctions in skill levels across certain categories.

5.3 LPs performance persistence in Venture Capital - Access or Skills?

For VC funds, we observe that the superior performance for top central LPs came from access to top performing/central GPs, rather than being driven solely by the skills (ability to pick the best GPs). However, we do not rule out the possibility of skills, as the current industry binary approach (tests) may not be optimal in distinguishing between LPs' decisions. This disentanglement is always challenging because at least three forces may be at: (1) skillful LPs selecting GPs (2) successful GPs being able to cherry-pick LPs that they believe are a good fit for them in the future and (3) LPs could have different investment goals/objectives. These phenomena are not independent of each other, and when analyzing we can have a combination of these forces and our results will always be biased depending our the data we are analyzing.

Acknowledging the above disclaimer, based on the techniques and data available to us at the moment, we observe that, on average, access to successful GPs can explain most of the differences in performance among LPs. For BO funds, given the absence of excess performance among LPs, these conclusions do not hold.

6 Interpreting LPs Network Measurement in Venture Capital - *LP Centrality*

Considering our findings, one may question what information LP centrality measurements are revealing. We understand that the centrality measure may be capturing LPs who exhibit loyalty and serve as a signal of quality for top-performing GPs (also top-central GPs). However, to fully comprehend this metric and our inference, we need to revisit some results presented and subsequently integrate them. Finally, we reconcile these findings with existing theories in venture capital that rely on LPs as crucial assumptions.

6.1 Loyal Limited Partners(LPs)

The first aspect is concerning our main LP centrality measure (Table 2), which is derived from LPs co-investments. We acknowledge that the top central LPs are those with greater/influencial connections to other LPs. However, this merely reflects their involvement in co-investments in funds and, consequently, with GPs.

Second aspect pertains to our bivariate network analysis of the findings outlined in Table 8. It is evident that GPs with a substantial base or exposure of LPs, captured by the high centrality measure, tend to exhibit higher performance. Essentially, in this scenario, the centrality measure for GPs can be construed as an indicator of superior quality GPs, as we observe that these GPs are correlated with having exposure to many LPs (highly demanded). This suggests that LPs might possess valuable insights into connected GPs - in other words, about their superior performance. Consequently, LPs who consistently invest with these top central GPs are likely to experience excess returns.

Combining these two aspects, our analysis revealed, as captured in Table 10 and 12, that top central LPs are more likely than other LPs to invest in top-central GPs, those exhibiting the highest performance (see Table 8). Since these top-performing GPs are in high demand (indicated by their high centrality measures), LPs consistently investing with them gain increased exposure to other LPs, consequently resulting in higher centrality measures for these LPs. Importantly, this also grants them access to superior performance. Thus, we infer that the LPs centrality measures (by co-investments) captures their exposure/loyalty to *top-central-performer* GPs.

6.2 Quality Signalizers Limited Partners(LPs)

In this section, we investigate whether top central LPs are good signalizers of GPs quality. To accomplish this, we will investigate whether LPs investing in sequential funds from the same GP (referred to as "LP Persistence") can serve as reliable predictors of performance for a GP's follow-on fund. If confirmed, it emphasizes the critical role of LPs in holding essential information about GP quality, with our centrality measure aiding in identifying these significant signalizers.

To measure LP persistence, we identified instances when LPs invested in consecutive pairs of funds, indicating the presence of the same LP in both the previous and current funds managed by a given GP. Our main explanatory variable consists of our top central LPs. Our selection criteria of previous and current fund followed the recommendations from Harris et al. (2023).

We employ OLS regressions on our pooled cross-sectional data for funds to analyze the relationship between performance and the number of LPs reinvesting. Our main empirical specification is as follows:

$$NetIrr_{it} = \beta_0 + \alpha_1 QuantityLPsReinvest_{it} + \alpha_2 Fundsize_{it} + \alpha_3 Sequence_{it} + FE + \varepsilon_{it} \quad (6)$$

The dependent variable is the performance metric (IRR%) and the main explanatory variable is the quantity of LPs that are reinvesting from the prior to the current fund (our LP persistence variable). We also include some control variables as natural logarithm of the fund size (in millions) and sequences, with the inclusion of vintage years fixed effects and clusters at the GP level. Additionally, we incorporated the quadratic form for each explanatory variable to capture any non-linear relationship.

The results from Table 15 demonstrate the significance of LPs' reinvestors classified in the top quartile centrality in predicting GPs' follow-on funds. The relationship is positive (slightly concave), significant, and of considerable economic magnitude. As the quantity of reinvestors in the current fund increases, the predictions for performance become higher, signaling that the presence of more reinvestors is a signal of the GP's quality. These results resonate with the predictive findings using past fund performance (Kaplan and Schoar, 2005), which form the basis for fund-level performance persistence, and exhibit a similar econometric fit captured by the adjusted R-square. Furthermore, we performed additional robustness tests utilizing robust regressions to address potential outliers influencing our results. Our findings reveal that the positive correlation between reinvestors and performance persists, even when we disaggregate our sample into subperiods.

These findings indicate that these top central LPs, previously found to have superior performance, exhibit robust predictive capability in fund-level analysis and may act as effective quality signalizers for GP quality.

6.3 Understanding the results through existing VC theories

In this section, we aim to connect the above findings (sections 6.1 and 6.2) with existing theories in venture capital that highlight the crucial role of LPs as key players in the field.

It's interesting to consider the results in light of the theory proposed by Lerner and Schoar (2004) regarding the nature of liquidity in private equity (PE) investments. According to the theory, GPs strategically seek out deep-pocket investors who demonstrate long-term commitment and are less susceptible to liquidity shocks. The LP centrality measure can help identify these deep-pocket investors — precisely the type of investors sought after by successful GPs. Since these top central LPs may have access to insider information about GPs (and are more capable/technical of absorbing the information), they are better positioned to make informed investment decisions. And naturally, if these GPs prove to be successful, they will outperform other LPs, thus having an important option to reinvest with the GP.

This could help explain why, in our robustness checks, factors such as LP size (AUM)[13] or

[13] Cavagnaro and Wang (2019) similarly did not find any significant difference in LP size that explains returns fo VC funds. However, one might question the findings of studies such as Dyck and Pomorski (2016), which identified size as a significant variable in a sample of pension funds. Yet, this specific/sample of pension funds could potentially be the deep-pocketed and loyal LPs that GPs desire, precisely the type of investors our network analysis might be capturing. Additionally, Barber et al. (2021) demonstrate that LPs might prioritize dual objectives, such as social impact, potentially introducing more variability in the analysis concerning size or even in the relationship between performance and experience.

LP experience (number of prior investments)[14] (refer to Tables 6 and 3, respectively) do not significantly impact LP returns. Successful GPs may prioritize factors beyond the size or experience of LPs, focusing instead on their potential long-term commitment.

The fact that top central LPs tend to reinvest with these top-performing GPs may also align with the theory proposed by Hochberg et al. (2014), which suggests that LP reinvestments (LP persistence) underpin the *well-known* phenomenon of fund performance persistence (Kaplan and Schoar, 2005), particularly prevalent in venture capital. The theory was developed to elucidate the persistence of performance in venture capital using LPs signaling as an important assumption of the model. They propose that current investors learns insights into the skills of fund managers while outside investors primarily base their judgments on historical returns. This dynamic provides current investors with significant influence when GPs seek to raise their follow-on funds. Without the support of these current investors, no-other LPs will fund him, as outside investors interpret their absence as a signal of lower managerial skill. The asymmetric information among LPs creates a holdup power that restricts GPs from increasing fees in proportion to their performance, and this, in turn, leads to the persistence of returns. In other words, one can interpret high centrality LPs as those investors who can effectively signal to outside investors the quality of a GP, aligning with existing theory.

In addition, the existence of LP performance persistence (table 15), can potentially be interpreted as the other side of the coin of the fund performance persistence phenomenon. Hochberg et al. (2014) mentions that one assumption underlying fund performance persistence is the existence of LP persistence (LPs reinvesting from one fund to the next within the same GP). So testing if LP persistence can predict fund performance can potentially help with a link between LP performance and fund performance persistence.

The connection of these two asymmetric information theories (Lerner and Schoar, 2004; Hochberg et al., 2014) have LPs as key underlying assumptions, and network analysis could be capturing those LPs that are preferred by the GPs, has better skills to identify good funds/GPs (as they are insider and probably have better man power condition) and are reinvesting in these top performer managers/GPs working as signlizers to other outside LPs.

Our findings can also resonates with the theory proposed by Maurin et al. (2023), which suggests that successful GPs selectively choose LPs based on their capacity to commit capital that can be utilized during challenging periods, thus playing an important role in GPs' fund structure management (selecting the right LPs to compose their investor/fund structure). From Table 9, we can observe a consistent pattern in the GP-LP matching, characterized by a stable ratio of approximately 2/3 (two-thirds) of top central LPs investing with top central GPs. In other words, the investment opportunities among these top GPs are not equally distributed among LPs. It is important to mention that we do not infer any causal direction regarding GPs selecting LPs (or vice versa). Instead, we just observe an unequal distribution among funding options for GPs (without

[14] Lerner et al. (2007) and Sensoy et al. (2014) also did not find any significant presence of experience in explaining returns.

mentioning any direction). However, one could interpret our findings as the equilibrium point of the theory by Maurin et al. (2023) where successful GPs have an upper hand selecting LPs. This trend persists across all periods in our dataset, both in terms of quantity and proportion, to top quartile GPs compared to other less central LPs. These findings are evident in VC and BO funds.

Overall, the centrality measure of LPs can potentially serve as a proxy for loyal and quality signalizers for successful VC GPs, aligning with various theories in VC that highlight the importance of LPs.

7 Conclusion

This paper examines the relationship between performance and the level of influence among Limited Partners (LPs). Unlike most existing literature that analyzes performance based on traditional administrative categories, this article employs network theory to categorize LPs based on their own influence within a network.

The results indicate that LPs with high centrality tend to achieve better returns than their counterparts when making investments in VC funds. Furthermore, this positive relationship between centrality and returns are still consistent when analyzing more recent sub-periods. This finding offers a different perspective to the results presented by Sensoy et al. (2014), which suggested no longer existing excess returns based on classic LP categories like Banks, Assets, Endowments, etc. In our view, the traditional categories might not be the best option to analyze the performance persistence among LPs, as they tend to be rigid boundaries. Instead, centrality measures could prove to be a more promising approach. For buyouts funds these findings do not hold.

In addition, we find strong indications that the persistence of LPs return came from access to top performing and central GPs, rather than being driven solely by the skills (ability to pick the best GPs) influencing their returns. However, we are not dismissing the possibility of skills; rather, we are observing that, on average, access to successful GPs can explain most of the differences in performance among LPs.

Moreover, we observe a distinct matching among top performance GPs and a select group of LPs (top central LPs), specially when we compare the proportion of investments from other LPs. In other words, the investment opportunities among these top GPs are not equally distributed among LPs; instead, they're concentrated among a smaller group of LPs. This pattern persists across all periods in our dataset. We don't infer any causal relationship between LPs' or GPs' power dynamics in these findings; we simply observe a consistent matching between them - *"possible equilibrium point"*. Essentially, this involves a small group of prospective LPs to be the most prevalent investors in their funds, while also offering opportunities to other LPs, albeit to a lesser extent.

In our view, the centrality measure of LPs can potentially serve as a proxy for loyal and quality signalizers for successful VC GPs. This understanding also resonates with several theoretical papers highlighting the significance of LPs in the VC landscape. Interestingly, we find that successful LPs are not necessarily related with their prior PE experience or size (measured by the AUM), suggesting that another dynamic is at play, potentially reinforcing our perspective on loyalty and serving as good signalizers of quality for GPs.

In summary, gaining insight into how LPs organize themselves through a novel perspective using Network theory can enhance our understanding of the pivotal role that LPs play in shaping the investment environment and provide valuable insights into the VC landscape.

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Table 1: Descriptive Statistics for the Sample of Private Equity Funds

This table presents descriptive statistics for 2,528 private equity investment funds of the BO and VC types raised between 1991-2015 (full sample period) and three subperiods from 1991-1998, 1999-2006 and 2017-2015. IRR (%) is the net internal rate of return earned by an LP, after fees and carry. Vintage year is the first year of investment/drawdown from the investor. The overall fund sequence number is related to sequence of funds raised by the same GP.

Fund Characteristics	Full Sample Period (1991-2015)				1991-1998				1999-2006				2007-2015			
	N	Mean	Median	Std.Dev.	N	Mean	Median	Std.Dev.	N	Mean	Median	Std.Dev.	N	Mean	Median	Std.Dev.
All funds																
Vintage Year	2.528	2005	2006	6	436	1996	1996	2	1.001	2003	2003	3	1.091	2011	2011	3
IRR (%)	2.528	15,4	12,5	29,9	436	26,0	14,2	49,9	1.001	9,5	8,4	16,9	1.091	16,7	15,5	27,2
Number of LPs investing in fund	2.528	16	10	19	436	11	8	12	1.001	18	11	22	1.091	16	10	19
Size (millions of dollars)	2.490	868,3	320,0	1.764,8	425	426,1	175,0	730,4	993	786,9	315,0	1.574,3	1.072	1.119,1	400,0	2.141,1
Overall fund sequence number	2.524	5	3	5,4	434	3	2	2,8	1.001	4	3	3,7	1.089	6	4	7,0
Venture funds																
Vintage Year	1.075	2004	2005	6	200	1996	1996	2	454	2002	2002	2	421	2011	2011	3
IRR (%)	1.075	14,8	8,3	42,5	200	39,1	19,4	68,2	454	1,7	1,7	15,9	421	17,3	14,4	40,8
Number of LPs investing in fund	1.075	11	8	10	200	8	6	7	454	13	10	12	421	9	7	8
Size (millions of dollars)	1.049	275,5	185,0	315,8	196	135,5	105,0	111,4	448	316,6	222,5	338,2	405	297,9	210,0	338,0
Overall fund sequence number	1.074	5	3,0	5,5	200	3	3	2,0	454	4	3	3,2	420	6	4	8,0
Buyouts funds																
Vintage Year	1.453	2005	2006	6	236	1996	1996	2	547	2003	2003	3	670	2011	2011	3
IRR (%)	1.453	15,9	14,3	14,9	236	14,9	13,0	20,0	547	16,0	13,1	14,8	670	16,3	15,9	12,7
Number of LPs investing in fund	1.453	20	13	23	236	14	10	14	547	22	13	27	670	21	13	23
Size (millions of dollars)	1.441	1.299,8	515,0	2.206,4	229	674,8	359,8	920,2	545	1.173,5	450,0	2.023,3	667	1.617,7	688,0	2.577,6
Overall fund sequence number	1.450	5	3	5,3	234	3	2	3,3	547	4	3	4,1	669	6	4	6,4

Table 2: Limited Partners - LPs Characteristics and Centrality Measures Standardized to Unit Variance

This table presents descriptive statistics for 903 unique LPs (Limited Partners) who invested in VC funds and 1155 LPs for BO funds for vintages between 1991-2017. Additionally, the statistics are provided for the entire period and also for three sub-periods (1991-1998, 1999-2006, and 2007-2015). "Total # of LPs" represents the total number of unique investors for given a specific sample period."Average # of Investments per LP" indicates the average number of investments made by LPs in a particular category. The results are divided by quartiles given LPs eigenvector centrality measure. The centrality measure is standardized to unit variance. LPs categorized in the first quartile exhibit the highest degree of centrality, while those in the fourth quartile demonstrate the lowest centrality measure within the network.

	Full Sample Period (1991-2015)					1991-1998				
	Total # of LPs	Avg # of investments per LP	Avg. Eigenvector Centrality	Median Eigenvector Centrality	Std. Dev. Eigenvector Centrality	Total # of LPs	Avg # of investments per LP	Avg. Eigenvector Centrality	Median Eigenvector Centrality	Std. Dev. Eigenvector Centrality
Panel A: VC funds										
1st Quartile LPs	226	30,5	2,4871	2,3159	0,7096	41	18,1	2,7655	2,7603	0,3544
2nd Quartile LPs	225	8,5	1,1143	1,1024	0,2547	41	7,7	1,7679	1,7430	0,2826
3rd Quartile LPs	226	4,4	0,4074	0,3739	0,1458	37	4,4	0,8699	0,9030	0,2727
4th Quartile LPs	226	2,4	0,0902	0,0845	0,0607	45	2,2	0,2567	0,2690	0,1418
Overall	903	11,5	1,0246	0,7079	1,0000	164	8,1	1,4000	1,3245	1,0000
Panel B: Buyout funds										
1st Quartile LPs	289	61,0	3,0594	2,9944	0,4511	46	24,9	3,3110	3,2689	0,2257
2nd Quartile LPs	288	16,6	1,9584	1,9216	0,2467	45	11,5	2,5166	2,4494	0,3009
3rd Quartile LPs	289	9,9	1,2454	1,2596	0,1869	45	6,0	1,7347	1,7260	0,1731
4th Quartile LPs	289	5,4	0,4736	0,4945	0,2663	46	3,9	0,7541	0,6555	0,4443
Overall	1155	23,2	1,6840	1,5733	1,0000	182	11,6	2,0786	2,0322	1,0000

	1999-2006					2007-2015				
	Total # of LPs	Avg # of investments per LP	Avg. Eigenvector Centrality	Median Eigenvector Centrality	Std. Dev. Eigenvector Centrality	Total # of LPs	Avg # of investments per LP	Avg. Eigenvector Centrality	Median Eigenvector Centrality	Std. Dev. Eigenvector Centrality
Panel A: VC funds										
1st Quartile LPs	150	22,0	2,6200	2,5289	0,5737	170	11,6	2,4030	2,3113	0,7806
2nd Quartile LPs	149	6,5	1,3434	1,3385	0,2742	170	4,4	0,7629	0,7101	0,2461
3rd Quartile LPs	149	4,0	0,6031	0,6013	0,1848	170	2,2	0,2910	0,2781	0,0629
4th Quartile LPs	150	2,0	0,1285	0,1089	0,0936	170	1,7	0,0796	0,0674	0,0587
Overall	598	8,6	1,1744	0,9079	1,0000	680	5,0	0,8842	0,4228	1,0000
Panel B: Buyout funds										
1st Quartile LPs	183	34,0	3,1697	3,1212	0,3383	264	31,5	2,8536	2,7611	0,5201
2nd Quartile LPs	183	11,9	2,2534	2,2697	0,2179	263	9,1	1,6518	1,6478	0,2419
3rd Quartile LPs	183	7,0	1,5043	1,5259	0,2359	264	4,7	0,9467	0,9339	0,1788
4th Quartile LPs	183	4,0	0,5643	0,5848	0,3157	264	2,6	0,2954	0,2923	0,1920
Overall	732	14,2	1,8712	1,8667	1,0000	1055	12,0	1,4367	1,2589	1,0000

Table 3: LPs investments and Performance

The table displays the characteristics of funds invested by LPs separated by quartiles given their centrality measure. "N" represents the number of investments made by that LP category in specific periods. "Fund Mean IRR" is the arithmetic mean of returns (IRR) from investments (VC or BO investment funds) made by LP categories. "Fund Sequence Number" refers to the sequence number of the fund given a particular GP. "Fund Size" is the total committed capital for the fund in millions of dollars. "Difference between 1st Quartile and Other Quartiles" represents the difference in means, including its statistical significance, between 1st Quartile LPs and other LPs in the other categories. The data was collected with a reference date of March 2022. Panel A focuses only on investments in VC funds and Panel B considers only investments in BO funds. LPs categorized in the first quartile exhibit the highest degree of centrality, while those in the fourth quartile demonstrate the lowest centrality measure within the network. "*** p¡.01, ** p¡.05, * p¡.1" indicates significance levels.

	Full Sample Period (1991-2015)					1991-1998					1999-2006					2007-2015				
	N	Fund Mean IRR (%)	Fund SD IRR(%)	Fund Sequence Number	Fund size (mm of U$)	*N*	Fund Mean IRR (%)	Fund SD IRR(%)	Fund Sequence Number	Fund size (mm of U$)	*N*	Fund Mean IRR (%)	Fund SD IRR(%)	Fund Sequence Number	Fund size (mm of U$)	*N*	Fund Mean IRR (%)	Fund SD IRR(%)	Fund Sequence Number	Fund size (mm of U$)
Panel A: Venture Capital																				
1st Quartile LPs	6.890	14,0	6,8	6,0	548,4	744	56,5	32,0	4,5	242,1	3.298	1,5	2,1	5,9	645,1	1.970	18,0	17,3	7,4	643,0
2nd Quartile LPs	1.923	12,1	8,0	5,4	459,7	316	39,9	23,0	4,1	206,6	974	1,7	1,9	5,2	548,2	740	16,0	14,6	6,1	375,4
3rd Quartile LPs	1.004	11,5	10,0	7,0	301,5	164	35,2	16,9	3,4	165,3	602	0,7	0,3	4,2	353,2	372	15,9	14,3	12,1	344,3
4th Quartile LPs	536	13,1	9,7	4,5	212,9	99	36,4	16,2	3,1	129,2	296	4,0	3,3	4,0	196,0	285	13,8	12,4	5,8	215,9
Overall	10.353	13,3	7,1	5,9	492,2	1.323	48,4	28,3	4,2	216,0	5.170	1,6	1,9	5,5	567,8	3.367	17,0	15,7	7,5	517,9
Difference between 1st Quartile and Other Quartiles		*-1.14**		*0,00*	*222.44****		*22.24****		*0.88****	*61.64****		*-0.65**		*1.11****	*242.27****		*2.59****		*-0.63***	*337.29****
Panel B: Buyouts																				
1st Quartile LPs	17.636	15,2	13,6	6,3	3.424,2	1.145	14,6	13,2	4,2	1.232,6	6.220	14,6	12,1	5,7	3.179,8	8.315	16,2	15,8	7,4	4.172,6
2nd Quartile LPs	4.773	15,3	13,7	6,2	3.344,4	517	12,9	11,0	3,9	1.152,5	2.180	15,1	12,5	5,8	3.175,6	2.392	16,4	15,7	7,4	3.804,2
3rd Quartile LPs	2.871	16,4	14,3	6,0	2.675,2	272	15,2	13,2	3,8	1.134,6	1.285	15,3	12,4	5,0	2.563,4	1.237	15,5	15,0	7,1	3.203,1
4th Quartile LPs	1.555	15,5	13,7	5,1	1.571,8	178	17,4	13,7	3,6	585,9	737	15,0	12,3	4,2	1.405,6	679	15,1	14,8	5,7	1.513,6
Overall	26.835	15,4	13,7	6,2	3.223,6	2.112	14,5	13,0	4,0	1.146,9	10.422	14,8	12,2	5,5	2.977,4	12.623	16,1	15,7	7,3	3.866,3
Difference between 1st Quartile and Other Quartiles		*-2.17****		*-0,07*	*418.76****		*-0,75*		*0.67****	*82.35**		*-0.45**		*0.42****	*353.90****		*0,22*		*0,02*	*802.63****

Table 4: LP Performance in PE Funds by Centrality Quartile

The table presents performance regressions (*equation* 1) of investments made by LPs for the period between 1991 and 2015, including all sub-periods. The results are separated by VC and BO funds. The dependent variable is the NetIRR of the funds invested by LPs winsorized by 1%. The regression includes dummy variables that identifies the centrality quartile of LPs, taking the value of one if a specific LP invests in that particular fund, and zero otherwise. The centrality dummy variable was obtained by network connections using the ex-ante strategy. First, we constructed networks by utilizing co-investments made by LPs in the previous five years to extract eigenvector centrality measures. Afterwards, LPs were classified into quartiles given the centrality measures. In addition, these dummies are time varying as LPs can change quartile position through time. For each vintage year in the sample, we generated a new network to derive updated centrality measures and subsequently determine their revised quartile positions. 1st Quartiles LPs are the base and will be omitted in the regressions. LPs categorized in the first quartile exhibit the highest degree of centrality, while those in the fourth quartile demonstrate the lowest centrality measure within the network. Ln Fund Size is a control variable represent the natural logarithm of the fund´s size in millions of dollars. Ln LP Experience is the natural logarithm of the total number of LPs investments prior to the current fund. Fixed effects are included for the vintage year of the fund, LP's country of origin, primary region and sector of fund investments, GP's country of origin, and fixed effects for interactions between fund focus and vintage year (only for VC funds). Standard errors are clustered at the fund level. "***" "**" and "*" indicate significance levels at 1%, 5%, and 10%, respectively.

	VC Funds				Buyout Funds			
	(1) 1991-2015	(2) 1991-1998	(3) 1998-2006	(4) 2007-2015	(5) 1991-2015	(6) 1991-1998	(7) 1998-2006	(8) 2007-2015
1st Quartile (Omttd)	-	-	-	-	-	-	-	-
2nd Quartile LPs	-1.314*	-1.711	-0.543	-0.814	-0.026	-1.067	0.073	-0.080
	(-1.849)	(-0.423)	(-0.854)	(-1.057)	(-0.118)	(-1.230)	(0.236)	(-0.269)
3rd Quartile LPs	-3.786***	-10.986**	-0.938	-2.459**	-0.285	-1.959*	-0.311	-0.111
	(-3.863)	(-2.231)	(-1.106)	(-2.056)	(-0.927)	(-1.724)	(-0.704)	(-0.289)
4th Quartile LPs	-5.727***	-15.734**	-2.297**	-3.534**	0.114	-3.756**	0.221	0.187
	(-4.618)	(-2.485)	(-2.043)	(-2.550)	(0.271)	(-2.211)	(0.374)	(0.355)
Ln fund size	1.276*	16.967***	0.021	1.530	-0.239	-0.509	0.088	-0.455
	(1.855)	(3.107)	(0.031)	(1.555)	(-0.824)	(-0.475)	(0.184)	(-1.176)
Ln LP Experience	-0.598**	1.276	-0.411	-0.395	0.026	-1.644**	0.093	0.105
	(-2.016)	(0.578)	(-1.018)	(-1.287)	(0.210)	(-2.355)	(0.445)	(0.752)
Constant	7.393*	-46.815	3.655	9.472	16.918***	21.815***	13.264***	19.263***
	(1.793)	(-1.566)	(0.950)	(1.647)	(7.848)	(2.729)	(3.972)	(6.444)
Observations	7,525	875	4,023	2,615	20,942	1,443	8,249	11,242
R-squared	0.515	0.479	0.253	0.344	0.253	0.405	0.356	0.278
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
LP Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Others FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund
Adjusted R-squared	0.504	0.456	0.235	0.319	0.249	0.389	0.350	0.272
F test	5.451	4.509	0.892	2.002	0.576	1.331	0.505	0.607

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: LP Performance in PE Funds by Centrality Level (Robustness Checks)

The table presents performance regressions (*equation* 2) of investments made by LPs for the period between 1991 and 2015, including all sub-periods, and its relation to LPs centrality measure. The results are separated by VC and BO funds. The dependent variable is the NetIRR of the funds invested by LPs winsorized by 1%. The primary independent variable, eigenvector centrality measure, was standardized to unit variance. The centrality variable was obtained by network connections using the ex-ante strategy. Ln Fund Size is a control variable represent the natural logarithm of the fund´s size in millions of dollars. Ln LP Experience is the natural logarithm of the total number of LPs investments prior to the current fund. Fixed effects are included for the vintage year of the fund, LP's country of origin, primary region and sector of fund investments, GP's country of origin, and fixed effects for interactions between fund focus and vintage year (only for VC funds). Standard errors are clustered at the fund level. "***" "**" and "*" indicate significance levels at 1%, 5%, and 10%, respectively.

	VC Funds				Buyout Funds			
	(1) 1991-2015	(2) 1991-1998	(3) 1998-2006	(4) 2007-2015	(5) 1991-2015	(6) 1991-1998	(7) 1998-2006	(8) 2007-2015
Eigenvector Centr. Measure (stdz) LPs	1.366***	5.692**	0.649	0.753**	0.083	1.248*	0.051	0.043
	(3.877)	(2.255)	(1.614)	(2.193)	(0.526)	(1.770)	(0.218)	(0.220)
Ln fund size	1.370**	17.085***	0.034	1.567	-0.244	-0.511	0.084	-0.461
	(1.985)	(3.115)	(0.051)	(1.593)	(-0.845)	(-0.475)	(0.176)	(-1.191)
Ln LP Experience	-0.648*	0.305	-0.584	-0.416	-0.013	-1.668**	0.061	0.075
	(-1.881)	(0.125)	(-1.196)	(-1.287)	(-0.088)	(-2.054)	(0.253)	(0.440)
Constant	2.886	-61.406**	2.337	7.178	16.862***	17.562**	13.271***	19.303***
	(0.728)	(-2.157)	(0.613)	(1.265)	(8.019)	(2.361)	(3.919)	(6.654)
Observations	7,525	875	4,023	2,615	20,942	1,443	8,249	11,242
R-squared	0.514	0.476	0.253	0.343	0.253	0.404	0.356	0.278
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
LP Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Others FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund
Adjusted R-squared	0.503	0.454	0.235	0.318	0.249	0.389	0.350	0.272
F test	6.915	6.295	0.968	2.338	0.418	1.415	0.178	0.799

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: LPs Performance including LP Size proxy (Robustness Check)

This table shows the regressions of fund IRR after controlling for LP size, as detailed in equation 3. Panel A presents the results for VC funds and Panel B for BO funds. The regression includes the same variables, fixed effects, clusters as outlined in Table 4, with the addition of the LP size variable. As LP size is not observable, we use three proxies to estimate LPs size. Proxy 1 is the natural logarithm of asset under management (AUM) obtained as 2022 as a proxy of size. For the second proxy we used the procedure suggested by Cavagnaro and Wang (2019). We start by dividing each LPs AUM by the total number of investments the LP made between 1991-2015. Afterwards, we multiplied this value by the total number of investments the LP made each year. The third proxy we divided each LPs AUM in PE by the total number of investments the LP made between 2013-2022. Then, we multiplied this value by the amount of investments each LP made 10 years prior 10.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1991-2015	1991-1998	1998-2006	2007-2015	1991-2015	1991-1998	1998-2006	2007-2015	1991-2015	1991-1998	1998-2006	2007-2015
Panel A: VC Funds												
1st Quartile (Omttd)	-	-	-	-	-	-	-	-	-	-	-	-
2nd Quartile LPs	-1.252*	-1.105	-0.492	-1.079	-1.272*	-1.395	-0.469	-1.050	-1.033	1.118	0.361	-1.740*
	(-1.746)	(-0.278)	(-0.772)	(-1.426)	(-1.765)	(-0.346)	(-0.730)	(-1.381)	(-1.123)	(0.234)	(0.370)	(-1.898)
3rd Quartile LPs	-3.786***	-8.938**	-1.005	-2.392*	-3.765***	-9.533**	-0.954	-2.253*	-5.082***	-10.311*	-0.629	-4.388***
	(-3.844)	(-1.991)	(-1.179)	(-1.936)	(-3.784)	(-2.025)	(-1.106)	(-1.825)	(-3.938)	(-1.940)	(-0.486)	(-3.359)
4th Quartile LPs	-5.855***	-14.158**	-2.524**	-3.532**	-5.970***	-14.159**	-2.456**	-3.641**	-6.482***	-10.327	-3.142*	-4.178***
	(-4.557)	(-2.354)	(-2.135)	(-2.488)	(-4.602)	(-2.341)	(-2.068)	(-2.543)	(-3.759)	(-1.265)	(-1.889)	(-2.799)
Ln fund size	1.394**	16.809***	0.078	1.618	1.409**	16.649***	0.075	1.659*	1.479*	20.542***	0.130	1.152
	(2.000)	(3.081)	(0.116)	(1.614)	(2.025)	(3.049)	(0.112)	(1.660)	(1.938)	(3.225)	(0.166)	(1.123)
Ln LP Experience	-0.351	4.308**	-0.428	-0.603*	-0.387	5.169**	-0.351	-0.589*	-0.508	5.642*	-0.364	-0.671
	(-1.144)	(2.001)	(-1.074)	(-1.712)	(-1.289)	(2.305)	(-0.866)	(-1.772)	(-1.201)	(1.824)	(-0.570)	(-1.586)
Ln LP Size (proxy 1)	-0.167	-3.225**	0.050	0.209								
	(-1.347)	(-2.372)	(0.541)	(1.238)								
Ln LP Size (proxy 2)					-0.164	-4.034***	-0.012	0.276				
					(-1.290)	(-2.800)	(-0.123)	(1.530)				
Ln LP Size (proxy 3)									0.022	-2.825**	0.193	0.346*
									(0.177)	(-2.505)	(1.508)	(1.904)
Constant	7.511*	-21.083	2.827	7.730	7.063*	-26.979	3.130	7.586	6.684	-51.290	0.885	10.601*
	(1.786)	(-0.621)	(0.712)	(1.325)	(1.685)	(-0.838)	(0.795)	(1.307)	(1.370)	(-1.379)	(0.185)	(1.738)
Observations	7,233	869	3,873	2,480	7,227	869	3,872	2,475	5,010	580	2,529	1,887
R-squared	0.517	0.483	0.255	0.345	0.517	0.485	0.254	0.345	0.509	0.469	0.223	0.348
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
LP Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Others FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund
Adjusted R-squared	0.506	0.459	0.237	0.319	0.506	0.461	0.236	0.319	0.494	0.435	0.198	0.315
F test	4.738	4.030	1.085	2.101	4.783	4.353	0.833	2.385	4.742	4.588	1.522	2.967
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Panel B: Buyout Funds												
1st Quartile (Omttd)	-	-	-	-	-	-	-	-				
2nd Quartile LPs	-0.005	-1.101	0.152	-0.107	-0.017	-1.139	0.137	-0.116	-0.079	-1.798*	0.294	-0.197
	(-0.023)	(-1.214)	(0.467)	(-0.347)	(-0.075)	(-1.261)	(0.418)	(-0.372)	(-0.300)	(-1.745)	(0.747)	(-0.566)
3rd Quartile LPs	-0.283	-1.831	-0.279	-0.135	-0.312	-1.820	-0.301	-0.139	-0.054	-1.916	0.138	-0.227
	(-0.873)	(-1.514)	(-0.607)	(-0.335)	(-0.955)	(-1.532)	(-0.653)	(-0.342)	(-0.138)	(-1.354)	(0.240)	(-0.480)
4th Quartile LPs	0.015	-3.747**	0.195	0.089	-0.030	-3.973**	0.181	0.048	-0.216	-5.024**	0.275	-0.067
	(0.034)	(-2.180)	(0.322)	(0.165)	(-0.068)	(-2.297)	(0.295)	(0.088)	(-0.421)	(-2.561)	(0.380)	(-0.110)
Ln fund size	-0.248	-0.484	0.064	-0.437	-0.252	-0.508	0.058	-0.442	-0.105	0.166	0.251	-0.350
	(-0.849)	(-0.448)	(0.132)	(-1.109)	(-0.862)	(-0.469)	(0.120)	(-1.120)	(-0.348)	(0.148)	(0.500)	(-0.863)
Ln LP Experience	0.083	-1.582**	0.107	0.203	0.073	-1.503**	0.117	0.163	0.064	-1.750*	0.103	0.108
	(0.627)	(-2.230)	(0.477)	(1.436)	(0.559)	(-2.083)	(0.529)	(1.155)	(0.408)	(-1.895)	(0.381)	(0.651)
Ln LP Size (proxy 1)	-0.066	-0.073	-0.014	-0.107								
	(-1.322)	(-0.288)	(-0.213)	(-1.602)								
Ln LP Size (proxy 2)					-0.084*	-0.174	-0.049	-0.103				
					(-1.699)	(-0.630)	(-0.765)	(-1.567)				
Ln LP Size (proxy 3)									-0.080	-0.204	0.006	-0.077
									(-1.244)	(-0.659)	(0.067)	(-0.962)
Constant	17.517***	22.259**	13.537***	19.928***	17.526***	22.713***	13.780***	19.784***	16.882***	20.089**	11.895***	19.659***
	(7.897)	(2.471)	(3.955)	(6.439)	(7.976)	(2.638)	(4.074)	(6.410)	(7.225)	(2.324)	(3.267)	(6.162)
Observations	19,830	1,406	7,719	10,697	19,776	1,404	7,700	10,664	13,913	1,022	5,041	7,845
R-squared	0.251	0.405	0.354	0.275	0.251	0.404	0.355	0.274	0.259	0.420	0.362	0.276
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
LP Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Others FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund
Adjusted R-squared	0.247	0.388	0.348	0.268	0.247	0.388	0.348	0.268	0.254	0.399	0.353	0.268
F test	0.707	1.062	0.397	1.175	0.900	1.167	0.509	1.057	0.285	1.405	0.183	0.425

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Robust Regressions - LPs Performance by Centrality Quartile (Robustness Check)

The table presents the robust regressions analyzing the performance of investments made by LPs from 1991 to 2015, including all sub-periods. The results are separated by VC and BO funds. The dependent variable is the NetIRR of the funds invested by LPs winsorized by 1%. The regression includes the same independent variables, fixed effects, clusters as outlined in Table 4 "***" "**" and "*" indicate significance levels at 1%, 5%, and 10%, respectively.

	VC Funds				Buyout Funds			
Dep. Variable: Net IRR (%)	(1) 1991-2015	(2) 1991-1998	(3) 1998-2006	(4) 2007-2015	(5) 1991-2015	(6) 1991-1998	(7) 1998-2006	(8) 2007-2015
1st Quartile (Omttd)	-	-	-	-	-	-	-	-
2nd Quartile LP	-0.634**	-0.380	-0.818**	-0.199	0.064	-0.342	0.181	0.040
	(-2.242)	(-0.193)	(-2.319)	(-0.416)	(0.382)	(-0.436)	(0.802)	(0.182)
3rd Quartile LP	-1.732***	-4.442*	-1.640***	-2.086***	-0.112	-1.579	0.118	0.111
	(-4.866)	(-1.775)	(-3.889)	(-3.100)	(-0.524)	(-1.542)	(0.403)	(0.396)
4th Quartile LP	-2.747***	-7.625**	-2.563***	-1.645*	0.155	-1.757	0.398	0.346
	(-5.977)	(-2.398)	(-4.692)	(-1.902)	(0.591)	(-1.371)	(1.097)	(0.998)
Ln fund size	0.171	6.797***	-0.073	1.584***	-0.101*	-0.394	0.175**	-0.312***
	(1.110)	(4.481)	(-0.431)	(5.001)	(-1.846)	(-1.098)	(2.320)	(-4.492)
Ln LP Experience	-0.286**	0.687	-0.246	-0.212	0.027	-0.885	0.150	0.063
	(-1.998)	(0.524)	(-1.341)	(-0.961)	(0.320)	(-1.546)	(1.205)	(0.615)
Constant	5.625	-29.136	-36.411***	-22.744***	5.898***	14.023*	-40.741***	-0.608
	(1.409)	(-1.040)	(-5.782)	(-4.892)	(2.782)	(1.653)	(-12.310)	(-0.338)
Observations	7,529	879	4,025	2,621	20,949	1,446	8,251	11,249
R-squared	0.784	0.691	0.526	0.520	0.330	0.398	0.518	0.356
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
LP Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Others FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund
Adjusted R-squared	0.779	0.675	0.515	0.500	0.326	0.381	0.513	0.350
F test	157.6	45.56	46.41	26.42	84.04	23.23	108.3	59.83

Table 8: Relationship between GP Centrality and fund returns

The table shows how differences in fund returns relates to GP centrality measures, as detailed in equation 4. The unit of observation is at fund level. The results were separated by VC and BO funds, between 1991-2015 and three subperiods from 1991-1998, 1999-2006 and 2007-2015. The dependent variable is the NetIRR of the funds winsorized by 1%. The table separates the results into BO and VC funds. For panel A, the regression includes dummy variables that identifies if the fund has a 1st quartile GPs, taking the value of one if a specific 1st quartile GP is the manager the fund, and zero otherwise. The centrality dummy variable was obtained by bipartite network connections using the ex-ante strategy. First, *undirected* networks were constructed using connections between LPs and GPs (through their funds) over the previous five years to extract eigenvector centrality measures for GPs. Afterwards, GPs were classified into quartiles given the centrality measures. In addition, these dummies are time varying as GPs can change quartile position through time. For each vintage year in the sample, we generated a new network to derive updated centrality measures and subsequently determine their revised quartile positions. For panel B, the independent variable is the GP eigenvector centrality measure, standardized to unit variance, as opposed to utilizing the previously explained dummy variable. Vintage year and regional focus of the funds fixed effects are included. Coefficient estimates and robust standard errors were clustered by vintage year. "***" "**" and "*" indicate significance levels at 1%, 5%, and 10%, respectively.

	VC Funds				Buyout Funds			
	(1) 1991-2015	(2) 1991-1998	(3) 1999-2006	(4) 2007-2015	(5) 1991-2015	(6) 1991-2001	(7) 2000-2015	(8) 2007-2015
Panel A								
Dummy 1st Quartile GP	7.698***	27.915***	4.915***	3.732**	0.917	0.397	-0.314	1.655*
	(4.311)	(5.358)	(14.517)	(2.326)	(1.106)	(0.143)	(-0.195)	(2.175)
Constant	11.101***	32.035***	-0.921***	14.933***	15.027***	14.740***	14.932***	15.233***
	(19.560)	(21.929)	(-8.914)	(26.907)	(55.261)	(23.007)	(27.624)	(57.099)
Observations	645	107	272	266	793	113	278	402
R-squared	0.392	0.264	0.158	0.091	0.183	0.347	0.190	0.148
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.364	0.179	0.123	0.0481	0.153	0.276	0.157	0.121
F test	18.59	28.70	210.7	5.411	1.222	0.0204	0.0379	4.732
Panel B								
GP Eigenvector Centr. Measure (stdz)	3.106***	13.231**	1.711***	1.831***	0.290	0.688	0.260	0.302
	(4.020)	(2.526)	(9.607)	(3.369)	(0.906)	(0.526)	(0.419)	(0.840)
Constant	10.592***	28.667***	-1.106***	14.465***	15.038***	14.169***	14.582***	15.497***
	(14.405)	(6.468)	(-6.306)	(27.707)	(47.008)	(11.249)	(24.926)	(41.118)
Observations	645	107	272	266	793	113	278	402
R-squared	0.391	0.268	0.153	0.096	0.183	0.348	0.191	0.144
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.364	0.184	0.117	0.0530	0.153	0.277	0.157	0.118
F test	16.16	6.379	92.30	11.35	0.820	0.277	0.175	0.705

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Investment proportion received by GPs (*GP-LP matching*)

The table shows the proportion of investments received by GPs. Panels A and B focuses in VC fund and panels C and D in Buyout funds. Panels A and B shows for 1Q GPs the quantity of investments and the corresponding proportions allocated to LPs, categorized by quartiles. Panels B and D shows for other quartile GPs (2nd, 3rd and 4th quartile) the quantity of investments and the corresponding proportions allocated to LPs. The level of GPs centrality was found using a biparte network and considering for each year the connections from the past 5 years. Privileged GPs are those managers classified in the 1st quartile (top quartile) in terms of Eigenvector variable given the 5 year past network (connections). Others GPs (non-privileged) were classified in the 2nd, 3rd and 4th quartile in terms of eigenvector variable. The LPs were classified in quartiles by their level of Eigenvector, as explained in table 4. #Investiments represents the quantity of investments realized by LPs in a specific fund.

Investments received by GPs in VC funds	1991-2015		1991-1998		1999-2006		2007-2015	
	#Invest.	*%total*	#Invest.	*%total*	#Invest.	*%total*	#Invest.	*%total*
Panel A: 1Q GPs (in VC Funds) and LPs investments								
LPs in 1st Quartile	2.217	66,5%	219	61,0%	1.202	66,6%	796	67,9%
LPs in 2nd Quartile	687	20,6%	90	25,1%	353	19,6%	244	20,8%
LPs in 3rd Quartile	334	10,0%	40	11,1%	191	10,6%	103	8,8%
LPs in 4th Quartile	97	2,9%	10	2,8%	58	3,2%	29	2,5%
Total Invest. in 1Q GPs	*3.335*	*100,0%*	*359*	*100,0%*	*1.804*	*100,0%*	*1.172*	*100,0%*
Panel B: Other Quartile GPs (in VC Funds) and LPs investments								
LPs in 1st Quartile	1.962	44,2%	212	37,7%	1.019	45,4%	731	44,9%
LPs in 2nd Quartile	1.087	24,5%	157	27,9%	468	20,8%	462	28,4%
LPs in 3rd Quartile	774	17,5%	116	20,6%	431	19,2%	227	14,0%
LPs in 4th Quartile	612	13,8%	78	13,9%	327	14,6%	207	12,7%
Total Invest. in Other GPs	*4.435*	*100,0%*	*563*	*100,0%*	*2.245*	*100,0%*	*1.627*	*100,0%*
Investments received by GPs in BO funds								
Panel C: 1Q GPs (in BO Funds) and LPs investments								
LPs in 1st Quartile	5.498	61,4%	218	50,9%	1.990	56,2%	3.290	66,0%
LPs in 2nd Quartile	1.978	22,1%	112	26,2%	881	24,9%	985	19,8%
LPs in 3rd Quartile	1.013	11,3%	63	14,7%	459	13,0%	491	9,9%
LPs in 4th Quartile	460	5,1%	35	8,2%	209	5,9%	216	4,3%
Total Invest. in 1Q GPs	*8.949*	*100,0%*	*428*	*100,0%*	*3.539*	*100,0%*	*4.982*	*100,0%*
Panel D: Other Quartile GPs (in BO Funds) and LPs investments								
LPs in 1st Quartile	6.403	53,1%	435	41,5%	2.294	48,6%	3.674	58,3%
LPs in 2nd Quartile	2.613	21,7%	279	26,6%	1.124	23,8%	1.210	19,2%
LPs in 3rd Quartile	1.764	14,6%	194	18,5%	745	15,8%	825	13,1%
LPs in 4th Quartile	1.288	10,7%	139	13,3%	561	11,9%	588	9,3%
Total Invest. in Other GPs	*12.068*	*100,0%*	*1.047*	*100,0%*	*4.724*	*100,0%*	*6.297*	*100,0%*

Table 10: Proportion of investments made by LPs, separated by quartiles, in GPs

The table shows the proportion of investments made by LPs in 1st and Other quartiles GPs. Panel A shows the investments in VC and panel B in BO funds. The table separates the LPs given their level of centrality in quartiles. The total # number of investment represents investments made by LPs, separated by their centrality quartile, in all GPs. # Investments in GPs 1Q shows the investments made by LPs only in 1st quartile GPs. # Investments in GPs Others shows the investments made by LPs only in 2nd, 3rd and 4th quartile GPs.

LPs investments separated in 1Q GPs and Other GPs	1991-2015			1991-1998			1999-2006			2007-2015		
	Total #Invest.	#Invest. in GPs 1Q	#Invest. in GPs Others	Total #Invest.	#Invest. in GPs 1Q	#Invest. in GPs Others	Total #Invest.	#Invest. in GPs 1Q	#Invest. in GPs Others	Total #Invest.	#Invest. in GPs 1Q	#Invest. in GPs Others
Panel A: VC GPs/Funds												
LPs in 1st Quartile	4.179	2.217	1.962	431	219	212	2.221	1.202	1.019	1.527	796	731
%total		*53,1%*	*46,9%*		*50,8%*	*49,2%*		*54,1%*	*45,9%*		*52,1%*	*47,9%*
LPs in 2nd Quartile	1.774	687	1.087	247	90	157	821	353	468	706	244	462
%total		*38,7%*	*61,3%*		*36,4%*	*63,6%*		*43,0%*	*57,0%*		*34,6%*	*65,4%*
LPs in 3rd Quartile	1.108	334	774	156	40	116	622	191	431	330	103	227
%total		*30,1%*	*69,9%*		*25,6%*	*74,4%*		*30,7%*	*69,3%*		*31,2%*	*68,8%*
LPs in 4th Quartile	709	97	612	88	10	78	385	58	327	236	29	207
%total		*13,7%*	*86,3%*		*11,4%*	*88,6%*		*15,1%*	*84,9%*		*12,3%*	*87,7%*
Panel B: Buyout GPs/Funds												
LPs in 1st Quartile	11.901	5.498	6.403	653	218	435	4.284	1.990	2.294	6.964	3.290	3.674
%total		*46,2%*	*53,8%*		*33,4%*	*66,6%*		*46,5%*	*53,5%*		*47,2%*	*52,8%*
LPs in 2nd Quartile	4.591	1.978	2.613	391	112	279	2.005	881	1.124	2.195	985	1.210
%total		*43,1%*	*56,9%*		*28,6%*	*71,4%*		*43,9%*	*56,1%*		*44,9%*	*55,1%*
LPs in 3rd Quartile	2.777	1.013	1.764	257	63	194	1.204	459	745	1.316	491	825
%total		*36,5%*	*63,5%*		*24,5%*	*75,5%*		*38,1%*	*61,9%*		*37,3%*	*62,7%*
LPs in 4th Quartile	1.748	460	1.288	174	35	139	770	209	561	804	216	588
%total		*26,3%*	*73,7%*		*20,1%*	*79,9%*		*27,1%*	*72,9%*		*26,9%*	*73,1%*

Table 11: LPs performance in 1st and Other quartiles GPs

The table shows the investment performance made by LPs in 1st and Other quartiles GPs. The table separates the LPs given their level of centrality in quartiles. In other words, LPs classified in the 1st quartile are considered investors more influential in the network. The sample comprises for periods between 1991-2015, in addition to subperiods from 1991-1998, 1999-2006 and 2007-2015. Panels A, B and VC are for VC investments and panels D, E and F are for BO investments. Panels A and D shows LPs performance, separated by quartiles, in 1st quartile GPs. Panels B and E shows LPs performance, separated by quartiles, in 2nd, 3rd and 4th quartiles GPs (other GPs). Last, panels C and F shows the performance differences between LPs investments in 1st and others GPs. # Investment represents investments made by LPs, separated by their centrality quartile, in GPs. Average IRR is the average of investments (funds) Net IRR (%). *Difference 1Q LPs to other LPs is the difference* in mean values between first quartile LPs and all other LPs. "***" "**" and "*" indicate significance levels at 1%, 5%, and 10%, respectively.

	1991-2015		1991-1998		1999-2006		2007-2015	
	#Invest.	Avg. IRR (1)	#Invest.	Avg. IRR (2)	#Invest.	Avg. IRR (3)	#Invest.	Avg. IRR (4)
Panel A: 1Q GPs (in VC Funds) and LPs investments								
LPs in 1st Quartile	2.217	16,1	219	67,0	1.202	3,6	796	20,8
LPs in 2nd Quartile	687	17,6	90	67,3	353	3,7	244	19,3
LPs in 3rd Quartile	334	11,9	40	44,1	191	2,7	103	16,5
LPs in 4th Quartile	97	11,9	10	47,9	58	3,3	29	16,6
Total	3.335	15,8	359	64,0	1.804	3,5	1.172	20,0
Difference 1Q LPs to other LPs		*-1,27*		*6,757*		*0,45*		*2.21****
Panel B: Other Quartile GPs (in VC Funds) and LPs investments								
LPs in 1st Quartile	1.962	11,0	212	48,4	1.019	0,1	731	15,4
LPs in 2nd Quartile	1.087	11,3	157	36,0	468	-0,1	462	14,5
LPs in 3rd Quartile	774	7,7	116	24,1	431	1,0	227	12,1
LPs in 4th Quartile	612	7,4	78	24,7	327	0,1	207	12,3
Total	4.435	10,0	563	36,7	2.245	0,2	1.627	14,3
Difference 1Q LPs to other LPs		*0,05*		*16.47****		*-0.84**		*0,664*
Panel C: Δ% IRR between VC Investment in 1Q GPs x Other GPs								
LPs in 1st Quartile		5.04***		18.62**		3.48***		5.48***
LPs in 2nd Quartile		6.26***		31.31***		3.79***		4.85***
LPs in 3rd Quartile		4.22***		20.02***		1,73		4.42***
LPs in 4th Quartile		4.49*		23,22		3.15*		4,32
Total		5.83***		27.35***		3.27***		5.78***
Panel D: 1Q GPs (in BO Funds) and LPs investments								
LPs in 1st Quartile	5.498	15,4	218	11,5	1.990	14,2	3.290	16,4
LPs in 2nd Quartile	1.978	15,1	112	10,8	881	14,4	985	16,2
LPs in 3rd Quartile	1.013	15,7	63	14,3	459	15,6	491	16,0
LPs in 4th Quartile	460	14,9	35	9,1	209	14,0	216	16,7
Total	8.949	15,3	428	11,5	3.539	14,4	4.982	16,3
Difference 1Q LPs to other LPs		*0.35**		*-1,165*		*-0.71***		*0.69****
Panel E: Other Quartile GPs (in BO Funds) and LPs investments								
LPs in 1st Quartile	6.403	15,1	435	11,9	2.294	13,7	3.674	16,3
LPs in 2nd Quartile	2.613	15,0	279	14,1	1.124	14,7	1.210	15,5
LPs in 3rd Quartile	1.764	14,6	194	12,3	745	13,7	825	15,8
LPs in 4th Quartile	1.288	15,7	139	17,8	561	15,1	588	15,7
Total	12.068	15,1	1.047	13,4	4.724	14,1	6.297	16,1
Difference 1Q LPs to other LPs		*-0.87****		*-4.89****		*-1.92****		*0,387*
Panel F: Δ% IRR between BO Investment in 1Q GPs x Other GPs								
LPs in 1st Quartile		0,3152		- 0,4708		0,5717		0,0198
LPs in 2nd Quartile		0,0600		-3.27*		- 0,3579		0,6913
LPs in 3rd Quartile		1.16**		1,9718		1.88**		0,1665
LPs in 4th Quartile		- 0,7950		-8.74***		- 1,1475		1,0019
Total		0.28*		-1.85*		0,3325		0,2553

Table 12: Probability of LPs investing in funds managed by 1st quartile GPs

The table shows the probability of LPs investing in funds managed by 1st quartile GPs. We used a probit model (equation 5) where the dependent variable equals to one if the investment made was in a fund managed by 1st quartile GP, zero otherwise. The analysis is at the LP level. All independent variables were defined in table 4. Vintage year and LP country fixed effect were added, including robust standard errors clustered by fund, following Sensoy et al. (2014). "***" "**" and "*" indicate significance levels at 1%, 5%, and 10%, respectively.

	VC Funds				Buyout Funds			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1991-2015	1991-1998	1998-2006	2007-2015	1991-2015	1991-1998	1998-2006	2007-2015
1st Quartile (Omttd)								
2nd Quartile LPs	-0.405***	-0.488***	-0.373***	-0.437***	-0.104***	-0.097	-0.128**	-0.084
	(0.062)	(0.147)	(0.091)	(0.104)	(0.040)	(0.098)	(0.065)	(0.059)
3rd Quartile LPs	-0.443***	-0.492	-0.442***	-0.471***	-0.100*	-0.225*	-0.127	-0.059
	(0.091)	(0.307)	(0.128)	(0.152)	(0.056)	(0.136)	(0.096)	(0.081)
4th Quartile LPs	-1.113***	-1.415***	-1.013***	-1.439***	-0.292***	-0.377**	-0.272**	-0.299**
	(0.122)	(0.303)	(0.162)	(0.253)	(0.084)	(0.184)	(0.118)	(0.142)
Ln fund size	1.140***	1.621***	1.050***	1.237***	1.000***	0.528**	1.029***	1.043***
	(0.123)	(0.419)	(0.155)	(0.223)	(0.070)	(0.213)	(0.109)	(0.103)
Ln LP Experience	-0.053	-0.179*	-0.069	-0.029	-0.006	-0.046	-0.025	0.005
	(0.033)	(0.100)	(0.052)	(0.045)	(0.024)	(0.074)	(0.042)	(0.031)
Constant	-7.725***	-9.952***	-6.130***	-8.262***	-7.437***	-4.427***	-6.832***	-8.294***
	(0.917)	(2.290)	(1.103)	(1.457)	(1.064)	(1.664)	(0.846)	(0.884)
Observations	5,805	692	3,128	1,955	15,194	1,070	5,773	8,345
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
LP Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R-squared	0.3005	0.3368	0.2787	0.3273	0.3720	0.1127	0.3988	0.3874
Cluster	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Returns on reinvested and abandoned funds

The table presents the mean returns (%NetIRR) of the follow-on (next) funds (from the same GP) reinvested or abandoned by LPs. Panel A focuses in VC funds and panel B in BO funds. In addition, we separated the reinvested and abandoned funds between GPs in 1st quartile and GPs in other quartiles. The sample comprises for periods between 1991-2015, in addition to subperiods from 1991-1998, 1999-2006 and 2007-2015. The unit of observation is at the LP investment level. Follow-on funds are funds that LPs invests in the next fund raised by the same GP. Reinvested means that LPs invest in a GPs current fund and decided to reinvest in a follow-on fund from the same GP, while abandoned means LPs did not invest in the follow-on fund. Mean difference tests were conducted for the difference between Reinv. (reinvested) and Abond (abandoned) funds. "***" "**" and "*" indicate significance levels at 1%, 5%, and 10%, respectively.

		1991-2015		**1991-1998**		**1999-2006**		**2007-2015**	
		N	**IRR Follow-on Fund**	**N**	**IRR Follow-on Fund**	**N**	**IRR Follow-on Fund**	**N**	**IRR Follow-on Fund**
Panel A: VC									
Reinvested	1st Quartile	1.574	15,6	246	23,2	848	7,9	479	25,6
Abandoned	LPs	1.137	15,5	84	26,6	641	9,3	411	23,0
Difference between Reinv. and Abond.			*0,14*		*-3,44*		*-1.39***		*2.58****
Reinvested	Other Quartile	1.159	12,3	294	13,8	560	6,6	304	21,6
Abandoned	LPs	993	12,3	97	19,2	599	7,3	296	20,2
Difference between Reinv. and Abond.			*0,06*		*-5,40*		*-0,70*		*1,44*
Panel B: Buyout									
Reinvested	1st Quartile	4.506	17,0	412	14,9	2.081	12,8	2.011	21,9
Abandoned	LPs	3.774	18,4	140	13,5	1.466	15,0	2.156	20,7
Difference between Reinv. and Abond.			*-1.20****		*1,42*		*-2.21****		*1.12****
Reinvested	Other Quartile	3.271	15,6	444	14,2	1.763	12,8	1.064	21,0
Abandoned	LPs	3.264	17,6	238	14,3	1.444	14,1	1.580	21,3
Difference between Reinv. and Abond.			*-1.97****		*-0,15*		*-1.30****		*-0,36*

Table 14: LPs performance in first time and later sequence funds

The table shows the differences in returns when we separate the sample into first time and later sequence funds. For the regressions we used equation 1. The sample comprises for periods between 1991-2015, in addition to subperiods from 1991-1998, 1999-2006 and 2007-2015. In addition, we segregated the analysis into VC funds and BO funds. First time funds are investment vehicles that were first raised by a specific GP in their overall portfolio. The dependent variable is fund IRR (in%). The observation are investments made by LPs in different funds. All variables are defined in previous table 4.

	1st time funds				Later Funds			
	(1) 1991-2017	(2) 1991-1998	(3) 1999-2006	(4) 2007-2017	(5) 1991-2017	(6) 1991-1998	(7) 1999-2006	(8) 2007-2017
Panel A: VC Investiments								
1st Quartile (Omttd)								
2nd Quartile LPs	0.997	12.478	0.046	-0.143	-1.120	-0.919	-0.436	-0.571
	(0.721)	(1.353)	(0.051)	(-0.239)	(-1.531)	(-0.228)	(-0.646)	(-0.726)
3rd Quartile LPs	2.987	21.371*	0.314	0.979	-3.689***	-11.102**	-0.947	-2.385*
	(1.482)	(1.768)	(0.242)	(0.513)	(-3.621)	(-2.263)	(-1.047)	(-1.884)
4th Quartile LPs	2.373	5.748	-2.590**	1.278	-5.160***	-14.167**	-2.092*	-3.240**
	(0.664)	(0.581)	(-2.128)	(0.958)	(-4.020)	(-2.100)	(-1.705)	(-2.255)
Ln fund size	0.867	24.084**	-5.557	7.998	1.345*	14.180**	0.386	2.323**
	(0.187)	(2.101)	(-1.589)	(1.335)	(1.905)	(2.170)	(0.562)	(2.140)
Ln LP Experience	0.517	-3.249	0.221	-0.322	-0.611**	1.898	-0.441	-0.438
	(0.679)	(-0.849)	(0.346)	(-0.902)	(-2.041)	(0.801)	(-1.054)	(-1.389)
Constant	4.372	-91.609	33.801*	-16.318	6.793	-33.636	1.272	4.416
	(0.185)	(-1.637)	(1.761)	(-0.539)	(1.581)	(-0.933)	(0.309)	(0.689)
Observations	477	69	289	113	7,034	804	3,730	2,492
R-squared	0.638	0.676	0.737	0.928	0.554	0.499	0.296	0.360
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
LP Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Others FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund
Adjusted R-squared	0.558	0.531	0.680	0.886	0.543	0.476	0.279	0.335
F test	0.542	1.336	2.170	1.689	4.609	3.518	0.618	2.226
Panel B: BO Investiments								
1st Quartile (Omttd)								
2nd Quartile LPs	-0.155	1.475	-0.799	1.290	-0.042	-2.002**	0.136	-0.056
	(-0.213)	(0.997)	(-0.900)	(1.249)	(-0.186)	(-2.097)	(0.425)	(-0.187)
3rd Quartile LPs	-0.902	3.237*	-1.490	1.061	-0.220	-3.101**	-0.167	-0.098
	(-0.789)	(1.858)	(-1.134)	(0.775)	(-0.758)	(-2.426)	(-0.411)	(-0.253)
4th Quartile LPs	0.027	3.918	-0.326	-0.449	-0.043	-5.888***	0.083	0.238
	(0.024)	(1.525)	(-0.256)	(-0.245)	(-0.103)	(-3.057)	(0.135)	(0.453)
Ln fund size	0.327	0.965	1.290	-3.905	-0.207	-0.662	0.219	-0.390
	(0.338)	(0.376)	(1.222)	(-1.313)	(-0.676)	(-0.531)	(0.424)	(-0.979)
Ln LP Experience	-0.775**	1.978	-0.767*	-0.251	0.064	-2.412***	0.183	0.156
	(-1.992)	(1.655)	(-1.722)	(-0.403)	(0.512)	(-3.161)	(0.819)	(1.115)
Constant	16.513***	1.442	10.768	41.116**	16.520***	25.577***	11.693***	18.584***
	(2.604)	(0.092)	(1.486)	(2.283)	(7.166)	(2.672)	(3.227)	(5.958)
Observations	1,515	203	919	387	19,418	1,237	7,323	10,853
R-squared	0.449	0.798	0.477	0.404	0.278	0.450	0.390	0.299
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
LP Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Others FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund
Adjusted R-squared	0.419	0.770	0.446	0.324	0.274	0.434	0.383	0.293
F test	1.422	1.036	1.238	0.798	0.463	2.336	0.546	0.759

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Top Central LPs predictive power - *Quality Signalizers*

This table shows fund performance on several explanatory variables for the period between 1991-2015. The dependent variable in all columns is fund performance, captured by the internal rate of return (IRR%) winsorized at 1%. *NetIRR Previous Fund* represents the internal rate of return (IRR%) of the prior fund of the current fund from the same GP, representing the classical fund performance persistence equation (Kaplan and Schoar, 2005). *Quant. 1Q Reinvestors LPs* is the total quantity of LPs classified in the top quartile centrality measure that reinvested in the fund. If there were no LPs reinvesting, the total quantity of LPs that reinvested was given 0 (zero). Robustness tests using robust regressions are conducted in columns ranging from (5) to (8). The square variables terms are to capture any non-linear relation of the principal explanatory variable. Ln fund size is the natural logarithm of the funds size in millions of dollars. The Ln Sequence is the natural logarithm of the funds sequence. We used fixed effects of vintage years and standard errors clustered by GP. The data was collected from Preqin with database of March 2022. "***" "**" and "*" indicate significance levels at 1%, 5%, and 10%, respectively.

	OLS Regressions				*Robustness Tests* Robust Regressions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable: Net IRR winsored 1%	91-15	91-15	91-15	91-15	91-15	91-15	91-01	00-15
Net IRR Previous Fund	0.260***							
	(4.084)							
Quant. 1Q Reinvestors LPs		0.438*	1.880***	1.903***	0.465***	0.993**	0.628*	0.388**
		(1.797)	(2.817)	(2.798)	(2.641)	(2.461)	(1.822)	(2.263)
(Quant. 1Q Reinvestors LPs)2			-0.078***	-0.078***		-0.027		
			(-2.914)	(-2.957)		(-1.387)		
Ln Fund Size	1.089	0.318	-0.554	9.556	0.246	-0.083	0.779	0.196
	(1.290)	(0.293)	(-0.478)	(1.178)	(0.280)	(-0.091)	(0.443)	(0.226)
Ln Fund Sequence	3.647**	2.533	1.914	-10.134	-1.671	-1.963	-4.802*	-0.985
	(2.050)	(1.148)	(0.871)	(-1.122)	(-1.310)	(-1.524)	(-1.850)	(-0.768)
(Ln Fund Size)2				-0.956				
				(-1.274)				
(Ln Fund Sequence)2				4.255				
				(1.304)				
Constant	-2.865	5.601	9.406	-9.304	49.356***	51.088***	45.096***	-2.479
	(-0.681)	(0.966)	(1.537)	(-0.437)	(7.505)	(7.674)	(4.536)	(-0.502)
Observations	536	536	536	536	536	536	181	430
R-squared	0.422	0.378	0.384	0.387	0.501	0.501	0.649	0.317
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster	GP	GP	GP	GP	NO	NO	NO	NO
Adjusted R-squared	0.395	0.348	0.354	0.354	0.477	0.477	0.628	0.287
F test	8.351	6.353	4.843	3.303	21.34	20.49	31.40	10.57

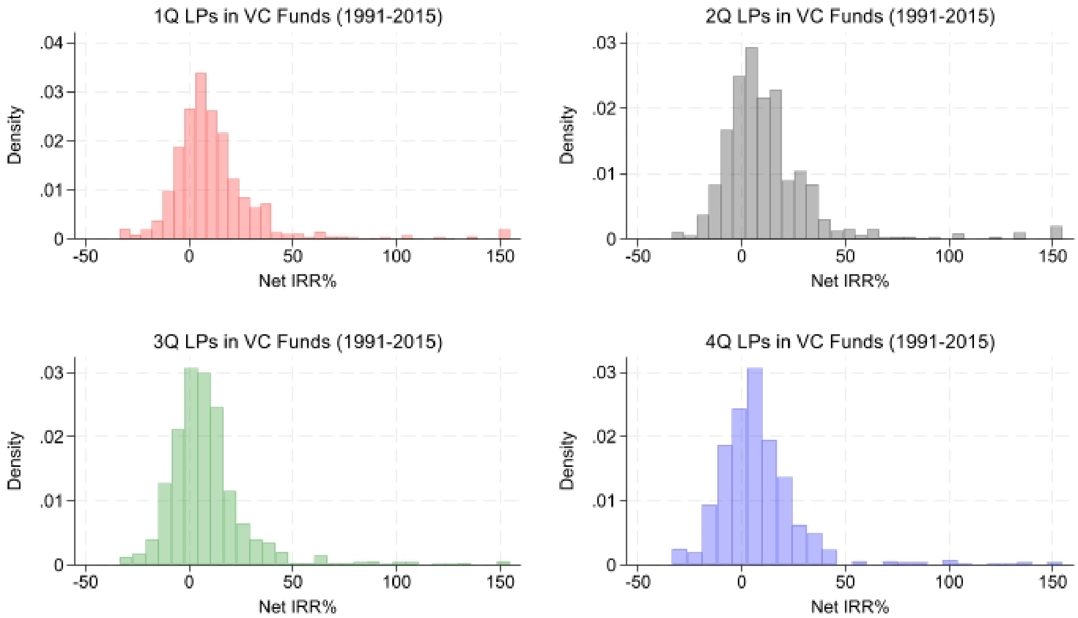
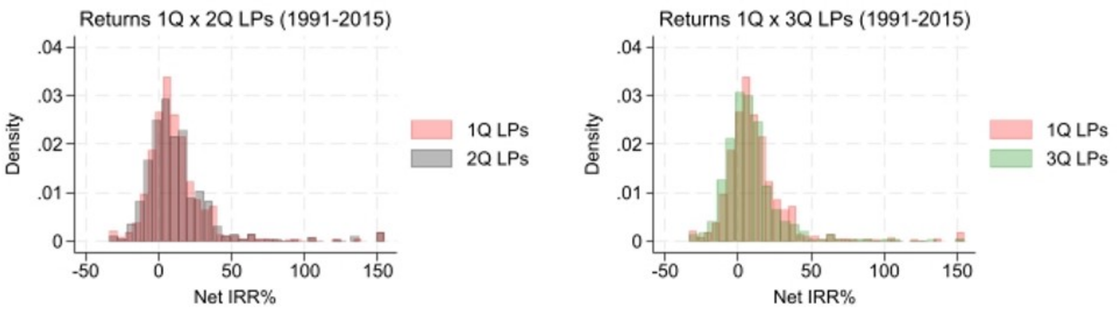
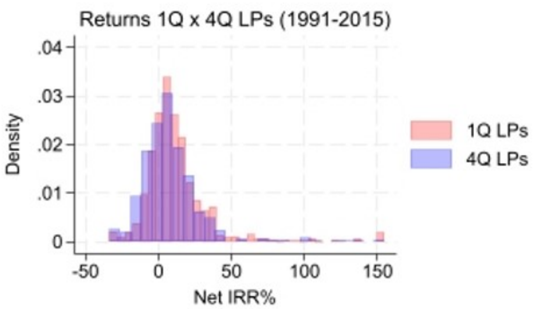


Figure 2: LPs Quartile Returns (Net IRR%) Distributions
The figure illustrates the performance distribution for each LP quartile in VC funds from 1991 to 2015. Performance is represented by Net IRR (%) with a 1% windsorization applied. This distribution exclusively encompasses LPs with 5 or more prior experiences in PE investments, reflecting the data utilized in the regressions detailed in Table 4. The separation into quartiles was by the LPs centrality measures captured by network connections using the ex-ante strategy. First, we constructed networks by utilizing co-investments made by LPs in the previous five years to extract eigenvector centrality measures. Afterwards, LPs were classified into quartiles given the centrality measures. LPs categorized in the first quartile exhibit the highest degree of centrality, while those in the fourth quartile demonstrate the lowest centrality measure within the network.





Summary statistics for return distribution across quartiles

	1Q LP	2Q LP	3Q LP	4Q LP
Skewness	3,00	2,91	2,80	2,73
Kurtosis	16,42	14,88	16,11	16,08
Max. Value	154,7	154,7	154,7	154,7
Min. Value	-33,6	-33,6	-33,6	-33,6

Figure 3: Overlap LPs Quartile (Net IRR%) Distributions
The figure displays the overlap performance distribution (Net IRR% Windsorized at 1% using the same data points as table 4) between returns from LPs classified as 1Q and those in other quartiles. The aim is to provide a more comprehensive analysis to identify potential outliers influencing results by integrating a visual comparison of the tail distributions between LPs quartiles. Additionally, a summary statistics table presents return distribution details including skewness, kurtosis, maximum (in %), and minimum values (in %).