Partners in Power: Job Mobility and Dynamic Deal-Making

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Abstract

This research considers how the connectedness of venture capital firms changes with the job mobility of managers between those firms. A continuous-time Markov chain model is developed to test whether managers are able to "drag" prior inter-firm relational ties with them as they move between employing firms. The findings support the hypothesis that increasing the stock of managers is material to creating inter-firm ties. However, managers are not found to drag their prior links to new network positions. This result is consistent with an institutional view of venture capital syndication, suggesting that interfirm relations are other than managerial in nature.

Venture capital, syndication, social network, strategy, job mobility, dynamics.

1. Introduction

Are interorganizational ties in fact interpersonal ties? Advantageous interorganizational ties of syndication between venture capital ("VC") firms are created and sustained by senior investment managers (often known as General Partners ("GPs")) (Sahlman, 1990). VC syndication ties are *plausibly* embedded in the social network of the relevant GPs. Then, when such a manager shifts employment to another VC firm, so these relations would follow. This effect can be seen as one of the motivations to recruit, resulting, as it might, in a more connected recruiting company and a less connected competing company (from which the new recruit came). But does interfirm job mobility cause a corresponding shift in interfirm ties? If positive, *job mobility* manifests the greater durability of interpersonal ties over interorganizational ties. Moreover, this would provide compelling *indirect* evidence that interorganizational ties are a manifestation of interpersonal ties.

We employ a continuous-time Markov chain model to test the extent to which UK-based VC firms are gaining or losing syndication links following the "event" of gaining or losing a GP. The findings provide no evidence that mobile GPs are causal agents in *dragging* interorganizational networks. But mobile GPs are responsible for helping their new employers to build syndication ties different from those that the mobile GP held previously. This result is consistent with Institutional Theory (c.f. DiMaggio and Powell, 1991). In the context of job mobility, interfirm relations are better understood at the firm-level than at the manager-level.

The next section outlines relevant literature. Following this, the research methodology is described. Then, the results are presented. Finally, conclusions are drawn and the study is summarised.

2. Literature Review

This section reviews research on why, how and when VC firms syndicate. It then moves onto determinants of patterns of syndication. Two further topics relevant to syndication and GP movements are given attention. These are, first, research on job and career mobility, and, second, director interlocks.

Inter-firm cooperative relations are strategically vital. Organizations having more relations have been related to, for example, better firm performance (Hagendoorn and Schakenraad, 1990), longevity (Baum and Oliver, 1991), and reputation (Podolny, 1993). Venture capital firms are an established exemplar of organisations that depend on cooperative relations with their peers (c.f. Bygrave, 1988; Podolny, 2001). Interrelations between venture capital ("VC") firms manifest in contracted agreements to co-invest, or to "syndicate" (Sahlman, 1990). Many VC firms have, at any given time, networks of syndication relations that mediate their strategic activities (Bygrave, 1987). Venture capital firms are often vested in ventures for three to four years, or more (Sahlman, 1990). Many of these investments are syndicated. For example, in all UK deals (1993-2002), 27% by volume and 38% by value were syndicated. (IE Consulting, 2003). For all UK deals (1993-2002), where an exit was achieved via stock market flotation, 44% by volume and 69% by value were syndicated (IE Consulting, 2003).

The importance of syndication to VCs has lead to numerous researchers asking: what *motivates* syndication? Financial arguments are invoked. Syndication is spurred by the need to dilute portfolio risk (Markowitz, 1952) in what is a relatively illiquid investment market (c.f. Lockett and Wright, 2001). Moreover, syndicated investments are believed to offer higher returns (Brander, et al, 2002), and preferable - usually larger - portfolio size (Jaaskelainen et al, 2002). Hochberg et al (2007) describe how VCs being more connected through syndication is causally significant in determining investment success. They find that VC firms with more connected network positions tend to enjoy a greater proportion of investment exits by IPO or trade sale, and to experience a greater probability that their investments survive to further rounds of funding and to exit.

Syndication is inspired by the need to share or access information, advice or expertise on the selection or management of investments (c.f. Bygrave, 1987). Syndication also provides access to the critical resource of additional capital, which in turn gives a VC greater scope for investment (i.e. more investment targets, along with the expectation of future fund-raising from the syndication partners). Hence, greater and smoother deal-flow is also suggested as a motivation to syndicate, along with improved selection of investment targets (c.f. Lockett and Wright, 2001).

Further motivations for syndication can be found in the ideas of social structure and reputation. Having more connections (via syndication) is linked to better reputation and more influence (Podolny, 2001) and getting more investment-relevant information, which, in turn, allows greater access to resources, such as further investment capital (c.f. Gulati, 1995). VCs might syndicate to flatter their short-term financial performance metrics i.e. to "*window dress*". This can be achieved by joining syndicates that are investing in high-profile and successful portfolio companies (Lerner, 1994). Finally, syndication has been seen as a collusive process by which to constrain rivalry between VCs and thus to improve the terms negotiated with the venture in favour of the syndicate members (PEI, 2003).

There is debate about the relative importance of the different motivations to syndicate. The frequency of a VC firm's syndication is better explained by its investment risk than by the value of funds invested (Bygrave, 1987). Moreover, sharing information is a more notable reason for syndication than diluting financial risk; venture capitalists can gain access to syndication networks by having information valued by other investors (Bygrave, 1987).

The ability to add value to portfolio companies can also motivate syndication (Brander et al., 2002). In the UK, competing finance, resource-based, and deal-flow explanations for syndication have been compared (Lockett and Wright, 2001). Financial factors out-weigh the exchange of resources or deal flow. However, value added (via exchange of resources), is imperative for venture capitalists focusing on early-stage investments rather than (later stage) buyouts (Lockett and Wright, 2001). Experienced venture capitalists tend to co-invest in first-round investments with investors having a similar, high-level of experience. This is consistent with the view that access to the opinions of other, seasoned investors is a reason to syndicate (Lerner, 1994). Less experienced venture capitalists might be encouraged to join a syndicate later in the investment cycle. Yet, when seasoned firms join as new investors in later rounds, the terms of investment are often less favourable, due to a rapid increase in the valuation of the venture. Because experienced firms tend to make restricted financial returns from such transactions, this provides support for the window dressing hypothesis (Lerner, 1994), which states that firms seek association with high-profile investment successes in order to better attract new investment funds.

The structure of syndication networks amongst US venture capital firms has been examined. The densities of the networks defined by VC syndication increase along two dimensions; the geographic proximity of VC firms, and their exposure to high-technology (and thereby high risk) enterprises (Bygrave, 1988). The structure of syndication networks also varies with both the flow of information and the frequency of syndication. Centrally-networked venture capital firms in the US tend to invest more often in geographically distant companies (Sorenson and Stuart, 2001). Centrality in the syndication network also varies with the formation of new syndication relationships. Central firms, regardless of their financial resources, can link to other firms with greater ease (Anand and Piskorski, 2001). In contrast, peripheral firms establish ties only if they hold relatively abundant financial resources. In this way, venture capital firms with high centrality tend to maintain their position over time (Anand and Piskorski, 2001).

In summary, syndication is a core activity of venture capital firms. It can be motivated by the desire for reputation, sharing information or colluding, gaining or protecting resources, sharing decision making, improving deal flow and quality, or diluting financial risk. The *significance* of the different motivations to syndicate varies with several factors; a VC's resources, experience, reputation, network position, geographical location or specialism, might all play a role.

Career and Job Mobility

The relations analyzed in this study are created by contractual agreement between VC firms; to coinvest in entrepreneurial businesses. Yet, research finds that *managers* are making those decisions to invest and sign contracts (Sahlman, 1990). Individual managers are *seeking* other individuals with whom to collaborate. Seen by these lights, interorganisational relations are founded and sustained by people; by the relevant managers. Thus, interorganisational syndication networks can be analysed fruitfully at the manager-level.

Consistent with this view, the stability of interorganisational relations is dependent on the stability of relations between managers. Hence, job or career mobility – a manager moving between employing firms, for example - *could* be material to network change. When managers move they have the ability, at that point, or thereafter, to "carry" their prior, cooperative relations with them. In this sense, managers are "dragging" interorganisational networks along with their job mobility. Managers are causal, dynamic agents in shifting networks over time.

The job mobility literature has been predominately intra-organisational in its scope. Job mobility has been defined as the frequency of transfers to different positions within an organization (Dewhirst, 1991). Studies have focused on managers seeking upward mobility *within* their employing organisations (c.f. Burt, 1992). Career-and-strategy research has - until the last few years - steered clear of interorganisational concerns (c.f. Gunz and Jalland, 1996).

The job mobility literature has three established themes: the conditions and contexts which help or hinder mobility; the covariance of pay and mobility (c.f. Boxman et al, 1991; Fujiwara-Greve and Greve, 2000) and, most recently established, how job mobility relates to knowledge transfer within and between organizations (c.f. Madsen et al, 2002).

A personal network rich in structural holes (i.e. socially connecting those who are not otherwise well-connected) assists promotion and pay growth (Burt, 1992; Podolny and Baron, 1997). Greater human capital, in the form of greater education, is related to more career mobility and associated social capital (Friedman and Krackhardt, 1997). The interfirm mobility of significant knowledge-holders can influence the transfer of knowledge between organizations (Almeida & Kogut, 1999). Using regression analysis, the authors show that the holders of patents can influence the citation level derived from that patent, by moving between firms and regions. In essence, some of the *flow of knowledge* between firms is *embedded in labour networks* between firms. This study highlights that a firm's stock of commercially-relevant knowledge can be partly dependent on acquiring staff from competing firms. Similarly Angel, (1991) finds, in a study of skilled US-based engineers, that job mobility can aid firms' ability to match supply and demand, and provide greater flexibility and knowledge sharing.

Developing the interorganizational theme, Ding and Stuart, (2006), find that academics' transition into entrepreneurialism is influenced by proximity to colleagues who have done the same. Career or job mobility can be seen as resulting from social connectedness to mobile alters. Cantner and Graf, (2006) analyze the network resulting from cooperation in R&D. They find, using network regression methods, that the changes in the network structure are better predicted by the job mobility of scientists and the technological overlap between the actors, rather than by past cooperation. Agrawal et al, (2006) examine how social ties facilitate knowledge flows by estimating the "flow premium" captured by a mobile inventor's previous location. This premium is the result of personal relationships formed through co-location within an institutional context. In the interorganizational stream of career mobility research, social ties persist over time, space, and organizational boundaries.

Director Interlocks

Distinct from job mobility, research on "interlocking directorates" concerns the effects of a company director affiliated to one company's board of directors also sitting on the board of another firm. This literature is explicitly interorganisational. The studies of director interlocks address how interlocks help or hinder *organisations,* and their interlocked directors. Such interconnections can be used to define a social network between firms (Mizruchi, 1996). This has been regarded as a test-bed of social embeddedness theory, applied to *interorganisational* relations. Senior managers use their ties to resolve uncertainty about the introduction of new policies (Galaskiewicz, 1985). Communication with trusted, experienced, outside sources is helpful to senior managers (Davis, 1991). Thus, empirical work has focused, with positive results, on how interlocks assist the spread of innovation, such as new financial or governance policies (c.f. Westphal and Zajac, 1997). Research has also focused, with mixed results, on how interlocks assist firms' financial performance (c.f. Fich, 2005)

Broken ties (where an interlock between firms is lost through the death or retirement of a director) are not typically re-established (Koenig et al, 1979; Ornstein 1980; Palmer 1983). The fact that broken ties were not typically reconstituted with new ties (to the same firm) suggests that interlocks are *not* purely *interorganizational* phenomena. They are social ties among the corporate elite. In this context, interorganizational ties can be understood as interpersonal ties (Koenig et al, 1979; Ornstein 1980; Palmer 1983).

3. Hypotheses: Job mobility and the formation of interfirm ties

The venture capital context offers GPs a role as strategic resource, where cooperative relations with other VC firms are causally relevant to firm performance outcomes. VC syndication relations are *plausibly* embedded in the social network and managerial agency of the relevant GPs. These themes of inter-VC connectedness and the social network of GPs have been identified as valuable to research:

> *"Future studies will examine the effectiveness of venture capital firms to see whether it is related to connectedness and centrality….Other investigations might look at factors such as the personal ties of individual venture capitalists,…." Bygrave (1988: 155)*

The literature states that inter-manager social networks can be material to managerial performance and organisational outcomes. Job mobility can increase an organisation's knowledge-assets and some interorganizational ties (via director interlock) do depend on the ongoing presence of the relevant managers. Research does not, however, address the possibility that interfirm cooperative relations might *be created* (or destroyed) by career mobility. In the realm of interpersonal ties interacting with interorganizational ties, *dynamic* issues have been little studied. Fundamental questions remain: can managers moving between organizations make or break interorganizational ties? What ties are changed? And over what timescale?

Two viewpoints are derived. First, consistent with the "broken tie" director interlock research (c.f. Palmer 1983), managers are the "holders" of interorganisational ties. Mobility between employing firms can be material to shifts in interfirm ties. Manager movement, on this view, can create specific ties for the new employer *and* destroy specific ties for the prior employer. Organisations are essentially aggregations of the relevant agents, i.e. the venture capital investment managers; the GPs. This view is "*Managerial*".

Second, while investment managers have some agency in crafting interfirm relations, perhaps the nature of the tie is essentially motivated by attributes of partner firms other than the nature of their managers. Examples might lie in a partner firm's institutional resources, or reputation, or technical and legal practices. This view might be labelled "*Institutional*" (c.f. Powell and DiMaggio, 1991). It suggests that rarely will the movement of investment managers be material to the formation or dissolution of specific interfirm ties. One should be careful to note, though, that manager movements can have an *unspecific* impact on tie formation and dissolution. This is because a venture capital firm's ability to employ or recruit investment managers might be a signal of both its attractiveness as a partner firm and of future activity in the market. However, in contrast to what the Managerial view would predict, syndication ties created this way are unspecific, in the sense that they do not tend to coincide with the interfirm ties of newly recruited investment managers' previous employers.

Three hypotheses are created to test various 'degrees of specificity' of tie creation patterns, ranging from consistency with the Managerial view to consistency with the Institutional view. This first hypothesis is about the creation of very specific ties after a job-movement.

(***H1***.) When a GP moves from one venture capital firm to another, there is an increased probability that the new employer establishes syndication ties with the partner firms of the former employer.

The following hypotheses are about unspecific tie creation, but still related to GP movements between VCs:

(***H2a***.) When a VC firm recruits a new GP, it will have a higher ability to form new syndication ties with any other venture capital firm, regardless of who were the previous employers of the new GP.

(***H2b***.) Likewise, when a VC firm's GP departs to another VC, the VC firm that loses the GP will have a lower ability to form new syndication ties.

The third hypothesis, finally, is 'fully unspecific' in its expectations about the pattern of tie creation, in the sense that these do not relate to GP movements but can be fully explained with reference to the 'stock' of GPs which a VC firm employs (and, of course, other explanatory variables on the firm level). This hypothesis is consistent with the Institutional view.

(***H3***.*)* When a venture capital firm employs more GPs, it will have a higher ability to form new syndication ties with any other VC firm, regardless of whether the GPs are newly recruited or not.

In the next section, the research methods are discussed. The syndication network's evolution poses some challenges to existing statistical approaches; these necessitate an adaptation of established methods.

4. Data and Methodology

This section describes the data and methods used in testing the hypotheses.

4.1 Data

The data are derived from a commercial database, developed by IE Consulting, a firm specialising in tracking European private equity markets. This provides a data source comparable to the Venture Economic database, used in several other studies (c.f. Gompers and Lerner, 1998). Supplementary data were garnered from the British Venture Capital Association's Directory of Members (BVCA, 2003), and from VC firms' websites.

The sample is a panel of the 39 leading UK VC firms. These VCs were ranked by their respective totals of portfolio companies between 1993 and 2003. Prior studies have used similar sampling (c.f. Podolny, 2001). The observations are granular to the firm-year level. When two VC firms syndicate (co-invest, within a given venture, for the first time), within a given year, that is counted as an interfirm network tie.

The British Venture Capital association has had around 150 full members in each of the years studied (c.f. BVCA, 2003). These firms represent almost all UK-based venture capital activity (IE Consulting, 2003). Our study of the most active 39 VC firms is estimated to constitute over 80% of all UK-based: venture capital deals; funds placed and under management; GPs; GP movements; and syndications. In contrast, we note that, in the case of all UK-based *private equity* activity (which includes, for example, buy-outs and financial restructurings), there have been, over the past 10 years, close to 3000 investing firms (IE Consulting, 2003). The venture capital sector is relatively small and specialised.

Two peculiarities of these data need to be noted, as they crucially determine the choice of the statistical model. First, there is no reliable way of determining which firm initiates a deal and thereby "invites" another VC firm to co-invest and hence to form a syndicate, so the network data are "undirected", i.e., the syndication relation is symmetric. Second, there also is no reliable way of determining when a syndication tie ends, i.e., what is the duration of any given co-investment.

GP movements between VCs are not recorded, as such, within the IE Consulting database. GP names are only recorded in so far as they appear in records of investment deal-making. Hence, names were tracked that appeared with different firms over time. Hence, the empirical "date of movement" is the first recorded instance of deal-making at a new VC employer. There are 663 VC syndications and 95 GP movements over the period 1996-2003. Data on VC syndication exists prior to 1996. However, it is not used because there is no recorded GP movement in this earlier period. Data on the number of GPs per firm is gathered from the annual BVCA directories of members (c.f. BVCA, 2003) and cross-checked with VC firms' websites. All but two firms in the sample were actively funding prior to 1996. The two exceptions started in 1999 and 2000 respectively.

Data is gathered that represents both the networking of firms, and their resources, in the form of funds placed in Euro (m) and their stocks of GPs. These firm-level analyses are matched to data on the mobility of GPs. Table 1 shows mean levels of funding and GPs, for the years 1996-2003.

(Table 1 about here)

4.2 **Methods**

We assess to what extent the formation of syndication ties between cooperating VC firms can be explained by the movement of GPs between their employing VC firms, and to what extent it can be explained by firm-characteristics. Tests use a modified version of the SIENA software, which instantiates stochastic agent-based models for network evolution (Snijders, et al, 2005). There appears to be no prior application of this method to the study of venture capital syndication.

Variables under Analysis

The variables under analysis are summarised in Table 2. The outcome variable is the network of cooperating VCs, i.e. the totality of syndications between VC firms. For the analysis, these data are recoded and represented in matrix notation, as follows. If in a given observation period **m**, two firms **i** and **j** form a new syndication tie, this is coded as $\mathbf{y}_{ij}^{m} = 1$. If they don't form such a tie, the coding is $\mathbf{y}_{ij}^{m} = 0$. In this procedure, a syndication tie is treated as new when, within our data set, there has not been a prior tie between the same partners. The coinvestment activity of all 39 firms is coded in symmetric, binary matrices $\mathbf{y}^1, \mathbf{y}^2, \ldots, \mathbf{y}^8$ for each of the eight years 1996 to 2003, and the syndication data enter our analysis in cumulative-dichotomised form. When a syndication tie repeats an earlier one between the same partner firms, or when more than one new syndication is formed between the same firms in the same period, then these additional syndications do not have an impact on the analysis. This data reduction was necessary for addressing the current restriction of the SIENA software to the analysis of binary networks, in combination with the data-peculiarity that we do not know when any particular syndication tie ends. The loss of information incurred by the recoding can be spotted in Table 2 by comparing the first two rows.

(Table 2 about here)

The main predictor variable is the directed network of GP movements, coded annually. In matrix notation, we have non-symmetric matrices $\mathbf{w}^1, \mathbf{w}^2, \ldots, \mathbf{w}^8$, where cell $\mathbf{w}_{ij}^{m}$ contains the number of GPs that were identified to have moved from VC firm **i** to VC firm **j** in period **m**. VCs' total numbers of employed GPs, and their total funds under management, estimated in nominal EUR millions, are included, for each of the eight years under study.

Data Processing

All data are processed with the software SIENA ("*Simulation Investigation for Empirical Network Analysis*", Snijders et al. 2005), which estimates dynamic agent-based models for the evolution of social networks according to Snijders (2001, 2005; Van de Bunt and Groenewegen, 2007). The network evolution process **Y** (the capital letter indicating the probability model as different from the observed data) is modelled in continuous time **t**, as follows. The starting conditions for all actors are defined by the first observation of network ($\mathbf{y}^1$) and actor characteristics. Network evolution proceeds by iterative application of the following four steps: (1) for each actor **k** in the network, a random waiting time τ_k is drawn. Suppose actor **i** is the one for whom the shortest waiting time was drawn. (2) Model time increases by τ_i. If the updated model time lies outside the observation period, the simulation process ends. If it still lies inside the observation period, actor **i** gets the opportunity to either propose a new syndication tie to one of the other actors **k** he is not yet syndicated with, or keep his network neighbourhood as it is. The decision whether and to whom to propose a new tie is based on actor **i**'s (utility) evaluations $\mathbf{u}_{ik}$ of the networks that would result from the contemplated tie additions, compared to each other and to the evaluation $\mathbf{u}_{i\sim}$ of the status quo. A tie is proposed to actor **j** if the evaluation $\mathbf{u}_{ij}$ is highest in that comparison. In this case (3) actor **j** considers honouring or rejecting the proposal, now based on actor **j**'s evaluation $\mathbf{u}_{ji}$ of the network that would result from such a new syndication tie, compared to actor **j**'s evaluation $\mathbf{u}_{j\sim}$ of the status quo. (4) If a tie is proposed and actor **j** honours the proposal, the tie comes into existence. This four-step procedure is repeated until in step (2), the model time reaches the end of the observation period.

The levers of modelling are the actor-specific waiting times $\boldsymbol{\tau}$ and the actor-specific evaluations $\mathbf{u}$ of the network. By spelling out parametrised probability distributions for these components, the process of network evolution can be simulated. Fit-optimising parameters and their standard errors can be obtained by means of simulation-based inference, enabling us to test hypotheses about the mechanisms that underlie network evolution. Waiting times are modelled by exponential distributions, and network evaluations by Gumbel (or, synonymously, extreme-value-type-I) distributions. All random components are assumed to be conditionally independent of each other, given the current state of the evolution process. The resulting overall model belongs to the family of continuous-time Markov chains (Norris, 1997).

In the terminology of Snijders (2001, 2005), the parameters $\boldsymbol{\lambda}$ of the exponentially distributed waiting times $\boldsymbol{\tau}$ are given by the *rate function*. In the present application, we make the simplifying assumption that the waiting times of all actors are drawn according to the same, constant rate function. The location parameters of the Gumbel distributed evaluations $\mathbf{u}$ are given by the *objective function* and also can be further modelled as linear combinations of actor, period or network neighbourhood characteristics, constituting a multiattribute random utility model (Pudney, 1989). Their scale parameters are fixed at one to ensure commensurability in the comparisons of different evaluations $\mathbf{u}$. The probabilities for extending or honouring a specific syndication tie proposal then follow a multinomial logit distribution, based on the objective function's values for the possible courses of action that are considered.

More detail on the model and its estimation is given in the appendix. Here it shall suffice to say that the objective function is where the determinants of network change are brought to bear. When actors prefer a specific characteristic of their network neighbourhood (e.g., when VCs prefer being linked to partners who employ many GPs, as hypothesis H3 claims), then this characteristic can be expressed as a component of the objective function, and estimation will yield a positive parameter estimate as the weight attached to this component.

Operationalisation of the hypotheses

The hypotheses H1, H2 and H3 are tied to model parameters. In analogy to the data notation introduced above, syndication ties between two firms $\mathbf{i}, \mathbf{k} \in \{1, \ldots, \mathbf{n}\}$ are denoted by $\mathbf{Y_{ik}} = \mathbf{Y_{ki}}$ and depend on time **t**. Managers' movements are denoted by $\mathbf{w_{ij}}$ and also depend on time **t**. Let us consider the situation of a movement from firm **i** to firm **j** and the possible shifting of syndication ties with third parties **k** that it might entail. Graphically, this corresponds to the situation in Figure 1.

(Figure 1 about here)

In principle, there are two options in operationalising the hypotheses. We can either assume a 'first party perspective' and model a VC's tie creation proposals as a function of GPs employed in the proposing firm, or we can assume a 'third party perspective' and model the extension of any VC's proposals as a function of the GPs in the potential partner firms. Considering that in an undirected network, both actors have to agree on the contract anyway, this seems to be a minor decision from the theoretical viewpoint. However, there is a clear advantage to assume the 'third party perspective' when considering the following methodological argument about hypothesis H3. Under the 'third party perspective', both partners' numbers of GPs employed enter the probability calculation for a syndication tie (see appendix), either as determinant of the probability to propose a tie to a specific other, or in the probability of this other to accept the proposal. In contrast to this, the number of GPs in the own firm does not provide a criterion for choosing among potential syndication partners (this would neither affect the probabilities to extend syndication proposals nor the probabilities to accept them). Therefore, the 'first party perspective' would require estimation of the main effects of the number of GPs employed in the home firm by means of the rate function, i.e., as indicating networking activity differences between actors. Considering that all other model parameters of interest enter the model in the utility calculations, we considered the 'first party perspective' the less desirable one, and settled on the 'third party' version. This allows us to interpret results in terms of utility. So, we model the dynamics of the syndication network from the viewpoint of partner firm **k** in the diagram, and tie the hypotheses to effects in the objective function that determine attractiveness of potential partners.

For operationalising the 'unspecific' hypothesis H3, the statistic $\mathbf{s}_\mathbf{k}^{\mathrm{H3}}(\mathbf{t}) = \sum_\mathbf{j} \mathbf{Y}_{\mathbf{jk}}(\mathbf{t})\mathbf{v}_\mathbf{j}(\mathbf{t})$ is included in the objective function of actor **k**, where $\mathbf{v_j}$ stands for the number of GPs firm **j** employs in the given period. When the weight attached to this statistic in the objective function is positive, this means that, ceteris paribus, the tendency of actor **k** to establish new ties to actors **j** is the higher, the more GPs **j** employs. Hypothesis H2 is operationalised by including, in the objective function of actor **k**, the statistics $\mathbf{s}_\mathbf{k}^{\mathrm{H2a}}(\mathbf{t}) = \sum_\mathbf{j} \mathbf{Y}_{\mathbf{jk}}(\mathbf{t}) \sum_\mathbf{i} \mathbf{w}_{\mathbf{ij}}(\mathbf{t})$ and $\mathbf{s}_\mathbf{k}^{\mathrm{H2b}}(\mathbf{t}) = \sum_\mathbf{j} \mathbf{Y}_{\mathbf{jk}}(\mathbf{t}) \sum_\mathbf{i} \mathbf{w}_{\mathbf{ji}}(\mathbf{t})$, where now the number of GPs employed by a potential partner firm $\mathbf{j}$ is replaced by the number of actors that join this firm (H2a, expected positive) or leave this firm (H2b, expected negative) in the period. Before operationalising the 'specific' hypothesis H1, two problems need to be addressed. First, there needs to be clarity about which ties have the potential of being dragged. Obviously, only ties that were present prior to a manager's movement could be dragged along with this movement. Yet because neither the duration of ties nor the duration of the GP's employment prior to the movement are known, there is uncertainty about how close prior to the movement a tie would need to have been established in order to qualify for dragging. A parameter $\boldsymbol{\varepsilon}$ operationalising this *backward horizon* is introduced to reflect this uncertainty. When a syndication tie was established within horizon $\boldsymbol{\varepsilon}$ prior to the director movement, it is assumed to qualify for dragging. Second, we need clarity about when such a potential dragging manifests itself. It would be unreasonable to assume that dragged ties are formed instantaneously upon movement, but it is equally unlikely that such a dragging would still occur several years after such a movement. Therefore, a parameter $\boldsymbol{\delta}$ is introduced, operationalising this *forward horizon*, and reflecting the uncertainty about the delay in forming a dragged syndication tie after the movement took place. The objective function statistic expressing patterns of the type illustrated above and taking account of the two horizon parameters is $\mathbf{s}_{\mathbf{k}}^{\mathrm{H1}}(\mathbf{t}) = \sum_{\mathbf{j},\mathbf{i}} \mathbf{Y}_{\mathbf{jk}}(\mathbf{t}) \int_0^{\varepsilon} \int_0^{\delta} \mathbf{Y}_{\mathbf{ik}}(\mathbf{t}-\tau-\eta)\mathbf{w}_{\mathbf{ij}}(\mathbf{t}-\tau)\,\partial\tau\,\partial\eta$. We thus follow a 2-parameter approach to testing H1. For a couple of parameter configurations ($\boldsymbol{\varepsilon},\boldsymbol{\delta}$) that covers a reasonable range (determined below), analyses of the network dynamics are performed, and the strength of the corresponding dragging effects is assessed. The dependence of results on the two horizon parameters will shed light on which (ε,δ)-values make most sense for the operationalisation of H1.

Descriptive summaries of the variables related to hypotheses H3 (number of GPs employed) and H2 (number of GPs on the move) are given in Table 2. For hypothesis H1, specific tie creation patterns - that could be interpreted as 'dragging' - need to be counted. The data contain altogether 250 patterns by which a single GP movement might be related to the creation of a new syndication tie by way of dragging. Table 3 renders the distribution of these patterns over the horizon variables ε (the age of the to-be-dragged tie when the GP leaves his old employer) and δ (the lag between the GP joining his new employer and the dragged tie being established). Note that for operationalising H1 (formula above), we work with the cumulative distribution, while the table renders non-cumulative counts (corresponding to the parameters τ and η in the formula).

(Table 3 about here)

It should be noted that in the table, tie creation patterns can occur more than once when there is more than one GP move that can be invoked to explain it. The 250 patterns tabulated refer to 71 (53%) of the inter-VC ties created after 1996, and involve 43 different GP movements (45%).

Table 3 suggests that if there is dragging involved in the creation of a specific tie, then it happens within relatively short horizons (forward and backward) around the date of GP movement. Therefore, analyses are run for operationalisations of H1 where

$0 < \boldsymbol{\varepsilon}, \boldsymbol{\delta} \leq 3$ (9 configurations), covering up to 214 potential dragging patterns (86%, cumulative, in the condition where $\boldsymbol{\varepsilon}$=$\boldsymbol{\delta}$=3).

Adding control parameters

It is natural that for any tie creation observed in the data, there might not only be different versions of dragging patterns responsible (as described above), but also mechanisms unrelated to dragging, or for that matter, unrelated to any of our hypotheses. In order to absorb the effects of some other mechanisms of network evolution that might operate next to (or instead of) the hypothesised effects, the following four additional parameters are added to the objective function. First, a parameter expressing a general trend to create unspecific ties is added, which is tied to the 'degree statistic' $\mathbf{s}_{\mathbf{k}}^{\text{trend}}(\mathbf{t}) = \sum_{\mathbf{j}} \mathbf{Y}_{\mathbf{jk}}(\mathbf{t})$. Second, a tendency for network evolution according to transitive closure tendencies is added, corresponding to the statistic $\mathbf{s}_{\mathbf{k}}^{\text{transit}}(\mathbf{t}) = \sum_{\mathbf{j}} \mathbf{Y}_{\mathbf{jk}}(\mathbf{t}) \sum_{\mathbf{i}} \mathbf{Y}_{\mathbf{ki}}(\mathbf{t}) \mathbf{Y}_{\mathbf{ij}}(\mathbf{t})$ of 'transitive triads'. It stands for a tendency of a VC to syndicate with partners of one's existing syndication partners, a strategy that could promote interfirm coordination and reduce risk (Podolny, 2001). Third, a tendency of VCs to manoeuvre themselves into intermediary positions between unrelated others is included. Expressed by the statistic $\mathbf{s}_{\mathbf{k}}^{\text{intermed}}(\mathbf{t}) = \sum_{\mathbf{j}} \mathbf{Y}_{\mathbf{jk}}(\mathbf{t}) \sum_{\mathbf{i}} \mathbf{Y}_{\mathbf{ki}}(\mathbf{t})(1 - \mathbf{Y}_{\mathbf{ij}}(\mathbf{t}))$, it is consistent with the advantages of brokerage (Burt, 1992); having access to unique information or resources. Moreover, it is consistent with a fundamentally distinct syndication strategy from that of transitive closure. Fourth, funds under management (EURm), for each firm, are added as a potential determinant of syndication ties. We operationalise this effect by including the statistic $\mathbf{s}_{\mathbf{k}}^{\text{funds}}(\mathbf{t}) = \sum_{\mathbf{j}} \mathbf{Y}_{\mathbf{jk}}(\mathbf{t})\mathbf{z}_{\mathbf{j}}$ in the objective function of actor **k**, where $\mathbf{z}_{\mathbf{j}}$ stands for firm **j**'s funds under management in any given period. The dynamics of this variable are given in Table 2.

By blending these four control mechanisms with our hypothesised effects, the model can explain a broad range of data. By fitting it to our particular data set, empirical evidence for the various mechanisms is assessed in terms of significance levels and effect sizes of the weight parameters attached to the objective function statistics. Model parameters were identified with the SIENA software.

5. Results

Two models were fit to the data: the full model, containing all the effects that have been described in the prior section; and a reduced model in which (next to the control effects) only those hypothesised effects are retained that received empirical support in the full model. Because the effect that operationalises hypothesis H1 depends on the horizon parameters $\boldsymbol{\delta}$ and $\boldsymbol{\varepsilon}$, the full model was estimated under the 9 different parameter settings reported above, $(\boldsymbol{\delta}, \boldsymbol{\varepsilon}) \in \{1,2,3\} \times \{1,2,3\}$. For reasons of parsimony, we only present those results of the estimation of these models that directly relate to the testing of the hypotheses H1 through H3. The results for the other parameters will be reported for the reduced model only, which are qualitatively equivalent to the full models' results under all parameter configurations.

Figure 2 renders the t-scores obtained when dividing the parameter estimates by the parameters' estimated standard errors. Assuming asymptotic normality, these scores are used for testing the hypotheses. In the diagrams, dotted horizontal lines are inserted to indicate significance thresholds for one-sided testing. What can be seen in the diagrams is that there is no evidence for hypotheses H2a and H2b, indicating that neither own GP recruitment nor GP loss due to others' recruitment significantly affects the attractiveness of a VC firm as syndication partner for other firms; the t-scores range between –1 and +1 for the corresponding parameters. Hypothesis H3 - about the amount of GPs in a firm affecting the firm's attractiveness to others - is confirmed, though weakly. The t-scores for the corresponding parameters in the full model are weakly significant, at least for a backward horizon parameter of ε=3. Because the effect testing H3 does not depend on the horizon parameters, this ε-dependence needs to be understood as an artefact of including the effect testing H1. This effect, finally, is in most conditions insignificant and (more interestingly) of opposite sign than expected under H1. It appears that if GP moves have any "dragging" effect, it is a negative one: ties between partners of the former employer and the new employer are shunned, not sought.

(Figure 2 about here)

In order to get rid of the ε-dependence of the only parameter with weak significance, a reduced model was estimated that did not include the effects operationalising H1, H2a and H2b. The estimation results of this final model are rendered in Table 4.

(Table 4 about here)

The parameter for H3 does not gain significance when dropping H1 and H2 from the testing scheme, but remains weakly significant ($p<0.1$ one-sided). Other effects are significant: the trend parameter is negative, indicating that VC firms tend to syndicate with few partners. The intermediary parameter is also negative; it is not viewed as a good strategy to create structural holes. The firm resource, "funds under management", had an insignificant effect on tie formation and dissolution, after controlling for the number of GPs employed.

6. Discussion

The findings do not support network evolution being specifically influenced by GP mobility. Both H1 and H2 can be rejected. The number of GPs employed, though, does have a weak positive effect on syndication, which is consistent with H3. These findings are coherent with an "*institutional*" interpretation (Powell and DiMaggio, 1991) of inter-VC cooperation. That is, partner VC firms are chosen on the basis of relatively stable institutional attributes. Partner VC firms are not chosen on the identity of the GP who might initiate a syndicate relationship. That GPs are a core resource of a VC firm (Bygrave, 1988) was consistent with our analyses. In addition, structural holes are not sought within inter-VC firm networks, which is consistent with syndication manifesting risk-aversion (c.f. Podolny, 2001).

Our findings contrast with the director interlock research that examines 'broken ties' (cf. Palmer, 1983). That research suggests that broken ties – dissolved through directors dying or retiring – are typically not reconstituted. While we do not address the breaking of ties per se, we find that, for a VC firm losing a GP, there is no significant drop in the creation of new syndication ties (i.e. with partners other than old partners.) This further suggests that GP mobility can be characterized as having a "socializing effect". This is due to GP mobility (insofar as it increases the stock of GPs in the new host VC firm) causing the introduction of new inter-VC ties, yet without significantly destroying prior tie-making capabilities. Because job mobility increases the span of the GP's contacts (inducing from the intra-organizational findings of Burt, 1992) this would also be favourable for career prospects.

Past studies have related ties between R&D departments to the career mobility of relevant knowledge-workers (c.f. Cantner and Graf, 2006, Agrawal et al, 2006). This stream of research supports the view that social ties persist over time, space, and organizational boundaries. It buttresses the position that shifting interorganizational ties and knowledge transfer are measurably dependent on career mobility. In contrast, we find now such dependency in the VC context. We speculate that R&D is, in general, a less institutionalized function than venture capital investment. Moreover, institutionalization is itself a response to the repetitive financial risks of venture capital investment. In short, the institutional view is consistent with our findings in the UK-based venture capital context. We find no evidence that a VC firms' funding levels mediate its attractiveness, but we speculate that firm-level qualities such as "culture" are significant; attributes that remain beyond this quantitative study.

In common with other empirical studies of venture capital, this essay has several limitations, each of which offers opportunities for further research. First, ideally, research would model person-to-person networks, embedded within firm-to-firm networks. Second, some VC firms are "sibling-like" in the sense that they have been spun-out of the same parent firm, such as a large general bank. Hence they might be likely to share syndication partners due to their common history. Third, there are challenges in the nature of the statistical model. GP movement is a relatively rare event; it is possible that the low-rate of GP mobility (0.3 movements per firm-year) means that the importance of this resource dynamic is out-weighed by others. It also might mean that GP's abilities are not (primarily) located in networks. This sparseness of data is aggravated by the available software's current limitation to binary tie data in the dependent network variable. This way, we base our analysis on less than one third of the total number of syndication activities in the observed time frame. As shown in Table 2, two thirds of the observed syndications are redundant in the sense that they repeat earlier collaboration of the same partners, or occur in parallel (i.e., multiple contracts between the same partners in the same period). Extension of the software's capabilities to handle valued tie data is pending. Fourth, venture capital activity lapsed following the equity market crash of March 2000. The interrelationship of economic conditions and the variables in our study remains unexplored. Finally, our data are consistent with the network effects of GP movement becoming evident within a one-to-three year period of the GP beginning to make investments on behalf of the new employer. This finding does not preclude significance in longer time periods.

7. Summary

This paper examines if interorganizational ties are in fact interpersonal ties. Specifically, the essay tests whether venture capital firms' syndication ties are "held" by GPs (the *managerial* view) or whether ties are "held" by VC firms (the *institutional* view). Data were employed on the top 39 VC deal-making firms in the UK, in the period 1996 to 2003. The units of analysis are firm-year observations of syndication ties (totalling 663), along with data on 95 movements of GPs between the VC firms. A stochastic model is employed to explore the dynamic effects of job mobility on the network of syndication partners. There is no evidence that GP mobility acts to break interfirm ties. Insofar as there is any effect of GP mobility, it is consistent with new GPs adding to the resources of the new host company and thereby enhancing the host's ability to form interorganizational ties. The findings support the view that syndication ties are interorganizational, rather than interpersonal. Future research might consider the significance of the ties of senior venture capitalists to other types of firm, such as banks, lawyers, and accountants. Social aversion is also noteworthy; some managers might diminish their employers' abilities to form ties.

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Appendix: detailed model description

Assume that at discrete moments $\mathbf{t}_1 < \mathbf{t}_2 < ... < \mathbf{t}_\mathbf{M}$ in time, a sequence of symmetric, binary social networks $\mathbf{y}(\mathbf{t}_1), \mathbf{y}(\mathbf{t}_2), ..., \mathbf{y}(\mathbf{t}_\mathbf{M})$ on a given set of $\mathbf{n}$ actors is observed, and assume that these networks are coded as symmetric adjacency matrices (the diagonal cells being meaningless and disregarded). This observed network sequence is modelled as a realisation of a continuous-time Markov chain $\mathbf{Y}(\mathbf{t})$ on the state space $\mathfrak{Y} = \{0,1\}^{\frac{1}{2}\mathbf{n}(\mathbf{n}-1)}$ of all possible undirected networks on the given set of actors. A state $\hat{\mathbf{y}}$ is called a *potential successor state* of another state $\mathbf{y}$ if $\hat{\mathbf{y}}$ can be obtained from $\mathbf{y}$ by adding one (symmetric) link to $\mathbf{y}$, formally, if there exists a pair of actors $\{\mathbf{i},\mathbf{j}\}$ such that $\mathbf{y}_{\mathbf{ij}} = 0$ and $\hat{\mathbf{y}}_{\mathbf{ij}} = 1$, while for all other pairs $\{\mathbf{k},\mathbf{l}\} \neq \{\mathbf{i},\mathbf{j}\}$, we have $\hat{\mathbf{y}}_{\mathbf{kl}} = \mathbf{y}_{\mathbf{kl}}$. Denote by $\mathfrak{S}_\mathbf{i}(\mathbf{y})$ the set of successor states that differ from $\mathbf{y}$ by a tie involving actor $\mathbf{i}$, and let $\mathfrak{S}(\mathbf{y})$ denote the set of all potential successor states of $\mathbf{y}$. Transitions between the states are modelled as occurring after exponentially distributed waiting times at rate $\lambda^{\text{total}}(\mathbf{y},\mathbf{t}) = \sum_\mathbf{i} \lambda^\mathbf{i}(\mathbf{y},\mathbf{t})$, where $\lambda^\mathbf{i}(\mathbf{y},\mathbf{t})$ indicates actor $\mathbf{i}$'s individual rate of change at time point $\mathbf{t}$, given the current state $\mathbf{y} = \mathbf{Y}(\mathbf{t})$ of the process. In the present case, we assume rates to be period-wise constant. Then, this current state of the process can transition to a potential successor state $\hat{\mathbf{y}} \in \mathfrak{S}(\mathbf{y})$, according to a probability distribution that is composed of three components. First is the probability that a specific actor $\mathbf{i}$ will be selected as taking the initiative to propose a new tie, this probability is $\lambda^\mathbf{i} / \lambda^{\text{total}}$. Second is the probability that this actor extends a proposal to another actor $\mathbf{j}$ to whom he's not yet tied. Third is the probability that this actor accepts the proposed tie. The latter two probabilities are based on evaluations of the candidate successor states. The evaluations by actor $\mathbf{k}$ of successor states $\hat{\mathbf{y}} \in \mathfrak{S}_\mathbf{k}(\mathbf{y})$ are modelled by an objective function $\mathbf{f}_\mathbf{k}(\mathbf{y}) = \sum_\mathbf{r} \beta_\mathbf{r} \mathbf{s}_\mathbf{k}^\mathbf{r}(\mathbf{y})$ in which network configurations of interest (or other determinants of network change), expressed in statistics $\mathbf{s}_\mathbf{k}^\mathbf{r}(\mathbf{y})$ that express local network neighbourhood characteristics, are weighted by model parameters $\boldsymbol{\beta}$, which are estimated from the data. A positive estimate indicates that actors prefer high scores on the corresponding statistic over low scores. Examples for such network configurations (statistics, effects) are given in the main text of the article. The probability for actor **i** to choose a successor state $\mathbf{y}' \in \mathfrak{S}_\mathbf{i}(\mathbf{y})$ has the familiar multinomial logit shape $\exp\left(\sum_\mathbf{r} \beta_\mathbf{r} \mathbf{s}_\mathbf{i}^\mathbf{r}(\mathbf{y}')\right) \Big/ \sum_{\hat{\mathbf{y}} \in \mathfrak{S}_\mathbf{i}(\mathbf{y})+\mathbf{y}} \exp\left(\sum_\mathbf{r} \beta_\mathbf{r} \mathbf{s}_\mathbf{i}^\mathbf{r}(\hat{\mathbf{y}})\right)$, and can be interpreted as stochastic optimisation of the objective function plus a Gumbel-distributed error term in a random utility framework (McFadden 1974). The choice by **i** of a successor state $\mathbf{y}'$ corresponds to the proposal of a new tie to an actor $\mathbf{j} \neq \mathbf{i}$ who is uniquely identified by the property that $\mathbf{y}' \in \mathfrak{S}_\mathbf{j}(\mathbf{y})$. Based on this actor's objective function, it is determined whether or not this proposed tie indeed is established. The probability for this is modelled based on a binary comparison of the current state **y** and the proposed successor state $\mathbf{y}'$ in terms of actor **j**'s objective function, and can be expressed as $\exp\left(\sum_\mathbf{r} \beta_\mathbf{r} \mathbf{s}_\mathbf{j}^\mathbf{r}(\mathbf{y}')\right) \Big/ \sum_{\hat{\mathbf{y}} \in \{\mathbf{y},\mathbf{y}'\}} \exp\left(\sum_\mathbf{r} \beta_\mathbf{r} \mathbf{s}_\mathbf{j}^\mathbf{r}(\hat{\mathbf{y}})\right)$, again in multinomial logit shape. Note that in the random choice models, there always is a positive probability to not change anything, i.e., maintain state **y** instead of choosing any successor state.

Estimation of the model proceeds by way of stochastic approximation of the model parameters. The SIENA software performs the estimation of models for undirected network dynamics with the method of moments (Bowman and Shenton, 1985). This method identifies parameters as solutions to a set of estimation equations in which model-derived simulated network statistics are matched to observed network statistics. Following Snijders (2001, 2005), the solution to the moment equation is obtained by a variation of the Robbins-Monro (1951) algorithm, and standard errors are obtained by the delta method. Assuming for ease of presentation that there are only two observation moments $\mathbf{t}_{\text{begin}} < \mathbf{t}_{\text{end}}$, the default choice of estimation equations is the set of equations $\mathbf{E}_{\langle\lambda,\beta\rangle}\left(\sum_{\mathbf{i}} \mathbf{s}_{\mathbf{i}}^{\mathbf{r}}(\mathbf{Y}(\mathbf{t}_{\text{end}}))\right) = \sum_{\mathbf{i}} \mathbf{s}_{\mathbf{i}}^{\mathbf{r}}(\mathbf{y}(\mathbf{t}_{\text{end}}))$ for parameters $\boldsymbol{\beta}$ in the objective function, and $\mathbf{E}_{\langle\lambda,\beta\rangle}\left(\left\|\mathbf{Y}(\mathbf{t}_{\text{end}}) - \mathbf{y}(\mathbf{t}_{\text{begin}})\right\|\right) = \left\|\mathbf{y}(\mathbf{t}_{\text{end}}) - \mathbf{y}(\mathbf{t}_{\text{begin}})\right\|$ for the (constant) rate parameter $\boldsymbol{\lambda}$, where $\|\cdot\|$ indicates the Hamming distance of the binary networks, i.e., the number of cells in which a change occurred. The equations mean that parameters are identified such that the expected (or, average simulated) sum over all actors **i** of the network statistics at the observation moments match the observed ones, and that the expected total number of network ties added corresponds to the observed number of ties added.

The model sketched here differs from the standard actor-driven model for network evolution by Snijders (2001, 2005) in several ways. First, by the restriction to successor states that add ties to the network (Snijders also allows for ties to vanish). This restriction was necessary because in our data, we do not have information about when a syndication contract ends. It introduces complications for model estimation by the method of moments, however, as now, the default estimation equations for the rate parameters, as proposed by Snijders (2001, 2005), are collinear with the equation for the trend parameter (tie changes, as modelled by the rate, in our data always increase network density, which is modelled by the trend parameter), which results in unidentifiable standard errors. To fix this, we exploit the natural leeway in the choice of these estimation equations, and apply a non-linear transformation (square root inside the sum) to the terms occurring in the equation for the trend parameter. The set of equations still is highly correlated after the transformation. However, high correlations of this sort are a general characteristic of network formation processes, and the estimation algorithm is designed for handling them. Second, the effect $\mathbf{s}_{\mathbf{k}}^{\mathrm{H1}}$ introduced in the article violates the Markov property because it depends on states in the further past of the process. As usual in such cases, the Markov property can be salvaged by replacing state space $\mathfrak{Y}$ with the generalised state space $\mathfrak{Y}^{\left[-(\varepsilon+\delta),0\right]}$, including possible past values of the process within the two horizon parameters' distance into the current state. Finally third, the networks we analyse are undirected, while Snijders (2001, 2005) focuses on directed networks. The possibility to analyse dynamic, symmetric networks has been added to the functions of the SIENA software since the release of version 2.1, and was recently introduced to interorganisational research by Van de Bunt and Groenewegen (2007).

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Table 1: Resources within each VC Firm Studied

	[1]Funds under Mgt	[2]No. GPs
VC1	676.68	138
VC2	202.76	16
VC3	51.81	19
VC4	69.75	15
VC5	26.04	7
VC6	146.56	8
VC7	14.94	9
VC8	165.18	9
VC9	17.38	8
VC10	382.89	4
VC11	23.04	8
VC12	16.83	9
VC13	126.34	5
VC14	10.63	7
VC15	69.17	6
VC16	42.26	6
VC17	95.88	4
VC18	9.77	8
VC19	106.93	7
VC20	19.23	5
VC21	105.25	4
VC22	3.11	5
VC23	6.21	5
VC24	2.48	5
VC25	3.40	4
VC26	24.87	4
VC27	26.57	5
VC28	89.89	4
VC29	20.65	3
VC30	51.31	3
VC31	140.76	6
VC32	12.57	5
VC33	22.33	5
VC34	10.06	3
VC35	111.77	3
VC36	121.40	3
VC37	6.45	4
VC38	8.25	4
VC39	6.00	4

[1] Funds under management calculated from funds committed in Euro (M), annual mean, per VC firm, 1996-2003.

[2] Number of GPs calculated from number of active GPs, annual mean per VC firm, 1996-2003. Source: IE Consulting (2003).

Table 2: Dynamics of the variables under study, reported as data set totals.

	1996	1997	1998	1999	2000	2001	2002	2003
# of syndications	125	81	83	83	157	73	40	21
# of new syndication ties	74	26	26	17	33	21	6	4
# of GP movements	11	13	5	15	14	15	14	8
# of GPs employed	418	525	469	471	470	294	207	146
funds under management (EURm)	2010	2830	2792	3938	4135	3771	2167	2729

Table 3: Bivariate distribution of tie creation patterns that can be interpreted as dragging, depending on how many years the dragged contact already was old in the previous employer VC when the GP moved (parameter **ε**) and how many years it took to establish the dragged tie with the new employer VC (parameter **δ**).

	δ=0	δ=1	δ=2	δ=3	δ=4	δ=5	δ=6	total
ε=0	36	25	15	5	7	3	1	92
ε=1	26	23	8	5	3	0	0	65
ε=2	18	14	8	0	0	0	0	40
ε=3	17	9	4	1	1	0	0	31
ε=4	7	4	3	2	2	0	0	16
ε=5	3	1	0	0	0	0	0	4
ε=6	0	2	0	0	0	0	0	2
total	107	78	38	13	10	3	1	250

Table 4: Estimation results for the reduced, final model.

	estimate	st.error	t-score	p-value
trend	-2.71	0.89	-3.05	0.002
transitivity	0.03	0.03	1.16	0.248
intermediate	-0.07	0.01	-5.80	<0.001
number GPs alter	0.13	0.07	1.76	0.078
funds alter	-0.003	0.003	-1.03	0.301

Figure 1: Dragging as interaction with a third party. The dotted arrow symbolizes a GP movement from an old employer **i** to a new employer **j**. The solid lines indicate syndication contracts. Presence of a contract between **i** and a third party **k** before the movement (on the left) should predict creation of a contract between **j** and **k** after the movement (on the right).

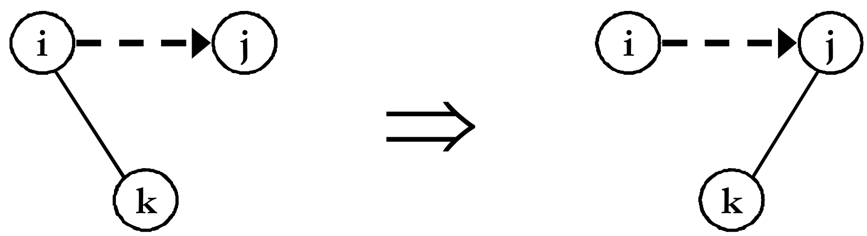

Figure 2: Dependence of test results for hypotheses H1, H2a, H2b and H3 in the full model on the horizon parameters **δ** and **ε**. The tables render t-scores for the parameters that express the hypotheses, i.e., the estimated parameter divided by its estimated standard error. Dotted lines render significance thresholds for one-sided testing.