Department of Land Economy
Environment, Law & Economics

UNIVERSITY OF CAMBRIDGE
Real Estate Research Centre

Working Paper Series
No. 2015-11

Title: Size Signals Success: Evidence from Real Estate Private Equity

Authors: Sebastian Krautz [1], Franz Fuerst[2]

Affiliation: Real Estate Management Institute, Wiesbaden[1], University of Cambridge, Department of Land Economy[2]

Contact corresponding author: Franz Fuerst, *ff274@cam.ac.uk*

Size Signals Success:
Evidence from Real Estate Private Equity

Sebastian Krautz*°and Franz Fuerst**

Working Paper

Abstract

Anecdotal evidence suggests that clout and connections matter more in private equity fundraising than actual performance. In this paper, a unique real estate private equity (REPE) dataset with buy-side and sell-side information is created by the authors to construct and analyze stacked interaction networks for each vintage year. Calculating and regressing centrality measures for industry embeddedness, the authors find that fund managers can benefit from their established connections to plan sponsors while fundraising. Adding fund size into the equation, it is demonstrated that the total capital under management and the size of previous funds have a significant and positive effect on fundraising speed.

Keywords: Real Estate, Private Equity, Fundraising, Market Concentration, Network Analysis, Industry Embeddedness, Centrality Measures

JEL Classification: G02, G11, G23

*Real Estate Management Institute at EBS Universität für Wirtschaft und Recht, Wiesbaden (✉ sebastian.krautz@ebs.edu); **Department of Land Economy at University of Cambridge (✉ ff274@cam.ac.uk). This research has been supported by the Cambridge University Land Society. We thank the participants of the joint AREUEA/AsRES/GCREC/IRES Global Real Estate Summit held on July 6-9th, 2015, in Washington D.C. as well as Greg MacKinnon for helpful comments.

Introduction

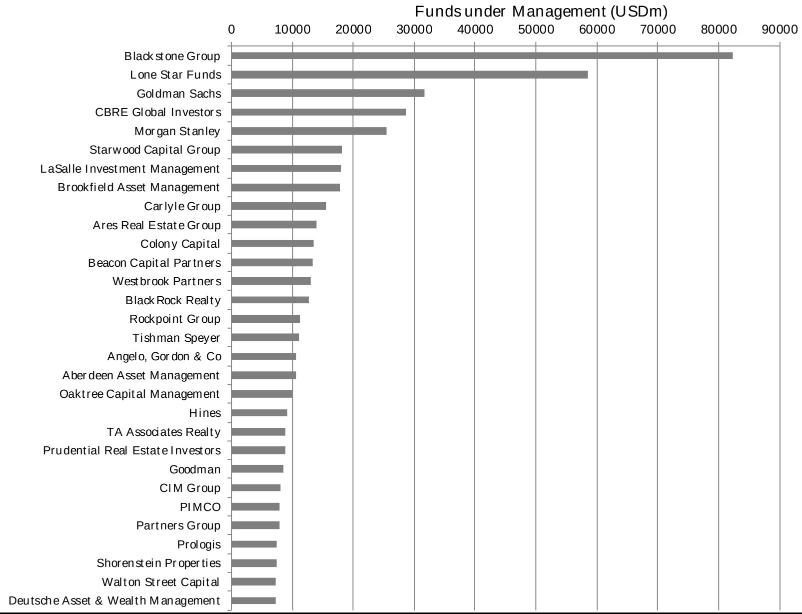
Due to low correlation with traditional asset classes, real estate private equity (REPE) funds, i.e. non-listed closed-end funds investing with a value-added or opportunistic approach in real estate, are increasingly favored by plan sponsors to gain real estate exposure outside of their home markets [Baum and Farrelly, 2009]. In many cases, the legal structure or a very limited secondary market hinder plan sponsors from rescaling or withdrawing their equity commitments during the lifetime of a fund. As a result, their capital is locked into the fund for several years and is only freed upon its liquidation. Due to this long-term commitment, careful selection of funds and fund managers may be of even greater importance for REPE than for investments offering a quick exit option. Our study sets out to investigate whether fund managers can benefit from structural factors such as capital under management, size of previously issued funds or a central position within the REPE industry when raising new funds, or if simply performance matters.

The REPE industry experienced dramatic growth before and after the crisis, with real estate private equity funds now playing an important role in the asset allocation of plan sponsors around the world. Just in the six years from 2009q1 to 2014q4, USD 375 billion of institutional capital was committed to 1,321 REPE funds [Preqin, 2015]. However, despite constant growth the industry’s playing field is unequal. In 2014, the ten largest REPE funds alone secured approximately 40% of all capital commitments that year, while many medium and small size firms faced difficulties raising money for their funds [Lee, 2015]. When studying fundraising statistics from recent years, it becomes apparent that 2014 was not a unique year.

With ever-larger funds, the biggest fund managers have been racing away from their smaller competitors. By far not the oldest player in the business, the Blackstone Group, as the industry leader, manages about as much capital as the second, Lone Star Funds, and third, Goldman Sachs, largest REPE managers together, or more than 200 times as much capital as the median fund manager [see Exhibit 1 for metrics of the 30 biggest fund managers in the sample].

Exhibit 1: Size and embeddedness of 30 biggest fund managers in the dataset

Fund Manager	Total fund volume in dataset (USDm)	No. of funds in dataset	Avg. fund size (USDm)	Earliest vintage	No. of known participation	Avg. number of known participation per fund
Blackstone Group	82,267	22	3,739.39	1994	485	22.0
Lone Star Funds	58,480	14	4,177.14	1995	298	21.3
Goldman Sachs Merchant Banking Division	31,692	22	1,440.55	1991	117	5.3
CBRE Global Investors	28,633	59	485.30	1985	322	5.5
Morgan Stanley Real Estate Investing	25,424	14	1,816.00	1973	228	16.3
Starwood Capital Group	18,049	13	1,388.35	1992	136	10.5
LaSalle Investment Management	17,929	47	381.47	1980	269	5.7
Brookfield Asset Management	17,857	10	1,785.70	2004	44	4.4
Carlyle Group	15,615	12	1,301.23	1997	147	12.3
Ares Real Estate Group	14,012	23	609.21	1993	191	8.3
Colony Capital	13,496	14	964.04	1995	116	8.3
Beacon Capital Partners	13,367	8	1,670.84	1998	193	24.1
Westbrook Partners	13,067	10	1,306.70	1995	199	19.9
BlackRock Realty	12,628	26	485.69	1981	221	8.5
Rockpoint Group	11,196	9	1,243.96	2003	112	12.4
Tishman Speyer	11,119	18	617.75	1997	77	4.3
Angelo, Gordon & Co	10,699	17	629.35	1997	176	10.4
Aberdeen Asset Management	10,597	21	504.60	1999	65	3.1
Oaktree Capital Management	9,914	10	991.44	1996	133	13.3
Hines	9,216	27	341.33	1996	71	2.6
TA Associates Realty	8,874	12	739.52	1980	274	22.8
Prudential Real Estate Investors	8,868	28	316.70	1974	347	12.4
Goodman	8,516	10	851.61	2005	30	3.0
CIM Group	8,000	5	1,600.02	2000	51	10.2
PIMCO	7,900	2	3,950.00	2011	12	6.0
Partners Group	7,893	13	607.16	2008	66	5.1
Prologis	7,393	15	492.86	2001	69	4.6
Shorenstein Properties	7,388	9	820.90	1993	55	6.1
Walton Street Capital	7,323	9	813.67	1996	154	17.1
Deutsche Asset & Wealth Management	7,306	23	317.65	1970	239	10.4



Source: Created by authors based on data from Preqin Ltd. (2015).

A quick comparison with other industries reveals that REPE's Herfindahl-Hirschman Index for market concentration is above-average relative to the finance industry and comparable to industries that require extensive capital investments in large-scale machinery, equipment and technology [see Exhibit 2]. This degree of concentration may seem puzzling at first glance given the 'boutique' label often associated with private equity investments.

Exhibit 2: Herfindahl-Hirschman Index for selected markets, based on 2014-year end market cap.

Index / Industry	Top-5	Top-10	Top-30
REPE (global)	0.2467	0.1464	0.0630
Geography specific			
FT Global 500	0.2065	0.1054	0.0361
S&P 500	0.4210	0.1856	0.0821
FTSE 100	0.2130	0.4247	0.0485
Industry specific (based on S&P 500)			
Consumer Discretionar	0.2055	0.1117	0.0490
Consumer Staples	0.2145	0.1263	0.0933
Energy	0.3006	0.2024	0.1139
Financials	0.2213	0.1300	0.0605
Health Care	0.2193	0.1202	0.0992
Industrials	0.2655	0.1299	0.0579
Information Technology	0.2455	0.1394	0.0823
Utilities	0.2075	0.1109	0.0488

Source: Created by authors based on data from Preqin Ltd. (2015) and Thomson Reuters Datastream (2015).

Today’s market structure and super-sized REPE funds might not be good for the industry overall. Aligned investment activities can lead to mispricing, decreased diversification ability and increased risk, e.g. through unpredictable returns, irrespective of fund size and manager skills [Baur, 2006; Chiang and Zheng, 2010]. Our study sets out to investigate drivers of REPE fundraising success and in particular, we aim to address the issue of whether fundraising success stems from previous established business relations with plan sponsors, or if simply performance matters. While the former would benefit well-connected managers, thus leading to accelerated growth, the latter situation would provide more equal chances for well-performing managers to raise follow-on funds.

Previous research on real estate private equity in a broad sense, i.e. including core and open ended funds, has focused mainly on drivers and the persistence of REPE fund performance. The established evidence suggests that the performance of REPE funds stems mainly from the performance of the underlying real estate market [e.g. Alcock, Baum, Colley and Steiner, 2013; Fuerst, Lim and Matysiak, 2014] and that (net-of-fee) market out-performance of REPE managers is, at most, a short term phenomenon [e.g. Hahn, Geltner and Gerardo-Lietz, 2005; Bond and Mitchell, 2010] and that fund performance declines with the sequence number of the fund [Tomperi, 2010]. In other words, past performance is not a reliable guide for selecting fund managers in this industry. Moreover, Martí and Balboa [2007] argue that it takes some three to five years after closing to invest the capital committed to a private equity fund and that returns only materialize several years later. Hence, when raising capital for the next fund, performance figures for previous ones might not yet be available. As a result - and in accordance with the signaling theory - the size of previous funds and the total capital under management serve as de facto proxies for company reputation and the ability to manage large amounts of capital. This means big funds attract capital simply on account of their size. Further, media attention increases in line with fund size, which could lead to lower search costs for the investor and, in turn, higher capital commitments [e.g. Sirri and Tufano, 1998].

Moreover, investment decisions are based on long-standing trust relationships between plan sponsors and fund managers (which stem from personal relationships and familiarity; not from past performance) and fund managers can exploit sunk costs for searching, underwriting, and familiarity through charging above average fees, even in a competitive fee-bargaining environment [Gennaioli, Shleifer and Vishny, 2015]. This led Hahn et al. [2005] to question whether the demand side of this market is behaving in an economically rational manner. Lastly, increasing concentration might be fuelled by herding behavior, which in the past occurred mainly during phases of high market volatility and/or market downturns [Philippas et. al., 2013; Zhou and Anderson, 2013]. This naive strategy of mimicking the investment decisions of peers, lowers search costs and allows the decision maker to 'share the blame' in cases where the chosen fund underperforms or even loses money [e.g. Scharfstein and Stein, 1990; Jenkinson, Jones, and Martinez, 2014]. Uneducated investment decisions which occur while herding, can also lead to biased expectations about potential risks and returns [Hwang and Salomon, 2004].

To find out the reasons behind the observed concentration, we could conduct a survey of plan sponsors asking about their motives for investing in a particular fund. However, this approach might be plagued by the stated preference problem, i.e. investors may not reveal their true motives or could even not be fully aware of them. Instead, in this paper we apply network analysis techniques to measure the 'embeddedness' of a fund manager in the relationship context and then use the calculated metrics to predict fund-raising success. We use the term 'plan sponsor' for institutional investors, such as pension funds, retirement systems, sovereign wealth funds, etc. to distinguish them clearly from fund issuing private equity companies that invest the fund's capital in property. We use the term plan sponsor interchangeably with limited partner (LP), where the latter describes the legal status in the fund structure. We refer to fund managers, REPE firms, and general partners (GPs) as firms that raise capital from plan sponsors. Once the equity commitments have reached the target size, the fundraising process is closed; the GP subsequently invests and manages the capital on behalf of the plan sponsors.

Sample Construction

As a basis for our analysis, we merged previously unconnected buy-side and sell-side data from the Preqin real estate database. Based on 14,720 equity commitments (participations), we established links between 2,216 plan sponsors investing with 837 fund managers in 2,717 REPE funds (see Exhibit 3). Subsequently, we incorporated party and fund specific data into the system.

Exhibit 1: Number of firms and connections in the dataset

	Full sample	Network (based on participation)
Plan sponsors (LPs)	2,216	2,216
Known LP commitments (participation)	14,720	14,720
REPE Funds	2,960	2,717
Fund managers (GPs)	879	837

Source: Created by authors based on data from Preqin Ltd. (2015).

The resulting REPE network has global coverage and spans from 1969q1 to 2015q1 (cut-off period). Among other things, the system allows us to identify subsequent funds (same GP, later year of fund issuance ('vintage')), subsequent participation (same LP, later vintage) and LP-GP business relationships, directionally measured through LP participation in funds issued by GPs (same GP, same LP). Additionally, we can track and measure the intensity of reoccurring business relations through subsequent participation (same LP, same GP, later vintage). In order to compare fund performance across different investment strategies, geographies, points in the market cycles etc., we use relative performance measures instead of the equity multiples or the net-of-fee internal rate of return (net-IRR). That is, we employ the excess-IRR, which is the deviation of a fund's net-IRR performance from its specific custom benchmark provided by Preqin, as well as the quartile ranking within the fund's specific peer group. The quality of Preqin data has previously been questioned; however, two factors mitigated our concerns about potentially inaccurate performance figures. Firstly, Preqin collects data mainly through filing request from public institutions, in accordance with the Freedom of Information Act (e.g. the 5 U.S.C. § 552 for the U.S. and the FIOA 2000 Ch. 36 for the U.K.), that are legally obliged to provide accurate information upon request. Moreover, Fisher and Hartzell [2013] compared Preqin data with sources from other commercial data providers and with non-commercial data provided by plan sponsors. As the authors found Preqin's performance figures to be comparable, we have faith in the data quality and think that potential backfill, selection or reporting biases should not be issues.

Exhibit 3 shows the excess-internal rate of return (IRR), measured as the difference in percentage points between the net-of-fee IRR of the fund and the fund's specific custom benchmark. The benchmark figures are provided by Preqin and take vintage year, investment strategy, geographies etc. into account. In further data exploration we checked the performance of 'Big funds' which are the 30 biggest funds in our dataset. All of them have a size of 4,000 USD million or bigger. 'Big managers' are defined as the five biggest fund managers in the dataset, measured by total capital under management at the time of data retrieval. Subsequent funds are all funds that a manager issued after the first fund, i.e. funds with serial number 2 or higher. All performance figures are equal-weighted and are not adjusted for fund-size.

Exhibit 2: Relative fund performance

Excess-IRR (%) (Δ%p to custom benchmark)	n	n w. excess-IRR data	Max.	Min.	Median	Mean	Std.Dev
Full sample	2,960	1,041	190.00	-106.60	-0.10	-0.533	15.462
30 biggest funds	30	15	36.90	-20.30	4.80	3.540	13.593
Funds issued by 5 big managers	132	62	36.90	-99.70	-2.60	-2.866	16.866
First fund of each manager	879	258	190.00	-106.60	2.00	2.064	19.184
All subsequent funds (sequence no. >= 2)	2,081	770	85.20	-100.30	-0.95	-1.412	14.046
Pooled funds only	2,670	962	190.00	-106.60	-0.10	-0.447	15.283
Separate accounts only	290	66	58.90	-87.10	-1.30	-1.894	19.233

Quartile	n	n with quartile data	Best	Worst	Median	Mean	Std.Dev.
Full sample	2,960	957	1	4	3	2.606	1.105
30 biggest funds	30	15	1	4	2	2.133	1.302
Funds issued by 5 big managers	132	64	1	4	3	2.625	1.202
First fund of each manager	879	203	1	4	3	2.468	1.144
All subsequent funds (sequence no. >= 2)	2,081	754	1	4	3	2.643	1.091
Pooled funds only	2,670	895	1	4	3	2.601	1.100
Separate accounts only	290	62	1	4	3	2.677	1.170

Source: Created by authors based on data from Preqin Ltd. (2015).

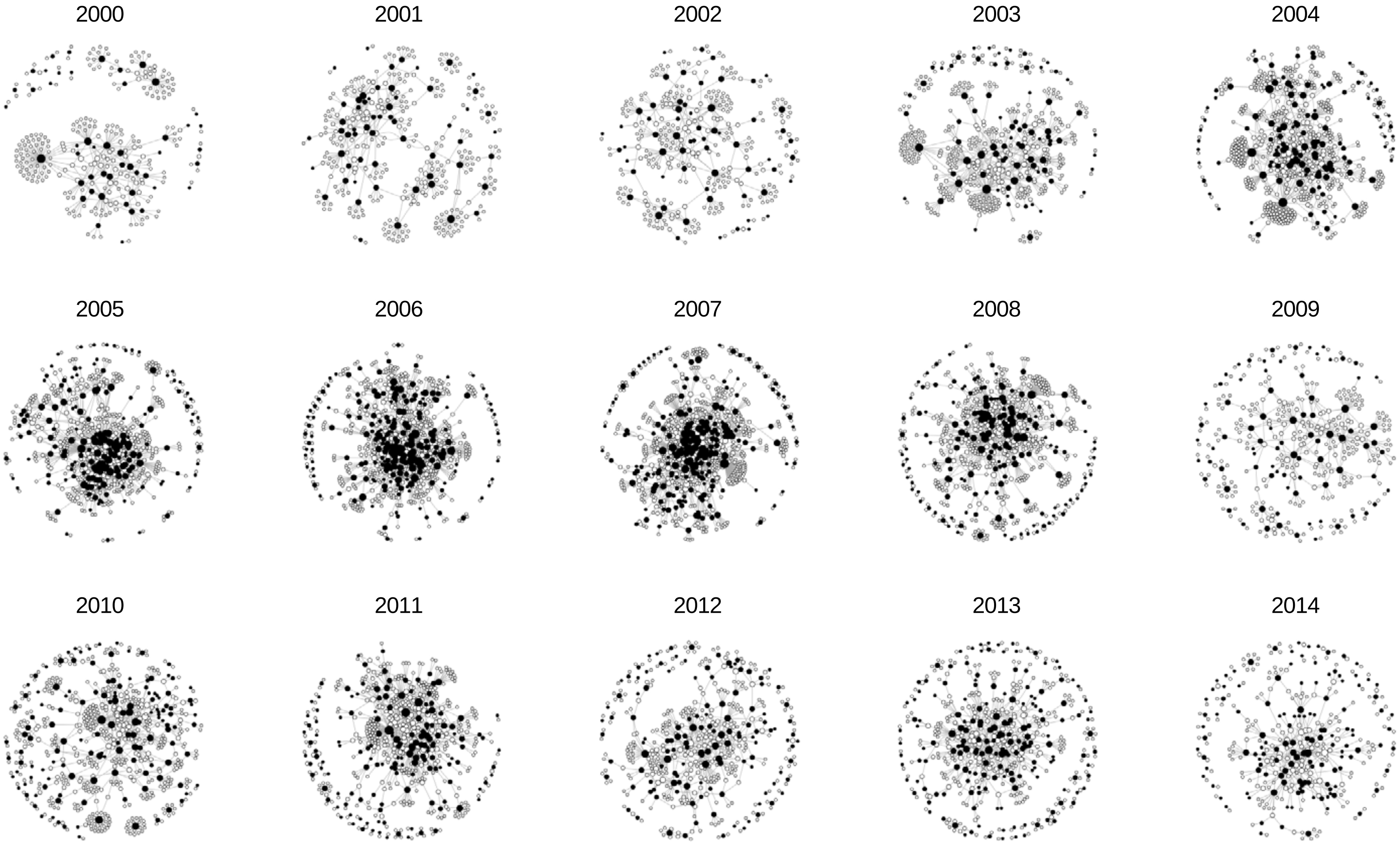
Network analysis to calculate industry embeddedness

The reputation of an REPE fund can be measured in several ways. In addition to the relative performance measures excess-IRR and quartile ranking of the previous fund, we assume that the size of the previous fund itself and the total amount of capital under management at the time of fundraising has a signaling effect towards plan sponsors. In addition to these observable factors, we use network analysis techniques to identify how many equity commitments from plan sponsors a fund manager can secure in each year a fund is closed. We assume that when a plan sponsor participates in a fund a business relation between the fund issuing manager and the plan sponsor is established and that the fund manager will try to use this connection when raising capital for the next fund. We assume further that managers with more participants in their funds, i.e. more connections to plan sponsors, are more centrally located (embedded) in the REPE industry and that this centrality can be measured through the total amount of plan sponsor connections in each vintage year.

Originating in graph theory and network analysis, centrality measures are frequently used in epidemic research to examine the spreading of viral and bacterial diseases. They have also been applied in computer science (e.g. Google PageRank) and more recently, in social science, for example to examine the dissemination of information in social (media) networks.

We deploy centrality measures as proxies for the embeddedness of a fund company, because we suspect that without having the need of a ‘cold call’, better connected fund managers might also be more successful fundraisers, hence grow faster. If connections cause growth and size causes connections, we might have a self-propelling system where size can cause greater size itself. Once a certain threshold is exceeded, this could cause an increasing degree of exclusion or non-recognition of competitors and in turn accelerated centralization of the market towards few big firms. To examine the relation between industry embeddedness and fundraising speed, we used our constructed LP-GP network to calculate degree centrality and eigenvector centrality measures of fund managers in each given vintage year [see Exhibit 5 for a graphical illustration of the constructed REPE network].

Exhibit 3: Illustration of the REPE networks



Note: GP = black; LP = white

The (in-)degree centrality is a simple count of the known participation that a GP can secure in each vintage year and the eigenvector centrality measure weights this participation additionally according to the centrality of the investing plan sponsor. This is calculated as

$$EigenvectorCentrality_{GP(f)} \propto \sum_{GP \neq LP} A_{GPLP}\, EigenvectorCentrality_{LP}$$

where A_{GPLP} is the adjacency matrix, i.e. $A_{GPLP} = 1$, if GP and LP have a connection through participation in a fund, and $A_{GPLP} = 0$ otherwise. The eigenvector centrality takes continuous values from 0 to 1, with 1 given to the most central GP. This measure weights the participation edge by the centrality of the participating LP. It is therefore useful for investigating the herding behavior of smaller LPs who follow the participation decision of big plan sponsors, assuming that they undertook thorough due-diligence and that their decision to participate is an indicator for the quality of a fund.

In addition to the degree centrality and eigenvector centrality measure, we include the size of the previous fund, the size of the fund manager (measured by total capital under management at the time of fundraising), as well as the relative performance measures excess-IRR and quartile ranking from the previous fund in our model. This allows us to gain a deeper understanding of the drivers leading to fundraising success. As proxy for fund raising speed or 'density' we use the average number of days that a fund manager needs to collect one million US-Dollars for a respective fund. We calculate this by dividing the fund size at closing with the number of days from fundraising start date to the closing date. For funds dominated by foreign currencies and where USD equivalents were not provided, we calculated the USD amount with the respective exchange rate from the closing date. With the average days as depended variable we built the following regression model

$$\begin{aligned} DaysPerUSDm_{if} &= \beta_0 + \beta_1 \left(LnFundSize_{if-1}\right) + \beta_2\left(Rel.Perform._{if-1}\right) + \beta_3\left(DgrCntr_{if-1}\right) \\ &\quad + \beta_4\left(EgnVctrCntr_{if-1}\right) + \beta_3\left(LnGPsize_{if-1}\right) + \varepsilon_i \end{aligned}$$

where $LnFundSize_{if-1}$ is the log of size from the previously issued fund, $Rel.Perform_{if-1}$ is the excess-IRR (regression set I) or quartile performance ranking (regression set II) respectively. $DgrCntr_{if-1}$ is the above described degree centrality measure for that the fund manager gained through issuing the previous fund. $EgnVctrCntr_{if-}1$ is the GP's eigenvector centrality measure from the previous vintage year. Lastly, $LnGPsize_{if-1}$ is the GP's amount of REPE capital under management, i.e. cumulated sum of previous REPE funds. As the quartile ranking is a categorical representation of the excess-IRR, we run the regressions individually including only one of the relative performance measures in the same set of regressions. Having in mind that the volume of the previous fund (f-1) is included in the size for the GP and that we calculated two centrality measures based on the same network, several tests for multicollinearity were conducted. We found the variance inflation factors and the variance-covariance matrix for the estimated coefficients to be in acceptable ranges.

Results

The regression output can be seen in Exhibit 6. The upper table holds the results for the set of regression run with the excess-IRR measure and the lower table includes the results for the regressions with the quartile performance ranking. Column I to V show the bivariate regression results including only one of each explanatory variables and column VI provides the multivariate regression results for the full model specification including excess-IRR and Quartiles respectively.

Exhibit 4: Regression results

	Excess-IRR											
	I		II		III		IV		V		VI	
y = DaysPerUSDm	Est. coefficient	Std.err.	Est. coefficient	Std.err.	Est. coefficient	Std.err.	Est. coefficient	Std.err.	Est. coefficient	Std.err.	Est. coefficient	Std.err.
exIRR(f-1)	-0.00322	0.0147									0.00125	0.013
LnFundSize(f-1)			-1.178***	0.147							-0.803***	0.285
DgrCntr(f-1)					-0.0573***	0.0144					0.0235	0.020
EgnVctrCntr(f-1)							-3.353***	0.916			0.263	1.337
LnGPsize(f-1)									-1.200***	0.106	-0.766***	0.175
Intercept	2.195***	0.209	9.154***	0.851	2.917***	0.238	2.647***	0.224	11.03***	0.771	12.24***	1.481
Observations	197		372		352		321		377		170	
R-squared	0.000		0.148		0.043		0.040		0.256		0.291	
F-Statistic	0.0481		64.45***		15.90***		13.40***		129.3***		13.46***	

	Quartile											
	I		II		III		IV		V		VI	
y = DaysPerUSDm	Est. coefficient	Std.err.	Est. coefficient	Std.err.	Est. coefficient	Std.err.	Est. coefficient	Std.err.	Est. coefficient	Std.err.	Est. coefficient	Std.err.
Quartile(f-1)	0.246	0.205									0.289	0.181
LnFundSize(f-1)			-1.178***	0.147							-0.766***	0.286
DgrCntr(f-1)					-0.0573***	0.0144					0.0311	0.022
EgnVctrCntrl(f-1)							-3.353***	0.916			-0.333	1.479
LnGPsize(f-1)									-1.200***	0.106	-0.808***	0.184
Intercept	1.491***	0.547	9.154***	0.851	2.917***	0.238	2.647***	0.224	11.03***	0.771	11.66***	1.585
Observations	201		372		352		321		377		195	
R-squared	0.007		0.148		0.043		0.040		0.256		0.255	
F-Statistic	1.439		64.45***		15.90***		13.40***		129.3***		12.92***	

*Note: Column I to V model with one explanatory variable only. Column VI: full model specification. * p<0.10, ** p<0.05, *** p<0.01*

Quite surprisingly, the regressions with the excess-IRR as well as the performance quartile ranking both return no statistically significant results (column I, top and bottom). Hence, we cannot confirm a relationship between relative past performance and subsequent fundraising success. Looking at the results of the other bivariate regressions in columns II to V (top and bottom figures show the same results) it can be observed that size and connections seem to matter: The size of the previous fund (column II; ß = -1.178, p<0.01) and the size of the fund manager (column V; ß=-1.200, p<0.01) have a significant and positive effect on the subsequent fundraising speed. Note that higher fundraising speed is associated with a lower average number of days that a fund manager needs to collect one million US-

Dollars for a new fund on offer. Hence, negative coefficients indicate a positive relationship between the variable and speed. Also, the estimated coefficients for both centrality measures, the degree centrality (column III; ß=-.058, $p<0.01$) and eigenvector centrality (column IV; ß=-3.353, $p<0.01$), indicate a positive and significant relation between company embeddedness and fundraising speed. However, in the full model specification, which incorporates all variables, only the size measures remain to be significant predictors for fundraising speed (column VI: ß=-0.803, $p<0.01$ and ß=-0.766, $p<0.01$ for LnFundSize(f-1) as well as ß=-0.766, $p<0.01$ and ß=-0.803, $p<0.01$ for LnGPsize(f-1), with excess IRR and performance quartiles respectively).

Conclusion

In this paper, we apply network analysis methodology to first find out which fund managers are well connected and deeply embedded within the real estate private equity industry and consecutively, to investigate whether the managers can benefit from their connections to plan sponsors when raising capital for new funds. In order to do this, we matched previously unconnected REPE-investor, -fund, and -manager data and created a global industry network for each year. To our knowledge, this is the first attempt to apply network analysis methods in the context of real estate private equity research.

Given the early stages of this research, a number of caveats are in order. In particular, the relatively low predictive power of the regression estimates is a concern, but it is in a range comparable to similar studies. In follow-up research, we will seek to enhance the model with additional variables so as to improve the predictive power of the identifying equation. Notwithstanding the limitations, our results do not confirm findings of previous research suggesting a positive relationship between fund performance and subsequent fund size [e.g. Tomperi, 2010]. Analyzed individually, the embeddedness of a fund manager (measured by degree centrality and eigenvector centrality) enables him to raise capital for follow-on funds faster. However, in the full model specification with size and relative performance measures, the significance of this embeddedness vanishes. In this setting, the only remaining significant predictors for fundraising speed are the size of previous fund and the fund manager’s total amount of capital under management. To put it crudely, being well-connected helps but sheer size seems to trump all other factors, at least for raising new real estate private equity funds more quickly.

References

Alcock, J., A. Baum, N. Colley, and E. Steiner. "The Role of Financial Leverage in the Performance of Private Equity Real Estate Funds." Journal of Portfolio Management, Vol. 39, No. 5 (2013), pp. 99-110.

Baum, A., and K. Farrelly. "Sources of alpha and beta in property funds: a case study." Journal of European Real Estate Research, Vol. 2, No. 3 (2009), pp. 218-234.

Baur, D. "Multivariate market association and its extremes." Journal of International Financial Markets, Institutions and Money, Vol. 16, No. 4 (2006), pp. 355-369.

Bond, S.A., and P. Mitchell. "Alpha and persistence in real estate fund performance." Journal of Real Estate Finance and Economics, Vol. 41, No. 1 (2010), pp. 53-79.

Chiang, T.C. and D. Zheng. "An empirical analysis of herd behavior in global stock markets." Journal of Banking and Finance, Vol. 34, No. 8 (2010), pp. 1911-1921.

Fisher, L.M., and J.D. Hartzell. "Real Estate Private Equity Performance: A New Look." Working paper, University of North Carolina at Chapel Hill, 2013.

Fuerst, F., W. Lim, and G. Matysiak. "Private Equity Real Estate: Asymmetric Effects of Gearing and Drivers of Performance." Working paper, University of Cambridge, 2014.

Gennaioli, N., A. Schleifer, and R. Vishny. "Money doctors." Journal of Finance, Vol. 70, No. 1 (2015), pp. 91-114.

Hahn, T.C., D. Geltner, and N. Gerardo-Lietz. "Real estate opportunity funds." Journal of Portfolio Management, Vol. 31, No. 5 (2005), pp. 143-153.

Hwang, S., and M. Salmon. "Market stress and herding." Journal of Empirical Finance, Vol. 11, No. 4 (2004), pp. 585-616.

Jenkinson, T., H. Jones, and J.V. Martinez. "Picking winners? Investment consultants' recommendations of Fund Managers." Journal of Finance, Forthcoming (2015).

Lee, E. (2015). "Winner takes all", PERE News, 02 April, 2015, https://www.perenews.com/News_And_Analysis/2015/April/News/FRIDAY_LETTER__Winner_takes_all/?highlight=winner+takes+all

Lerner, J., A. Schoar, and W. Wongsunwai. "Smart institutions, foolish choices: The limited partner performance puzzle." Journal of Finance, Vol. 62, No. 2 (2007), pp. 731-764.

Malhotra, D.K., and R.W. McLeod. "Closed-End Fund Expenses and Investment Selection." Financial Review, Vol. 35, No. 1 (2000), pp. 85-104.

Martí, J., and M. Balboa. "Characterization of the reputation of private equity managers: Evidence in Spain." Journal of Business Venturing, Vol. 22, No. 4 (2007), pp. 453-480.

Philippas, N., F. Economou, V. Babalos, and A. Kostakis. "Herding behavior in REITs: Novel tests and the role of financial crisis." International Review of Financial Analysis, No. 29 (2013), pp. 166-174.

Preqin Ltd. "Quarterly Real Estate Update Q1 2015". In: Preqin Ltd. (Ed.). Quarterly Real Estate Updates, New York. https://www.preqin.com/docs/quarterly/re/Preqin-Quarterly-Real-Estate-Update-Q1-2015.pdf

Scharfstein, D.S., and J.C. Stein. “Herd Behavior and Investment.” American Economic Review, Vol. 80, No. 3 (1990), pp. 465-479.

Sirri, E.R., and P. Tufano. “Costly search and mutual fund flows.” Journal of Finance, Vol. 53, No. 5 (1998), pp. 1589-1622.

Tomperi, I. “Performance of private equity real estate funds.” Journal of European Real Estate Research, Vol. 3, No. 2 (2010), pp. 96-116.

Zheng, L. “Is money smart? A study of mutual fund investors' fund selection ability.” Journal of Finance, Vol. 54, No. 3 (1999), pp. 901-933.

Zhou, J., and R.I. Anderson. “An empirical investigation of herding behavior in the US REIT market.” Journal of Real Estate Finance and Economics, Vol. 47, No. 1 (2013). Pp. 83-108.