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RESEARCH ARTICLE

Firm Performance and the Evolution of Cooperative Interfirm Networks: UK Venture Capital Syndication[1]

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Risk aversion explains much of the structure of interfirm cooperation.

Being well connected explains outperformance.

Venture capital firms benefit from syndication with a range of successful peers.

Interfirm networks improve performance outcomes and higher performance is contagious between cooperating firms.

Introduction

Forming networks of inter-organizational cooperation is vital to firms. Network position and connectedness (the count of interfirm cooperative ties) is correlated with, for example, firms' longevity, profitability, and innovativeness (Ahuja, 2000). Being well connected is a kind of resource. Consistent with the resource-based view, a high quantity and quality of interfirm relations can be viewed as a source of sustainable competitive advantage (Kay, 1993).

Given the importance of cooperative networks, research has turned to the underlying question of how and why networks change. The study of network evolution is prominent (Checkley *et al.*, 2010; Koka *et al.*, 2006). To better understand how cooperative interfirm networks evolve, this article addresses two interrelated objectives. What drives the selection of firms' network partners over time? What network changes, if any, explain firms' performance outcomes? These issues are viewed in the context of venture capital firms, and their syndication activity, over time.

Venture capital firms depend on inter-organizational cooperation. A high proportion of their investments in young, high-growth potential ventures are shared — or 'syndicated' — between VC firms (Bygrave, 1987). This study takes venture capital syndication to define a strategic network, that is, when two venture

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capital firms co-invest in a venture, they define an interfirm tie of cooperation between them. The numerous VC firms co-investing (and divesting) in numerous ventures over the years creates a dynamic network.

The following section selectively reviews the current understanding of interfirm network evolution. This section also examines the relationship between social network position and performance outcomes, and emphasizes the context of venture capital. This is followed by a discussion of the research methods and an analysis of the study's results. Finally, conclusions and recommendations are drawn.

Literature review

The venture capital context

Syndication is important in VCs. In the UK, 27% by volume and 38% by value of VC investments were syndicated during the period 1993–2002. In VC investments with an exit via stock market flotation or initial public offering (IPO), 44% by volume and 69% by value were syndicated (Checkley *et al.*, 2010; IE Consulting, 2004). Similar figures have been observed for the US VC market (Gompers and Lerner, 2001; Jääskeläinen, 2011). IPOs are critical to VCs because they typically offer the highest returns on investment in ventures.

Increasing connectedness is precedent, by one to three years, to improved performance, as measured by investment exits and IPO generation (Hochberg *et al.*, 2007; Seppa, 2001; Seppa and Jaaskelainen, 2002). All the prior researchers used dynamic regression analysis on a panel of US-based VC firms. In US venture capital, the formation of more syndication ties is followed by enhanced performance.

Interfirm network evolution

Interfirm ties lead to garnering unique skills or knowledge for the relevant firms (Kogut, 1988; Powell *et al.*, 2005). Transferring skills or knowledge creates the prospect for outperformance to be contagious between firms. Interfirm ties permit access to strategic resources not otherwise conveniently obtainable. The larger a firm's resource deficiency, the greater that firm's impetus to forge alliances (Ahuja, 2000). Based on this analysis, a well-resourced firm has less motivation to attach to another correspondingly successful firm. Firms search for more varied and distant relationships as they mature and become less resource deficient (Hite and Hesterly, 2001).

Firms seek partners on the basis of their observable resources. Firms with more, or better, observable resources are more attractive as partners. The attractiveness of a firm can be gauged with information on its resources, or with the potential partner's past performance (Baum *et al.*, 2000). The 'resource dependence' view argues that a firm with valuable resources is an attractive partner. Success recorded in the past — such as IPO generation for a VC — is a means by which a firm's resources are observed.

The causal links between performance (defined by IPO generation) and firm connectedness (defined by the syndication network) are explored by testing the following two hypothesized causal specifications:

(H1) IPOs (one partner) → SYNDICATION

The first hypothesis concerns whether the IPO performance of a single VC causes a change in the connectedness of this VC in the syndication network (consistent with the resource dependence view).

(H2) IPOs (both partners) → SYNDICATION

The second hypothesis concerns who chooses whom to syndicate; for example, whether high performers prefer to syndicate with, likewise, high performers (inconsistent with the resource dependence view).

Resource dependence arguments emphasize that inter-organizational networks aid in resource acquisition. However, the specific choice of exchange partner might be influenced by incentives unrelated to resource accretion. Partner choice is determined by prior exchanges

(Granovetter, 1985). Firms face considerable uncertainty in potential partners' qualities; therefore, they prefer to preserve and cultivate existing relationships (Gulati, 1995). Firms also favor cooperating with other firms that appear similar to themselves, perhaps in their technological specialism or status. Tie formation is driven by 'homophily' (Powell *et al.*, 2005).

Network connectedness, or 'centrality,' is a proxy for status (Cook and Emerson, 1978). Status indicates an actor's quality and the former increases in value with uncertainty about the quality of market participants (Podolny, 1994). Firms are more discriminating in their exchange relationships when uncertainty is amplified. In periods of greater uncertainty, firms are more likely to exchange with established partners, and with organizations of comparable status (Podolny, 1994).

Status is also self-reinforcing (Merton, 1968). For example, the acclaim for a collaborative journal article tends to amass disproportionately to the best-known author. This effect allows a well-connected firm to harvest an 'accumulative advantage' (Powell *et al.*, 2005). This argument contrasts with the resource dependence view analyzed above. These latter arguments are labeled the 'social structural view.'

The study explores the causal links between firm 'connectedness' (defined by the syndication network) and performance (defined by IPOs) by testing the following two hypothesized causal specifications:

(H3) SYNDICATION → IPOs (one partner)

The third hypothesis concerns whether the connectedness of a VC affects the performance of this VC (consistent with the social structural view).

(H4) SYNDICATION and IPOs (one partner) → IPOs (other partner)

The fourth hypothesis concerns whether performance is contagious via the syndication network, that is, whether the syndication of any VC with a (previously) high-performing partner VC enhances the (first) VC's own performance (consistent with arguments for skill or knowledge transfer, which manifest network strategies concurring with resource dependence, but not inconsistent with the social structural view).

In summary, this study models network evolution and its causal relation to firms' performance outcomes. Questions arise regarding the elements of network structure and firm attributes. Syndication is seen to arise from the desire to gain knowledge. New insights can lift performance. In this context, does the 'contagion effect' extend a firm's achievement to the syndication partners? Does social structure confine the advantage to elites of firms?

Data and research methods

The analysis uses firm-year data. The data come from a commercial database developed by IE Consulting, a firm specializing in tracking European private equity markets. This provides a UK-based data source comparable to the US-based Venture Economic database used in prior venture capital studies (Bygrave, 1987; Lerner, 1994). Supplementary data are garnered from the British Venture Capital Association's Directory of Members (BVCA, 2003), and from VC firms' websites.

The IE Consulting database contains 10,000 observations of UK venture capital funding rounds, covering a six-year period, from the beginning of 1995 to the end of 2000. The venture capital industry allows frequent observation of interfirm relations — that is, the formation of syndicates — and thereby admits of statistical analysis. Syndication is also objectively definable, and a publicly announced and legally contracted relationship. Finally, syndicates themselves change over the years (Bygrave, 1987); syndication can be treated as a longitudinal variable, permitting causal tests.

The sample is a panel of the 40 leading UK VC firms. These firms constitute more than 80% of all relevant resources and activities in the UK; syndications, funds

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invested, and IPOs generated (IE Consulting, 2004). They are ranked by their respective totals of portfolio companies. Prior studies have used a similar sampling strategy (Podolny, 2001). A time series of observations from each VC firm is taken. When two VC firms syndicate (co-invest, within a given venture, for the first time), within a given year, that is counted as one relation or 'tie' between them. They thereby form a dyad. The observations are annualized event data; they record for each year the event of forming a new tie (that is, co-investing in a uniquely defined venture).

The data set includes investments in nearly 1000 portfolio companies during the six years from 1995 to 2000 (1993 and 1994 are used for lagged values, as discussed later). This six-year interval offers homogeneous data (that is, does not include extremes of market turbulence) and is sufficiently large to produce a robust statistical model. Note that some of the 'top 40' firms did not exist at the start of the period under examination. Therefore, the total number of firm-year observations of 'active' firms is moderately less than 240 firm-years (=40 firms × 6 years). Beyond the top 40 most frequently syndicating VCs in the UK, virtually no syndication occurs over the six years in question.

The focus of analysis is the posited causal interrelation of a firm's performance and its connectedness in the social network, as defined by syndication. Firm performance is assessed by a firm's number of IPOs in a given year. A stochastic agent-based model is employed (Snijders, 2005 and Snijders *et al.*, 2009 provide a primer in these methods), which can express a variety of network change mechanisms under conditions of interdependence and dynamic feedback. A stochastic agent-based model also facilitates hypothesis testing. The model is designed to meet the challenge of the numerous mutual dependencies (that is, every network variable depends directly on every other network variable) that both characterize network analyses and bedevil traditional panel data regression methods. The nodes in the network represent social actors (here, VC firms) and the network ties represent a social relation (here, co-investment or, synonymously, syndication by VC firms).

The model posits that the network evolves as a stochastic process 'driven by the actors,' that is, the model can embody theories about how actors change their outgoing ties. The probabilities of tie changes are, in part, endogenously determined, as a function of the network structure itself. They are also, in part, exogenously determined as a function of characteristics of the nodes ('actor covariates') and characteristics of pairs of nodes ('dyadic covariates'). In their multivariate guise (Snijders *et al.*, 2007), stochastic actor-based models can be used to analyze longitudinal social network data, coupled with the changing attributes of actors, as joint dependent variables. This framework allows exploration of the relation between VCs' syndication network and VCs' performance (as given by their annual IPO count). Upon request, the authors can provide a more detailed, technical account of the methods.

Empirical results

A descriptive overview of the data under test is provided below. The section then discusses the results of the causality tests. These findings are subsequently brought together in a discussion.

Descriptive statistics

Table 1 shows the total of the counts for the VC performance and connectedness metrics. Four VC firms produce no IPOs over the six years in question.

Table 2 provides descriptive statistics for the principle variables. Each is taken across a panel of 40 VC firms, for six years each (plus two lagged years, 1993 and 1994). The variable 'IPO' is also analyzed with one-, two-, and three-year lags; taking longer lags could have been desirable from a VC modeling point of view, but each extra lag results in a loss of data and thus degrades the overall statistics. Three-year lags are found to be the longest to maintain model rigor. Notably, less than 5% of any ties

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Table 1. Details of VC firms

	No. ties	No. IPOs	Firm age at 2000	No. GPs	Risk	Funds under management (€m committed)
VC1	329	76	55	1192	2.83	4536.70
VC2	86	13	21	124	2.98	1263.76
VC3	64	4	14	135	2.89	359.75
VC4	25	5	19	92	3.00	338.00
VC5	44	8	17	51	2.91	130.23
VC6	27	15	26	57	2.75	496.22
VC7	65	4	15	63	2.86	104.43
VC8	17	1	15	56	2.91	693.14
VC9	41	7	16	40	2.79	103.68
VC10	6	8	23	45	2.99	2230.33
VC11	48	3	19	44	2.82	104.88
VC12	26	2	12	46	2.90	58.64
VC13	27	6	32	33	3.00	588.38
VC14	8	1	3	38	2.50	54.16
VC15	35	8	15	46	2.75	267.35
VC16	24	4	17	42	3.00	229.48
VC17	30	10	15	28	2.89	577.39
VC18	38	4	15	55	2.93	70.67
VC19	15	3	20	49	2.98	514.99
VC20	17	3	16	41	2.98	142.72
VC21	29	3	16	33	2.93	735.62
VC22	15	0	17	26	2.42	18.80
VC23	25	8	3	27	2.64	46.26
VC24	41	9	15	37	2.57	20.10
VC25	2	3	15	36	3.00	29.15
VC26	16	3	29	28	2.94	142.87
VC27	19	4	16	31	2.87	180.63
VC28	29	5	15	28	3.00	772.87
VC29	0	0	16	36	2.98	263.95
VC30	24	5	16	26	2.50	138.49
VC31	21	5	17	29	2.91	411.69
VC32	1	0	3	32	2.00	637.35
VC33	5	1	17	26	2.45	55.06
VC34	3	1	15	5	1.92	28.76
VC35	12	3	1	19	1.07	76.00
VC36	19	2	12	27	3.00	525.08
VC37	15	3	20	25	3.00	547.10
VC38	23	9	16	18	2.70	36.30
VC39	29	2	3	17	1.26	28.85
VC40	22	0	16	11	0.47	10.89

Data source: IE Consulting (2004). All variables except 'risk' are calculated as a sum from 1995 to 2000. Risk is calculated as a mean for 1995–2000. (Firm age established at year 2000; note that five firms had not started trading as of 1995.)

that are ever replicated take longer than three years until replication. Most VC firms invest in all major industrial sectors and most have offices in more than one region of the UK.

Table 3 shows correlations across the variables under consideration. Centrality is positively correlated to all of the performance outcomes. The next section addresses the issue of causation.

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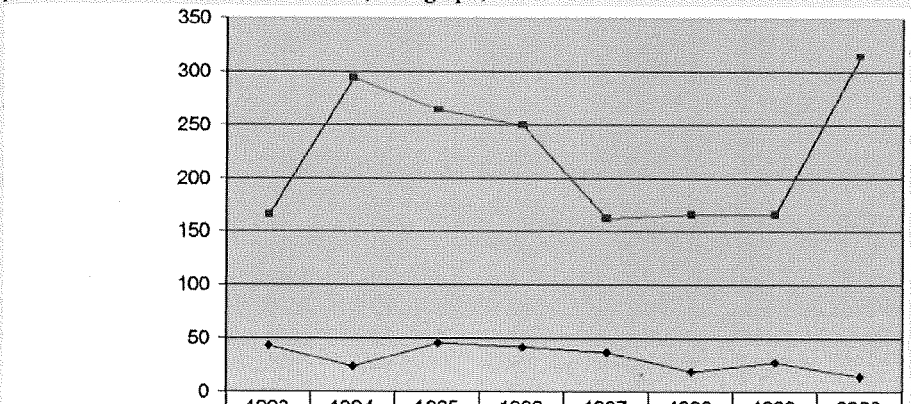
Table 2. IPO and syndication counts for 1993–2000 (with graph)



	1993	1994	1995	1996	1997	1998	1999	2000
IPO Count	43	24	45	42	37	19	27	14
Syndication Count	166	294	264	250	162	166	166	314

Data source: IE Consulting (2004). All data summed across all 40 VC firms in the sample, for each of the years analyzed.

Table 3. Correlations of modelled variables

		1	2	3	4	5	6	7
1	constant network rate (period 1)							
2	constant network rate (period 2)	0.12						
3	constant network rate (period 3)	0.07	0.10					
4	constant network rate (period 4)	0.06	0.10	0.05				
5	constant network rate (period 5)	0.03	0.11	0.10	0.08			
6	degree (density)	0.69	0.56	0.35	0.33	0.28		
7	transitive triads	0.78	0.51	0.17	0.15	0.10	0.87	
8	sqrt degree of alter	0.75	0.56	0.30	0.27	0.22	0.99	0.94
9	rate IPOrec9500 period 1	0.04	−0.05	−0.01	−0.02	−0.05	−0.02	−0.01
10	rate IPOrec9500 period 2	0.02	−0.04	0.02	0.00	−0.05	−0.01	0.01
11	rate IPOrec9500 period 3	−0.03	0.01	−0.03	0.00	0.03	−0.03	−0.02
12	rate IPOrec9500 period 4	0.01	0.04	0.03	−0.03	0.01	0.04	0.03
13	rate IPOrec9500 period 5	−0.02	−0.04	−0.08	−0.01	−0.05	−0.04	−0.04
14	IPOrec9500 linear shape	−0.02	−0.03	0.00	−0.02	−0.01	−0.03	−0.02
15	IPOrec9500 quadratic shape	−0.01	−0.04	−0.01	−0.04	0.04	−0.02	−0.04
16	IPOrec9500: effect from firm age	−0.02	0.00	0.08	−0.01	0.03	0.03	0.03
17	IPOrec9500: effect from funds	0.04	0.04	0.10	0.00	0.02	0.08	0.07
18	IPOrec9500: effect from GPs	0.01	0.02	0.06	−0.02	0.02	0.03	0.01
19	IPOrec9500: effect from deals	0.00	0.01	0.06	−0.02	0.03	0.02	−0.01
20	IPOrec9500: effect from risk	−0.05	0.01	0.06	−0.02	0.02	−0.02	−0.01
21	IPOrec9500: effect from #sectors	0.00	0.02	−0.01	0.03	0.05	0.01	−0.02

Data source: IE Consulting (2004). All calculations performed with Siena version 3.17. All primitive variables calculated for each of the years 1995–2000. 'Network rate' refers to change in the number of ties between each of the six annual periods modeled. 'Degree density' refers to the ratio of actual network ties to all possible network ties. 'Transitive triads' refers to the ratio of ties to 'friends of friends' to all possible ties. 'Sqrt degree of alter' refers to the square root of the (connectedness) degree of alters in the network. 'Rate IPOrec9500 period N' refers to the rate of change of IPO generation from period N to $N + 1$ (for the years 1995–2000). 'IPOrec9500 linear shape' and 'IPOrec9500 quadratic shape' refer to the modelling requirements to estimate 'preference curves' for actors (that generate IPOs) in the network. 'IPOrec9500: effect from firm age' refers to the serial correlation of a firm's age and its record of generating IPOs. The remaining variables relate to a firm's funds under management, number of GPs (i.e., investment managers), deals done (i.e., investments made), level of investment risk taken, and the number of sectors in which it has invested.

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Explanatory statistics: Network evolution and causality

This section presents the formal tests of the hypotheses. Results are shown from two models (in **Table 4**), one for each of the hypothesized causal directions. Each of the two models contains an analysis of the lagged values, with the time lag varying up to a maximum of three years. Part 1 models the change in the firms' syndication levels as the dependent variable. Part 2 assesses performance, measured in terms of IPO count, as the dependent variable.

Dependent variable: Change in syndication levels

No effect occurs of a VC firm's past years' IPOs on its selection of syndication partners. Having achieved many IPOs does not imply higher involvement in subsequent syndication activity. No special selectivity is found within IPO deal-making ability; for example, firms with high levels of IPO activity are not emphasizing the selection of each other nor are they avoiding each other.

VCs syndicate with few partners in any given year. A triangulation or 'clique effect' occurs; that is, VCs tend to syndicate with a partner of a partner. A Matthew effect is in evidence; VCs prefer to syndicate with well-connected VCs. Past syndications tend to be repeated.

No effect is found of common investments in the same industrial sector (i.e., as defined by the investee ventures) on syndication. Geographical proximity (that is, VCs having offices in the same region of the UK)

8	9	10	11	12	13	14	15	16	17	18	19	20
−0.01												
−0.01	0.11											
−0.02	0.01	0.05										
0.04	0.07	−0.03	0.05									
−0.04	0.02	0.01	−0.01	0.06								
−0.03	0.17	0.13	0.12	0.37	0.26							
−0.03	0.26	0.09	0.00	0.07	0.23	0.44						
0.03	−0.21	−0.08	−0.01	−0.03	−0.19	−0.13	−0.10					
0.07	−0.03	−0.15	−0.12	−0.10	−0.30	−0.30	−0.04	0.40				
0.02	0.04	−0.06	−0.13	−0.18	−0.27	−0.46	0.19	0.24	0.64			
0.01	0.09	−0.04	−0.10	−0.12	−0.20	−0.20	0.43	0.18	0.58	0.94		
−0.02	−0.06	0.02	0.01	0.17	−0.05	0.38	0.17	0.17	−0.03	−0.11	0.01	
0.00	−0.01	0.01	−0.03	−0.09	0.16	0.21	0.31	0.04	−0.05	0.10	0.20	0.10

Table 4. Results from Part 1 and Part 2

Part 1

Dependent variable: syndication, $1996 \leq t \leq 2000$

Effect	Estimate	St. error	*p*-Value	OR
IPO one partner				
$(t-1)$	−0.008	0.068	0.912	0.993
$(t-2)$	0.014	0.046	0.765	1.014
$(t-3)$	0.058	0.047	0.215	1.060
IPO both partners				
$(t-1)$	0.038	0.027	0.167	1.039
$(t-2)$	−0.016	0.028	0.568	0.984
$(t-3)$	0.011	0.022	0.619	1.011
Control variables				
density	−2.283	0.112	<0.001	0.102***
triangulation	0.442	0.194	0.023	1.556*
Matthew effect	0.341	0.010	<0.001	1.406***
syndication $(t-1)$	0.487	0.075	<0.001	1.627***
syndication $(t-2)$	0.012	0.011	0.263	1.012
syndication $(t-3)$	0.018	0.007	0.008	1.018**
portfolio overlap	0.008	0.006	0.186	1.008
joint office locations	0.065	0.038	0.083	1.067+
firm age	−0.006	0.006	0.350	0.994
# GPs employed	0.003	0.058	0.960	1.003
risk	0.018	0.117	0.880	1.018

Part 2

Dependent variable: IPO count, $1996 \leq t \leq 2000$

Effect	Estimate	St. error	*p*-Value	OR
# syndication partners				
$(t-1)$	0.097	0.047	0.037	1.102*
$(t-2)$	0.085	0.034	0.012	1.089*
$(t-3)$	−0.0001	0.026	0.997	1.000
IPOs syndication partners				
$(t-1)$	0.104	0.070	0.139	1.110
$(t-2)$	0.203	0.106	0.057	1.224+
$(t-3)$	−0.036	0.066	0.587	0.965
Control variables				
trend (linear)	−0.981	0.195	<0.001	0.375***
trend (marginal)	−0.043	0.090	0.632	0.958
firm age	0.003	0.014	0.853	1.003
funds (€ million)	−0.002	0.003	0.617	0.999
# GPs employed	0.003	0.052	0.954	1.003
risk	−0.353	0.242	0.144	0.703
diversification (# sectors)	0.171	0.139	0.219	1.187

Notes: OR = odds ratio of increasing predictor by one unit on dependent variable increase.
All statistics generated with software Siena version 3.17.
$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

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promotes syndication. Syndication levels are not affected by VC firm age, number of GPs, or the risk level of the investments made.

Dependent variable: Change in IPO count

The number of a VC firm's syndication partners, in recent years, statistically determines IPO levels. The average number of IPOs of these partners determines a VC's own IPO generation. Evidence ($p = 5.7\%$) is found for a 'contagion effect,' with a time lag of one to two years.

A VC has few IPOs (less than 3) in any given year and no evidence is found for decreasing marginal returns on further IPOs. The control variables have no bearing on IPO generation.

The results in synthesis

Network effects are found revealing that connectedness is positively related to subsequent performance. VC firms produce more IPOs when they have increased their syndication activity one or two years ago. The pattern of syndication is triangular. Preferred partners tend to be partners of partners with regionally co-located offices. Well-connected firms are preferred. A contagion effect is present. Having a partner with an IPO one to two years ago contributes to a VC firm's IPO activity. The significance of the focal variables of connectedness and performance is robust to the addition of the control variables.

Discussion

The findings provide support for Hypotheses 3 and 4. Performance is positively related to connectedness, and greater connectedness is precedent to improved performance (in terms of IPO count) for a VC firm and its syndication partners. In contrast, no support is found for Hypotheses 1 and 2. Improved performance does not cause connectedness. Successful firms do not seek syndication with similarly successful firms. Homophily (Powell *et al.*, 2005) fails to explain tie formation for UK-based VC firms. It is unrelated to partner selection in terms of investee risk level or sector specialization. More mature firms do not follow different syndication strategies in the network. This finding contradicts Hite and Hesterly's (2001) results.

The UK VC market differs from that of the USA. One explanation is that market size and market age effects explain the differences. The UK market is younger and less than one-fifth the size of the US market, in terms of VC funds invested. Less differentiation in UK-based VCs' syndication strategies would be evident.

In explaining the causal relationship between success and centrality, the social structural view is stronger than resource dependence. The social structural view predicts that organizations benefit from being centrally placed in networks. The evidence for triangulation, repetition of syndication ties, and a Matthew effect is consistent with risk aversion in syndication strategy (Podolny, 2001). The focal results resonate with research on the US market (Hochberg *et al.*, 2007), which suggests that connectedness causes outperformance. The UK also shows evidence of contagion effects, suggesting success in producing IPOs can transfer to syndication partners within two years. Speculatively, this phenomenon could be a product of beneficiary resources generated from the prior IPO itself. Alternatively, it could derive from the gain of insight to — or capabilities in — the IPO process. Yet, no evidence is found that a VC's level of funds under management mediates its IPO generation. This suggests success contagion is due to transfers of information, skill, or social contacts and reputation, rather than to transfers of capital.

Along with metrics of VC centrality and performance, the analysis considers the time lags over which causal effects take place. Causation acts within a two-year cycle. VCs are commonly syndicating deals that then come to IPO within two years of the syndication. Many of the value-adding activities of the VC in a syndicate — such as helping to plan and build the management team — are completed within two years. Contagion effects are only

evident with two-year lags, which is consistent with the value of transferred information, skills, reputations, or relationships waning beyond that period.

A conceptual model is now developed of the drivers of network evolution and firm performance. This model blends, with the empirical findings, both resource dependence and social structural theory. Financial resources have an obvious logical priority in network formation; a VC firm cannot create ties in the first place if this firm has no funds to co-invest. Resources (as a hygiene factor) create ties. Ties also create resources, resulting in network effects; evidence suggests that having more partners, and more successful partners, nurtures outperformance. Nonetheless, partner selection is also driven by risk aversion; that is, consistent with the repeated ties and triangulation effects found in the model, and with prior social structural research (Podolny, 2001), albeit with no link to performance outcomes. Risk mitigation arguments shed light on partner selection. Social structure and contagion arguments shed light on performance outcomes. The discussion concludes by further condensing the model: resources allow VC firms to engage; risk mitigation allows VC firms to endure; ascending the social hierarchy allows enrichment.

VC managers should seek to syndicate frequently and particularly with other VCs that have produced IPOs within the last two years. Prospects of IPO generation are enhanced. The advantage accrues more because the network allows access to timely skills, relevant information, or propitious social ties rather than being due to material resources. Network effects and social contagion are prime concerns for cooperative strategy.

In common with other studies of cooperative networks, this research contains limitations, each of which presents opportunities for further study. This article is based on the method of testing formal ties of VC syndication. Significant informal ties of cooperation may exist between firms which involve, for example, the sharing of expertise. The understanding of informal ties can be improved with further study.

Can this model be generalized further? By adapting part of a US-based framework (Seppa, 2001), this article offers a robust empirical model of six years of UK-based venture capital activity. Some of the findings are comparable with prior empirical research in other national VC markets; usually meaning the USA. Some dimensions of the model are consistent across time and geography. Future studies might test these network evolution methods beyond the venture capital context. In the realm of venture capital, advantages lie in testing data sets covering a 12-year cycle (12 years being the maximum term for most VC funds).

The status of the theories tested is now addressed. Through the explicit treatment of time, a shifting emphasis is seen in the power of different theories to explain. Highlighted here is the relative rarity of temporal empirical work in financial strategy and network studies. The development and application of prior theory owes much to a preponderance of non-temporal or 'static' analyses. A temporal lacuna is also evident in other phenomena where time matters; not only VC syndication, but also in other strategic networks. In short, a broad scope is argued for the models of networks that make richer use of time. This study is proposed as a step in that direction.

Conclusion

This study contributes to knowledge in three ways. First, it provides an empirical agent-based model of the evolution of an interfirm cooperative network in a way that offers causal insight into firms' performance outcomes. Recently, developed stochastic methods offer significant advantages over the dynamic panel data regression methods employed in prior studies. Second, this study develops new theoretical insights to the drivers of network formation. Third, it draws upon an original data set from the world's second-largest venture capital market developed in the UK, suggesting commonalities along with some notable differences from the much-studied US market.

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The findings are consistent with a 'network effect.' More interfirm connectedness causes higher performance outcomes. In addition, evidence is uncovered for the contagiousness of superior performance. The partner firm's performance can affect the focal firm's performance.

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References

Ahuja G. 2000. The duality of collaboration: Inducements and opportunities in the formation of interfirm linkages. *Strategic Management Journal* 21: 317–343.

Baum JAC, Calabrese T, Silverman BS. 2000. Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. *Strategic Management Journal* 21: 267–294.

BVCA. 2003. British Venture Capital Association Report on Investment Activity. London.

Bygrave WD. 1987. Syndicated investments by venture capital firms: A networking perspective. *Journal of Business Venturing* 2(2): 139–154.

Bygrave WD, Timmons JA. 1992. *Venture Capital at the Crossroads*. Harvard Business School Press: Boston, MA.

Checkley MS, Steglich C. 2007. Partners in power: Job mobility and dynamic deal-making. *European Management Review* 4(3): 161–171.

Checkley MS, Añón Higón D, Angwin D. 2010. Venture capital syndication and its causal relationship with performance outcomes. *Strategic Change* 19(5/6): 195–212.

Cochrane JH. 2005. The risk and return of venture capital. *Journal of Financial Economics* 75(1): 3–52.

Cook KS, Emerson RM. 1978. Power, equity and commitment in exchange networks. *American Sociological Review* 43: 721–739.

Gompers PA, Lerner J. 2001. *The Money of Invention: How Venture Capital Creates New Wealth*. Harvard Business School Press: Boston, MA.

Granovetter M. 1985. Economic action and social structure: A theory of embeddedness. *American Journal of Sociology* 91: 481–510.

Gulati R. 1995. Familiarity breeds trust? The implications of repeated ties. *Academy of Management Journal* 38: 85–112.

Hite JM, Hesterly WS. 2001. The evolution of firm networks. *Strategic Management Journal* 22(3): 275–286.

Hochberg YV, Ljungqvist A, Lu Y. 2007. Whom you know matters: Venture capital networks and investment performance. *Journal of Finance* 62(1): 251–301.

IE Consulting. 2004. *Database of Private Equity Activity in Europe*. IE Consulting: London.

Jääskeläinen M. 2011. Venture capital syndication: Synthesis and future directions. *International Journal of Management Reviews*. DOI: 10.1111/j.1468-2370.2011.00325.x.

Kay J. 1993. *Foundations of Corporate Success*. Oxford University Press: Oxford.

Kogut B. 1988. A study of the life cycle of joint ventures. *Management International Review* 28: 39–52.

Koka BR, Madhavan R, Prescott JE. 2006. The evolution of interfirm networks: Environmental effects on patterns of network change. *Academy of Management Review* 31: 721–737.

Lerner J. 1994. The syndication of venture capital investments. *Financial Management* 23(3): 16–27.

McFadden D. 1973. Conditional logit analysis of qualitative choice behavior. In Zarembka P (ed.), *Frontiers in Econometrics*. Academic Press: New York; pp. 105–142.

Merton RK. 1968. The Matthew effect in science. *Science* 159: 56–63.

Podolny JM. 1994. Market uncertainty and the social character of economic exchange. *Administrative Science Quarterly* 39: 458–483.

Podolny JM. 2001. Networks as pipes and prisms of the market. *American Journal of Sociology* 107(1): 33–60.

Powell WW, White DR, Koput KW, Owen-Smith J. 2005. Network dynamics and field evolution: The growth of inter-organizational collaboration in the life sciences. *American Journal of Sociology* **110**(4): 1132–1205.

Pudney S. 1989. *Modelling Individual Choice*. Blackwell: Oxford.

Seppa TJ. 2001. Essays on the valuation of syndication of venture capital investments. Unpublished Doctoral Dissertation, Helsinki University of Technology, Institute of Strategy and International Business, Espoo, Finland.

Seppa T, Jaaskelainen M. 2002. Frontiers of entrepreneurship research: How the rich become richer in venture capital. Firm performance and position in syndication networks. Available at: http://www.babson.edu/entrep/fer/Babson2002/XIII/XIII_P8/XIII_P8.htm.

Snijders TAB. 2005. Models for longitudinal network data. In Carrington PJ, Scott J, Wasserman S (eds), *Models and Methods in Social Network Analysis*. Cambridge University Press: New York; pp. 215–247.

Snijders TAB, Steglich CEG, Schweinberger M. 2007. Modeling the co-evolution of networks and behavior. In van Montfort K, Oud H, Satorra A (eds), *Longitudinal Models in the Behavioral and Related Sciences*. Lawrence Erlbaum: Mahwah, NJ; pp. 41–71.

Snijders TAB, Steglich CEG, van de Bunt GG. 2009. Introduction to actor-based models for network dynamics. *Social Networks* 32: 44–60.

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