

The best of both worlds:

The benefits of open-specialized and closed-diverse syndication networks for new venture success

Anne L.J. Ter Wal¹ Oliver Alexy² Jörn Block^{3,4} Philipp G. Sandner^{2,5}

¹ Department of Innovation & Entrepreneurship, Imperial College Business School, London South Kensington Campus, London SW7 2AZ, United Kingdom
T: +44 (0) 20 759 41460, E: a.terwal@imperial.ac.uk

² TUM School of Management, Technische Universität München
Arcisstr. 21, 80333 München, Germany
T: +49 (0) 89 289 25741, E: o.alex@tum.de

³ Professur für Unternehmensführung, Universität Trier
Universitätsring 15, DM-Gebäude, 54296 Trier, Germany
T: +44 (0) 20 759 41460, E: block@uni-trier.de

⁴ Erasmus Research Institute of Management (ERIM), Erasmus University Rotterdam (EUR)
P.O. Box 1738, 3000 DR Rotterdam, Netherlands

⁵ Frankfurt School of Finance and Management
Sonnemannstraße 9-11, 60314 Frankfurt am Main, Germany
T: +49 (0) 69 154008 727, E: email@philipp-sandner.de

Accepted for publication in *Administrative Science Quarterly*
16 December 2015

Abstract: There is a critical theoretical tension in social capital research between open networks which provide non-redundant information that is diverse, and closed networks which offer redundant information that is easier to interpret: how do actors derive diverse, yet interpretable information from their networks? We integrate network structure and actor knowledge similarity arguments to propose two types of network configurations that combine these advantages. Closed-diverse networks offer diversity due to the heterogeneity of actors' knowledge domains and allow triangulation through shared third-party ties to help interpretation. In open-specialized networks, structural holes offer diversity, while shared interpretative schema and overlap between received information and actors' prior knowledge help the interpretation of new information without the help of third parties. In contrast, actors in open-diverse networks suffer from overloading due to lack of shared schema or overlapping prior knowledge for the interpretation of diverse information, and actors in closed-specialized networks suffer from overembeddedness because information diversity is compromised. Using CrunchBase data on early-stage venture capital investments in the U.S. information technology sector, we test the effect of investors' social capital on the success of their portfolio ventures. Controlling for venture and investor quality and potential selection effects, we find support for our predictions.

Keywords: venture capital; social capital; startups; brokerage; closure; network diversity

JEL codes: G24, L26, M13

INTRODUCTION

Social capital and network theorizing have achieved a firm foothold in our thinking about how individuals and organizations derive information advantages from the networks in which they are embedded (Kwon and Adler, 2014). In particular, there is a strong research tradition in management around the structural dimension of social capital (Kilduff and Brass, 2010). Here, a central debate revolves around which network structures provide greater information advantages: open, sparse structures rich in structural holes or closed, dense structures with many shared third-party ties (e.g. Ahuja, 2000; Gargiulo and Benassi, 2000; Burt, 2005)? Open networks are thought to yield information advantages in the form of access to diverse information (Burt, 2004), based on the principle that information obtained from mutually unconnected parties—that is, from a structural hole—is likely to be non-redundant. In contrast, being embedded in closed, densely connected networks is believed to allow access to detailed and in-depth information that is easier to interpret. In closed networks, pairs of actors have many joint third-party connections which induce trust in and commitment to their relationship and which create information redundancy, which, in turn, allows for greater channel bandwidth (Uzzi, 1996; Reagans and McEvily, 2003; Aral and Van Alstyne, 2011). In short, the open network argument places value on the diversity advantage of non-redundant information while the closed network perspective emphasizes ease-of-interpretation advantages of redundant information.

How then can network actors access diverse information which they can *also* effectively interpret? That is the key theoretical tension that motivates this paper. We investigate this tension by looking at the effect of investors' social capital on the success of the early-stage ventures in their portfolio. Investments in early-stage startups are risky as investors typically have very little on which to base their evaluation other than the founders themselves and their idea. Thus, investors should be particularly inclined to exploit their

social capital emanating from prior syndication relations, in a bid to monitor and advise their portfolio firms, to their own and the venture's benefit alike (Bygrave, 1987; Hsu, 2006; Milanov and Shepherd, 2013; Liu and Maula, 2015). The extent to which investors will be able to advise ventures, however, depends on their ability to access diverse information *and* interpret it effectively.

Generally, actors in open networks have access to diverse information but also may have limited means to interpret it (Shipilov and Li, 2008). Interpretation may be particularly challenging because information providers in open networks may give little contextual information that could help interpretation (Aral and Van Alstyne, 2011), and have little incentive to be accurate and unbiased (Schilling and Fang, 2014). Investors in open networks may learn from their bridging connections about the ingredients of venture success in unfamiliar settings but lacking channel bandwidth may make it difficult to interpret how these insights may apply to their own context. The literature on open networks and structural holes has been largely silent about how actors in open networks effectively 'absorb' the diverse information they access. It treats the interpretative ability of actors as exogenously determined rather than as a function of network structure and composition.

Conversely, actors in closed networks can more easily interpret information, yet may lack requisite diversity. Uzzi (1996) argued that repeated interactions within closely-tied groups of actors typical of closed networks carry the risk of a strong convergence of ideas and insights which, in combination with a lack of inflow of information from sparse connections, can lead to a lack of information diversity. Investors embedded in cohesive networks have access to in-depth specialist information about how firms in a specific sector can succeed but may lack inflow of divergent perspectives which could put current insights in a new light, or challenge current thinking. Although subsequent research has made important advances to our understanding of how closed networks can be diverse in order to overcome

such problems (Reagans and McEvily, 2003; Rodan and Galunic, 2004; Fleming, Mingo, and Chen, 2007), our understanding of the mechanisms that allow shared third parties to contribute to the interpretation of diverse knowledge may be incomplete. There is an emphasis on the indirect benefits provided by shared third parties such as induced commitment and trust (Reagans and McEvily, 2003; Tortoriello and Krackhardt, 2010; Tortoriello, Reagans, and McEvily, 2012) but it is neglected that third parties can contribute more directly through collective interpretation of the information they received also from the same, shared alter.

In an attempt to integrate into network theory the ability of network actors to interpret information, we propose that it is necessary to consider both network structure and actor knowledge similarity to fully understand how actors obtain and effectively interpret diverse information. Building on research on network range (Reagans and McEvily, 2003), knowledge heterogeneity (Rodan and Galunic, 2004; Fleming, Mingo, and Chen, 2007), and boundary spanning (Hargadon and Sutton, 1997; Tortoriello and Krackhardt, 2010), we define actor knowledge similarity as the extent to which network actors are specialized in the same knowledge domains. We argue that actors can access and interpret diverse information from two of four prototypical network configurations (see Figure 1).

First, closed-diverse networks feature numerous shared third-party ties among dissimilar actors. In this case, access to diverse information is enabled by the heterogeneity of the actors' knowledge domains, and shared third-party connections are a conduit that allows corroboration of potentially different interpretations of that diverse information via triangulation (Brown and Duguid, 1998; Gavetti and Warglien, 2015). Thus, we hypothesize that closed-diverse networks offer advantages over both closed-specialized networks which lack information diversity, and open-diverse networks that provide information that cannot be interpreted effectively. Second, open-specialized networks are sparse structures among actors

with similar specializations. In those networks, the focus on similar knowledge domains is accompanied by shared interpretative schema (Simon and Feigenbaum, 1964; Simon, 1966; Brewer and Nakamura, 1984) and redundancy between the information received and the receiver's prior information (Shannon and Weaver, 1948) which help actors to interpret new information without the help of third parties. We predict that open-specialized networks offer benefits over open-diverse networks which lack shared interpretative schema, and closed-specialized networks where diversity is compromised. Therefore, open-specialized and closed-diverse networks provide 'the best of both worlds' by combining the diversity stemming from the network structural dimension with the ability to interpret information deriving from the actor knowledge similarity dimension, and vice versa.

We test our arguments by studying the value of investors' social capital to the early-stage ventures in which they invest. Ventures that receive investor funding gain not only from access to those investors' financial and human capital but also because the investors act as important channels of information which can give the new venture a competitive edge (Hochberg, Ljungqvist, and Lu, 2007; Hallen, 2008; Lungeanu and Zajac, 2015; Pahnke, Katila, and Eisenhardt, 2015). Investors and the networks they build through syndication constitute an important form of social capital which new ventures can exploit to sustain profitability and long-term survival (Stuart, Hoang, and Hybels, 1999; Sorenson and Stuart, 2001). New ventures benefit from their investors' access to diverse insights from across various domains, provided that the investors are able to interpret this information and apply it to the specific domain of the venture. We examine how the information advantages that newly funded early-stage ventures obtain from the syndication networks of their first-round investors contribute positively to their success in attracting additional funding.

Drawing on CrunchBase, a dataset which includes almost all investments in the U.S. information technology industry (Block and Sandner, 2009), we find that ventures have the

highest chances of success if their syndicating investors have either open-specialized or closed-diverse networks. These effects are manifested beyond the direct effects of venture or investor quality, and robust to controlling for the possibility that certain investors could have chosen more promising ventures at the time of first funding. We assess the role of structural holes, structural equivalence, and differences between emerging and established sectors to further probe the role of information redundancy as the core mechanism driving our results.

SYNDICATION AND INVESTOR SOCIAL CAPITAL

The Value of Investor Social Capital to Funded Ventures

Syndication relationships are a key ingredient of investors' social capital as prior syndication relationships allow investors to build networks that offer informational advantages to support their investment decisions (Bygrave, 1987; Hsu, 2006; Dimov and Milanov, 2010; Milanov and Shepherd, 2013; Liu and Maula, 2015). Specifically, embeddedness in syndication networks provides investors with information about new investment opportunities which is shared within a high-trust environment and is not accessible to those not part of the network (Sorenson and Stuart, 2001). For example, high social capital venture capitalists have been shown to have a higher willingness to invest large sums in startups because their privileged access to information on venture quality lowers the perceived risk of the investment and increases the evaluation of future cash flows (Alexy, et al., 2012).

The social capital that investors build through past syndication experience is an important asset for both the investors and the invested venture (Hochberg, Ljungqvist, and Lu, 2007; Hallen, 2008). After the first investment round, investors typically assume an advisory role which makes their accumulated social capital from past investment activities available to the venture. This fosters the venture's development and increases the returns to the investors (Stuart, Hoang, and Hybels, 1999; Sorenson and Stuart, 2001). For startups, investors' network resources are a form of second-order social capital, a nascent concept

describing the advantages from connections to high social-capital alters (Galunic, Ertug, and Gargiulo, 2012). These network resources are an important asset for early-stage ventures in which investors typically need to be actively involved to help them grow, but where their own resources and knowledge may be insufficient for high-quality advice. Several studies show that the number of an investor's network connections positively affects the performance of the invested venture (e.g., Hochberg, Ljungqvist, and Lu, 2007), ultimately increasing the likelihood of a successful exit (Shane and Stuart, 2002; Hsu, 2006; Fitza, Matusik, and Mosakowski, 2009). We argue that two aspects of investors' social capital are particularly valuable to their portfolio companies: (1) the informational *diversity* in their network, and (2) their *ability to interpret* how that information applies to the specific context of the venture.

First, the value of investors' social capital to their portfolio firms is a function of their access to diverse information on which they can base their advice (Lungeanu and Zajac, 2015). Individual investors might have deep sector-specific and location-specific expertise but diversity of expertise from across one's own domain is also important in this context (Bellavitis, Filatotchev, and Kamuriwo, 2014). Syndication with other investors exposes investors to unfamiliar information and insights into other sectors and locations (Sorenson and Stuart, 2001; Hochberg, Ljungqvist, and Lu, 2007; Liu and Maula, 2015). Although investors have a tendency to syndicate with others with similar industry profiles (Sorenson and Stuart, 2001), heterogeneous syndication ties are formed every time that investors with different backgrounds and portfolios are attracted to the same target companies (Sorenson and Stuart, 2008), when they can bring complementary resource endowments to the investment (Hochberg, Lindsey, and Westerfield, 2015), or when investors decide to alter their investment policies on the basis of inconsistent performance feedback from prior investments (Baum, et al., 2005). Insights from one setting or knowledge domain can potentially be valuable in some other setting by providing a new solution unknown in that

setting (Hargadon and Sutton, 1997; Hsu and Lim, 2014), or bringing a new perspective to a problem (Rosenkopf and Nerkar, 2001; Perry-Smith, 2006).

Second, however, the syndicate's ability to interpret diverse information meaningfully cannot be taken for granted. There may be interpretative barriers to understanding the information and assessing its value (Bruner, Goodnow, and Austin, 1956; Simon and Feigenbaum, 1964; Dougherty, 1992) which may limit the investors' ability to integrate information from various sources to generate new insights (Simon, 1966; Mors, 2010; Wadhwa, Phelps, and Surash, 2016). Thus, the quality of the advice provided to portfolio ventures will depend on the investors' ability to interpret the information obtained, and to assess how it could be applied to the specific setting of the venture. In this paper we address how investors' social capital enables them to advise a venture on the basis of information that is diverse and meaningfully interpreted. Below, we review the network structure and actor knowledge similarity literatures which form the base of the argument presented in this paper which rests on merging the two.

REDUNDANCY, NON-REDUNDANCY, AND NETWORK ADVANTAGE

The Tension between the Value of Open and Closed Syndication Networks

An established stream of work in the network literature argues that network structure shapes the informational advantages that actors can derive from their social capital (Zukin and DiMaggio, 1990; Granovetter, 1992). This has triggered debate over which network structures provide the greatest informational advantages. The debate revolves around a defining aspect of network structure: the level of redundancy in the information that actors can access from the network (Burt, 1992). Redundancy is a function of the degree of closure among a focal actor's direct ties. An actor connected to two alters who are directly connected to each other will likely access redundant information (Coleman, 1990; Uzzi, 1996). If the alters are unconnected—that is, if the focal actor spans a structural hole—the information

they provide to the focal actor is likely to be non-redundant (Burt, 1992; 2004). There is a theoretical tension in that both redundant and non-redundant information provide important advantages, and both are proposed as pivotal to social capital. Some researchers suggest that these advantages are not necessarily irreconcilable. For example, the timing might differ in that structural holes advantages may emerge more quickly and be shorter-lived than closure advantages (Soda, Usai, and Zaheer, 2004; Zaheer and Soda, 2009; Baum, McEvily, and Rowley, 2012). Also, the advantages of open and closed networks may operate at different levels in the network, for example within or beyond teams (Zaheer and Soda, 2009). Finally, open and closed structures might co-exist concurrently and at the same level in a network (Oh, Chung, and Labianca, 2004; Schilling and Phelps, 2007; Reagans and McEvily, 2008). While these studies suggest important contingencies related to the value of structural holes and closure, they do not address the fundamental tension related to how networks can combine the advantages of redundant information in closed networks and the advantages of non-redundant information in open networks.

On the one hand, information redundancy associated with closed networks is argued to be advantageous because it eases interpretation. There is a high likelihood that information may reach network actors via multiple routes in the network. Given that it might vary how each provider communicates the information, redundancy enables information receivers to cross-check or triangulate the information (Krackhardt, 1999; Tortoriello and Krackhardt, 2010). As Shannon and Weaver (1948) argue in their theory of communication, redundant information reduces the probability of interpretation error because information receivers may, for example, understand different aspects of a particular message from different sources. In certain circumstances, new information may only be judged credible if confirmed by multiple sources (Centola and Macy, 2007). The interpretation of information in closed networks is eased also by the increased channel bandwidth of ties in such networks (Aral and Van

Alstyne, 2011): information richness and detail is enhanced because two parties are more committed to the exchange if they have a common third party (Reagans and McEvily, 2003). The increased bandwidth allows for exchange of sensitive and complex information (Fleming, Mingo, and Chen, 2007).

On the other hand, an alternative line of argument points to information advantages of *non-redundancy*, suggesting that the flows of non-redundant information typical of open networks tend to incorporate greater information diversity which can help change or challenge existing perspectives (Burt, 1992; 2004). Network actors who connect otherwise disconnected individuals gain access to information that is diverse by virtue of the missing connection between alters. These actors may operate ‘at the nexus of diverse information’ (Fleming, Mingo, and Chen, 2007: 445) which they can exploit to their own advantage (Burt, 1992), or use instrumentally to establish collaboration between previously disconnected parties (Obstfeld, 2005; Lingo and O'Mahony, 2010).

A theoretical tension related to the value of open versus closed networks arises because the ease-of-interpretation advantage of redundant information in closed networks is a disadvantage in an open network, and the diversity advantage of non-redundant information in open networks is a disadvantage in a closed network. The literature on open networks—with the exception of process studies on brokerage (Obstfeld, 2005; Lingo and O'Mahony, 2010)—does not elaborate how actors interpret information (Burt, 2010): in the structuralist tradition of research on open networks, actors accessing diverse information from structural holes are implicitly ascribed the ability to process it effectively, and to use it to their advantage. However, this might not be straightforward for the information-receivers in the absence of redundancy from overlapping ties, and without the ability to triangulate the information to ease its interpretation (Coleman, 1990; Shipilov and Li, 2008). The assumption of interpretative ability is particularly problematic since information providers in

open networks have few incentives to expend effort and time on information exchange leading to reduced information bandwidth (Aral and Van Alstyne, 2011), and lack pressure from shared third parties not to behave opportunistically (Burt 2005; Shipilov and Li, 2008; Tortoriello and Krackhardt, 2010). In contrast, closed networks can suffer from a lack of non-redundancy. From a purely structuralist perspective, it would seem that actors in closed networks have access to high-bandwidth information they can effectively interpret, but which potentially lacks diversity (Uzzi, 1997; Gargiulo and Benassi, 2000). Repeated interactions among close-knit groups of actors could lead to convergence of ideas and insights which combined with a lack of inflow from sparse connections reduces information diversity and introduces the risk of groupthink. Network actors in closed networks can fail to challenge collectively held beliefs and become ‘trapped in their own nets’ (Uzzi, 1997; Gargiulo and Benassi, 2000).

In the context of social capital in syndication networks, open syndication networks occur if only selected pairs of investors have prior syndicated investments. These networks contain non-redundant, diverse perspectives on the elements contributing to venture success but it may be difficult for the investors to make sense of how insights from non-shared investments might apply in a new context. Closed networks among groups of investors occur if most actor pairs have co-invested in the past. In these networks, there is redundant information on what was or was not successful in past portfolio companies, which facilitates the formation of shared beliefs among network actors about why ventures succeed or fail. However, it introduces the risk of taken-for-granted views and ingrained assumptions going unchallenged.

Actor Knowledge Similarity: Specialized vs. Diverse Syndication Networks

We have argued that a network structural perspective does not explain how network actors gain access to diverse interpretable information. The level of information diversity and the

ability of the network actors to interpret it depend also on the heterogeneity of these actors' knowledge. The interplay between network structure—open versus closed networks—and actor knowledge similarity—diverse versus specialized networks—offers a solution to the puzzle how actors can access information that is both diverse and interpretable, that is, combining ‘the best of both worlds’.

We draw on a number of studies suggesting that it is the relative similarity of the actors in the network—in addition to its structure—which facilitates access to diverse information and affects actors’ ability to interpret it. We build on the concepts of network range (Reagans and McEvily, 2003; Tortoriello, Reagans, and McEvily, 2012) and knowledge heterogeneity (Rodan and Galunic, 2004) to emphasize that the information value of social capital not only depends on network structure but also on the knowledge properties of the network actors. We define actor knowledge similarity as the extent to which network actors are specialized relative to one another. In specialized networks, actors focus on similar knowledge domains and most of the information circulating tends to fall within those domains. Diverse networks have actors specialized in dissimilar knowledge domains, and thus can provide access to unfamiliar information. In the context of syndication networks, specialization occurs when the investors in a network are similar in terms of the sectoral focus of their past investments. The concept of actor knowledge similarity differs from network range in that the former captures not the dispersion of the knowledge in the network but the extent to which the network actors are similar (Harrison and Klein, 2007). If each actor spans many domains and these domains are the same for all actors, range (dispersion) is high but actor similarity is also high.

Building on the argument that ventures thrive when their investors advise them with diverse information they can sensibly interpret and apply to the venture’s context (Luncheon and Zajac, 2015; Wadhwa, Phelps, and Surash, 2016), we predict that the level of actor

knowledge similarity moderates the relationship between syndication network closure and venture success. Specifically, we maintain that actor knowledge similarity *also* influences the levels of information redundancy and non-redundancy in the network, and its inclusion in network theorizing holds the key to how networks can provide access to information that is both diverse and interpretable. Figure 1 depicts the network configurations that combine the network structure and actor knowledge similarity properties of a syndication network, and summarizes the value that these configurations of investor social capital embody for the ventures in which they invest.

--- Insert Figure 1 about here ---

The Value of Closed-Diverse Syndication Networks

The first type of syndication network (Figure 1, upper right) which provides diverse, interpretable information has a high level of network closure among diverse network actors. This corresponds to a situation where the focal investors and their past syndication partners have, in different compositions, regularly co-invested in the past but are dissimilar in terms of their aggregate profile of sub-sectors of past investments. That is, in addition to co-investments that produce high levels of closure, each of the network actors has been involved in additional investments in other sectors. The flows of information in these networks are likely to be rich because the presence of shared third parties incentivizes the actors to spend time and effort on the exchange (Reagans and McEvily, 2003).

Such *closed-diverse networks* offer a diversity advantage because each actor can bring to the table insights into best practice, ongoing trends, and developments from various sectors. This information is valuable in providing a perspective on how domain-specific knowledge relates to knowledge in other domains (Reagans and Zuckerman, 2001; Rosenkopf and Nerkar, 2001; Fleming and Waguespack, 2007). Exposure to insights from unfamiliar domains can stimulate investors to reflect on their own knowledge domain,

challenge taken-for-granted views, and broaden the range of alternatives beyond those common to the domain (e.g., Hargadon and Sutton, 1997; Perry-Smith, 2006; Grégoire, Barr, and Shepherd, 2010).

Closed-diverse networks also offer built-in advantage for the interpretation of the diverse information. Outside-domain information can be difficult to interpret (Dougherty, 1992; Bechky, 2003; Tortoriello and Krackhardt, 2010), and applying it to a specific context is a non-trivial task (Mors, 2010). Embeddedness in a closed-diverse network can ease the interpretation of diverse information in two ways. First, as documented extensively in the literature, two parties exchanging information tend to be more committed to spending time and effort on the exchange if they have common third-party connections (Reagans and McEvily, 2003). Awareness of common connections increases trust in the relationship, and discourages willful provision of incorrect information (Coleman, 1990; Walker, Kogut, and Shan, 1997; Tortoriello and Krackhardt, 2010; Rosenbaum, Billinger, and Stieglitz, 2014). Investors may more easily interpret diverse information from closed networks, because alters expend more effort on communicating insights from other settings in greater detail.

Second, the presence of shared third parties enables redundancy in interpretative cues through triangulation which, in turn, facilitates own interpretation. In closed triadic structures, actors may receive the original information directly from the information provider, as well as others' interpretations of it via shared third parties who likely received the same information from the provider. Paying attention to other people's interpretations of the same information has been shown to improve one's own interpretation (Weick and Roberts, 1993; Gavetti and Warglien, 2015). It can uncover overlaps and differences in interpretation, allowing focal actors to make inferences about the accuracy of their interpretation. This triangulation process is effective specifically in diverse networks. Interpretation through interaction is a distributed cognition process (Michel, 2007) which may be particularly

effective with heterogeneous alters who are likely to interpret the same information differently, and thus be able to offer the focal actor different versions of the same story to triangulate. Taken together, groups of interconnected diverse actors provide a platform for the collective interpretation of diverse information (Brown and Duguid, 1998; Gavetti and Warglien, 2015; Tortoriello, McEvily, and Krackhardt, 2015).

In the context of investor syndication networks, investors may collectively interpret for example, the implications of new trends in emerging sectors for ventures in their portfolio, perhaps exchanging and discussing the business plans of various firms in the process (Bygrave, 1987; Hsu, 2006; Milanov and Shepherd, 2013; Liu and Maula, 2015). The combined diversity and interpretation advantages of closed-diverse networks imply that syndicates with a closed-diverse network will be able to formulate high-quality advice for the venture based on diverse information from across sectoral boundaries whose application to a particular sub-sector has been sounded out with trusted third parties.

Syndicates with closed-diverse networks can provide more valuable information to the venture than syndicates with *closed-specialized networks* which lack variety of outside-domain information (Figure 1, upper left). Members of close-knit groups can suffer from groupthink, and hesitate to explore new ideas as they prefer the prevailing schema shared within the group (Janis, 1972; Wang, et al., 2013). The advantage of information richness typical of closed networks is undermined by the lack of non-redundant information. The term overembeddedness was coined by Uzzi (1997: 58) to describe such situations in which “all firms in a network are connected through embedded ties, [which] can reduce the flow of new and novel information into the network because [...] there are few or no links to outside actors who can potentially contribute innovative ideas”. We extend the concept of overembeddedness to include lack of inflow of novel ideas due to excessive levels of actor knowledge similarity in the network. The downsides associated with scarce connections to

parties outside the dense cliques in the network are exacerbated if the respective actors are very similar. Triangulation does not work in closed-specialized networks and can even lead the actors to believe erroneously that incorrect information is correct. Cross-checking information via third parties who both received the original information from the same source and interpreted it from the same perspective, is unlikely to lead to interpretation differences that can be triangulated, hence inaccurate or outdated information remains unchallenged. Investors in a closed network of actors with similar investment profiles are likely to provide their ventures with incomplete and possibly biased advice: they have access to only a limited view of best practice, trends, and developments in a specific sector, which may lead to advice based on shared myths which cannot be challenged by the inflow of diverse information. This limitation will be reflected by the venture's lower levels of success.

Closed-diverse networks also offer advantages over *open-diverse networks* (Figure 1, lower right), in which the value and accuracy of the information cannot be judged effectively since there are no opportunities for triangulation through shared parties. There is a risk that syndicates with open-diverse networks may advise ventures based on information whose application to a particular sector or venture they cannot adequately assess. Investors' misjudged interpretation of how insights from one sector may or may not transfer to another sector could damage the venture's probability of success. Taken together, we predict that:

H1a: Venture success is more likely if the investing syndicate has a closed-diverse network rather than a closed-specialized or open-diverse network.

The Value of Open-Specialized Syndication Networks

The second type of syndication network providing diverse, interpretable information is a network with a low level of network closure among similarly specialized network actors (Figure 1, lower left). In *open-specialized networks*, actors focus on the same knowledge domains but form networks rich in structural holes. This corresponds to a situation where the

focal investors and their past syndication partners have little past experience of co-investment despite their focus on the same sub-sectors. Actors in such networks have substantial incentives to share information despite the absence of shared third parties, although information bandwidth may be lower. Like any other prior tie, the sparse connections in open networks result from a previous shared commitment, in our context a shared investment, which makes it more likely the two parties will form a bond of trust and be ready to share information with each other (Sorenson and Stuart, 2001). Information sharing in open-specialized networks is likely also because similarity breeds trust. Gulati and Sytch (2008: 182) show that “organizations that are more similar to each other can derive greater stocks of trust from [their] joint history compared to more heterogeneous sets of partners”.

Analogous to the value of closed-diverse networks, the value to ventures of open-specialized syndication networks is based on the combination of non-redundancy which brings information diversity, and redundancy which facilitates interpretation. Open-specialized networks have a diversity advantage; the open structure safeguards the syndicate’s access to diverse, non-redundant information since each network actor brings insights and experience from different investments, possibly in different geographic contexts (Lingo and O’Mahony, 2010). Actors likely have different views about the sector-specific ingredients for venture success, helping investors to challenge and update insights obtained from their specific experience, and prevent local bias (Jääskeläinen and Maula, 2014).

Open-specialized networks also have an ease-of-interpretation advantage. Above we argued that, when considering structural arguments only, it is not clear how actors in open networks can overcome the interpretative hurdles associated with information that is diverse, non-redundant, and potentially unfamiliar (Shipilov and Li, 2008), and has lower bandwidth compared to information from closed networks (Aral and Van Alstyne, 2011). We propose that actors in open networks can overcome these interpretative barriers if these networks are

specialized. Information receivers will be better able to interpret information if it comes from similar others and relates to a familiar domain (Bruner, Goodnow, and Austin, 1956). It is the receiving actor's prior knowledge that creates redundancy with the received information which makes it easier to interpret, and makes it understandable even if it is incomplete or of poor quality (Shannon and Weaver, 1948). Information receivers in open-specialized networks will possess both the interpretative schema to assess the meaning of information relative to what they already know, and the evaluation abilities to judge its relation to prior knowledge (Simon and Feigenbaum, 1964; Simon, 1966; Brewer and Nakamura, 1984; Hwang, Singh, and Argote, 2014). Thus, relative to outside-domain information, the need for triangulation to interpret within-domain information, and the need for a sounding board to understand how it applies to the focal venture are much reduced. This allows the information-receiver to interpret information without the help of third parties (Hwang, Singh, and Argote, 2014), and to advise ventures on the basis of diverse, properly interpreted information.

Investors in open-specialized networks have access to a variety of insights into how firms can succeed in a specific sub-sector. The views of the various prior partners in their network will likely differ, because, due to the structural hole between them, these partners have not converged on a consensus on what makes a successful business in the particular sub-sector. The familiarity of the information-receiving investors with the sector, and their prior knowledge in that domain ensure that they can interpret and apply divergent views to decide the best course for the focal venture even when the information accessed lacks bandwidth and detail, and there are no shared third parties on whose interpretation of the information they can rely. The combined diversity and interpretation advantages of open-specialized networks implies that syndicates with open-specialized networks will be able to formulate high-quality advice for the venture, based on diverse information from within sub-sectors whose application was facilitated by prior knowledge of the domain.

Syndicates with open-specialized networks offer greater information value to a venture than those with *open-diverse networks* (Figure 1, lower right) where there is little or no redundancy between the information received and the receiver's prior knowledge, and actors have no shared interpretative schema. We borrow from research on information processing (see, e.g., Bruner, Goodnow, and Austin, 1956; Simon, 1974; Sweller, 1988) and recent research on networks (Mariotti and Delbridge, 2012) and use the term *overloading* to describe a situation where actors in an open and highly diverse network lack the ability to correctly process the huge diversity of information arising from both open structures and actor knowledge diversity. In addition to the actors lacking the carrying capacity to deal with the volume of diverse information (Simon, 1956; Hansen and Haas, 2001; Hwang, Singh, and Argote, 2014), their ability to absorb and interpret it may be compromised (Simon and Feigenbaum, 1964; Simon, 1966; Ghosh and Rosenkopf, 2014). The absence of shared third parties to help corroborate diverse information, and the reduced ability to make independent judgments because of mismatches in investors' interpretive schema and lack of prior knowledge, implies that investors in open-diverse networks are not able to interpret diverse information meaningfully. Investors with an open network of actors with dissimilar investment profiles may provide investors with unsound, speculative advice based on a broad range of insights from unfamiliar sectors, which has been likely misinterpreted and applied erroneously to the context of the focal venture. Thus, we argue that investors in open-diverse networks are unable to formulate coherent advice that will be of value to their ventures. Open-specialized syndication networks are also superior to *closed-specialized networks* which lack the requisite variety to help investors update sector-specific insights and challenge assumptions. Thus, we predict:

H1b: Venture success is more likely if the investing syndicate has an open-specialized network rather than an open-diverse or closed-specialized network.

--- Insert Figure 2 about here ---

Information Redundancy and Network Configuration

We argued above that both closed-diverse networks and open-specialized networks combine the ease-of-interpretation advantages of information redundancy, and the diversity advantages of non-redundancy. First, this argument is based on the assumption that information redundancy is a function of network closure and actor knowledge heterogeneity. Regarding the former, we assume that open networks are rich in structural holes which are at the basis of non-redundancy: investors access diverse information through bridging ties across structural holes between parties with no mutual prior syndication relations. Although, typically, structural holes typically are pervasive in open networks, the number of bridging ties across structural holes in relatively open networks also depends on the distribution of the alter-alter ties in the network (see Figure 2A and 2B). Although it is always the case that networks with fewer (more) alter-alter ties have lower (higher) levels of redundancy, bridging ties may more accurately capture the level of (non)-redundancy in the network structure than the characterization as open or closed. We will offer additional analyses to gauge to what extent bridging ties across structural holes form indeed the fundament of advantageous non-redundancy in open-specialized networks and disadvantageous non-redundancy in open-diverse ones.

Second, it can be argued that information redundancy based on network structure does not depend only on the interconnectedness of the alters. It depends also on the extent to which these alters are structurally equivalent (Lorraine and White, 1971; Reagans and Zuckerman, 2008), that is, the extent to which they are tied to the same third parties. Two unconnected investors may bring little diversity to the syndicate if they are informed by the same investors in the second ‘shell’ of the network from the syndicate’s perspective (see Figure 2C and D). Closure captures the redundancy of information that syndicate members

may get from alters' direct participation in certain prior investments (first network neighborhood), while structural equivalence captures the redundancy of information that alters may get from *their* alters and which they may pass on to the syndicate (second network neighborhood). We will explore how redundancy in the second network neighborhood may moderate the value of redundancy in the first neighborhood.

Third, in relation to closed-diverse networks, we argued how closure may have two separate positive effects: the augmented effort of investors with shared third-parties and the ability to triangulate interpretative cues. We will try to disentangle these two explanations empirically, by introducing a control for *tie strength*, which should correlate more with the first advantage than with the second.¹

Fourth, we portray open-specialized and closed-diverse networks as equally advantageous since both combine ease-of-interpretation and diversity advantages. However, open-specialized networks offer within-sector diversity, whereas closed-diverse networks offer diversity from across sectoral boundaries. Starting from the notion that within-sector diversity may be more valuable for early-stage ventures in emerging industries, and between-sector diversity more valuable for ventures in established sectors, we explore how these two types of diversity may be advantageous for the success of different types of firms.

DATA AND METHOD

Data

To test our hypotheses, we draw on CrunchBase (www.CrunchBase.com), a public database which provides an almost complete overview of recent venture capital funding in the U.S. IT and Internet industry (Block and Sandner, 2009; Alexy, et al., 2012). CrunchBase data are the source used by TechCrunch, a popular blog and major information source on startups, especially in the IT and Internet sector. CrunchBase provides data on new ventures,

¹ We are indebted to one of our reviewers for this insightful suggestion.

entrepreneurs, and investors in U.S. high-tech industries, including funding histories and board compositions for both private small firms and large publicly listed corporations. Data on investors include information on business angels, large venture capital funds such as Sequoia Capital, and corporate venture capital funds such as Siemens Venture Capital. In contrast to VentureXpert, CrunchBase includes recently founded ventures and those that have not yet received funding, allowing for fine-grained and reliable longitudinal data on syndication networks. We collected our CrunchBase data in May 2014, which includes information on 10,266 ventures that received funding in a total of 37,146 funding rounds, by unique 5,032 investors (primarily venture capital funds).

Our analysis focuses on companies located in the U.S. and operating in the IT and Internet area. Since we are investigating the impact of syndication networks on additional funding, for our regressions, we consider only firms that have received a first round of funding; we also exclude firms with only one investor (i.e., non-syndicated investments)—of course, we use all data to construct our network measures. We limited the time frame of our analysis to ventures that received first funding between 2005 and 2011, so that we have sufficient time left to construct network variables based on prior investments, and sufficient data from more recent years to observe venture success events in more recent years. Our final dataset includes 2,371 syndicated first-round investments, involving 1,646 unique investors.

In addition, to construct some of our control variables, we constructed trademarks portfolios based on the U.S. Patent and Trademark Office data, and obtained patent data from the PATSTAT database (version October 2013) provided by the OECD and the European Patent Office which contains all patent applications and patents granted worldwide.

Dependent Variable

Our interest is in analyzing the effect of network structure and actor knowledge similarity of investors' social capital on venture success. We define *venture success* as the venture's

ability to attract a second round of funding which is essential for the survival and eventual success of a new venture (De Clercq, et al., 2006). In particular, firms active in high-tech sectors typically require several rounds of funding at comparatively short intervals to fund the development and diffusion of their products and services (Gompers, 1995). Thus, *ceteris paribus*, receiving a second round of funding is a clear and positive signal either that the initial investors are happy with the venture's progress and are willing to contribute additional resources, or that the venture has been able to attract new, possibly larger and more experienced investors (e.g., Lerner, 1994; De Clercq, et al., 2006). The *ceteris paribus* assumption also implies that we need to control for the funding received in the first financing round, and characteristics of the venture and the first-round investor syndicate (see below). While our sample includes ventures that received first-round investment between 2005 and 2011, we observe second-round funding up to the end of 2013 which allows us to observe funding events also for the most recent companies given an average time of 19 months between first- and second-round funding. Since CrunchBase data are updated frequently and have been shown to be accurate, we are confident that we have not missed any second-round funding events that occurred before the end of 2013.

Independent Variables

Our independent variables relate to the syndicate's social capital at the time of first-round investment in the focal venture. Following the approach in Oh, Chung and Labianca (2004), we operationalize syndicate social capital as the aggregate ego-level network of the syndicate group. Thus, the syndicate's social capital includes prior syndication relationships among syndicate members, additional prior syndication partners of individual members, and potential alter-alter ties between these partners. Ties are defined to exist between all investor pairs that co-invested in a venture in the five years up to and including the month prior to the focal investment. Figure 1 depicts the variables. Investors A, B, and C syndicate a first-round

investment in venture X at time t . In all network configurations, A-B, A-C and B-C have prior co-investments in the preceding five-year period. Also, A previously syndicated with D and E, B with E and F, and C with G. The prior syndication relationships between nodes D, E, F, and G differ between open and closed networks. Our network closure and actor knowledge similarity variables are calculated on the aggregate network structure of nodes A to G.

Starting with our structure-related variables, *network closure* is a local density measure, computed as the number of ties among network actors over the maximum number of possible ties, $(\frac{N*(N-1)}{2})$ where N is network size). The measure ranges from 0 (fully open network) to 1 (fully closed network) (see also Obstfeld, 2005; Fleming, Mingo, and Chen, 2007). In the lower two quadrants in Figure 1, there are eight ties amongst 21 potential ties, yielding a closure value of 0.38. We ran alternative specifications of our models with measures for bridging ties, structural equivalence, and tie strength. *Bridging ties*—those that span a structural hole—are measured as the proportion of the syndicate’s links to prior partners that are bridging ties (Burt, 2010): ties to partners with no indirect ties through mutual contacts. Ties are also considered bridging if two syndicate members are tied to the same prior partner. *Structural equivalence* is defined as the extent to which alters of a node (in our case, the syndicate) overlap in their links to third parties, and captures redundancy among alters’ information sources (Lorraine and White, 1971; Reagans and Zuckerman, 2008). For each alter, we compiled a list of third-party partners in the five years before the focal investment. We computed a Jaccard coefficient of overlapping partners for each pair of alters. Our measure of equivalence is expressed as the average pairwise coefficient across all pairs. Finally, *tie strength* is a dummy variable indicating that the investors in the network have syndicated with each partner at least twice on average.

Actor knowledge similarity is obtained on the basis of the past investment portfolios

of all network actors, based again on their investments during the five years preceding the focal investment. The technological specialization of each investor in the network is described by a vector of length 32, where a cell describes which fraction of investments was in startups in a specific sub-sector of the IT industry. Actor knowledge similarity is calculated as the average cross-product of the vectors for each pair of network actors (Bonacich, 1972). In the two left-hand side quadrants in Figure 1, all actors each invested 100% in BLUE, except for node B which invested 50% in BLUE and 50% in GREEN. It follows that the vector cross-products for the six dyads involving B take the value 0.5 whilst the remaining 15 cross-products take the value 1, yielding an average actor knowledge similarity score of $((6 * 0.5) + (15 * 1)) / 21 = 0.857$. The actor knowledge similarity measure ranges from 0 (fully diverse network) to 1 (fully specialized network).

Control Variables

Our control variables are organized on three levels. The venture-level set includes the log of the *amount raised* from the first round funding which allows us to control for the initial startup conditions such as founder's social capital and perceived quality of the idea. Shane and Stuart (2002: 160) argue that if the effect on the first round of funding is properly accounted for, these initial conditions will be of little importance for subsequent funding rounds. We also include cumulative counts for *patents* and *trademarks* which are important quality signals (e.g., Baum and Silverman, 2004; Audretsch, Bönte, and Mahagaonkar, 2012; Block et al., 2014) and may have some liquidation value should the startup fail, both aspects that might increase investors' propensity to invest (Tyebjee and Bruno, 1984; Shane and Stuart, 2002; De Clercq, et al., 2006). In the case of trademarks and patents, we rely on applications for intellectual property protection rather than granted rights since the latter is often a lengthy process and investors typically do not wait for its conclusion. We identified all the legal applicants associated for all ventures in our sample and accounted for misspelt

names and complex organizational structures such as subsidiaries with different names or multiple legal entities. We set the value for patents and trademarks to 0 for ventures for which we found no data. Other venture-level controls include *year of first funding* to account for cyclical effects (6 dummies) (Cumming, Fleming, and Schwienbacher, 2005), *IT sub-sector* in which the venture is specialized (31 dummies), and three *location* dummies for U.S. states with high concentrations of IT firms (California, New York, Massachusetts) to account for geographic clustering of investments (see Sorenson and Stuart, 2001; Chen, et al., 2010).

The second set of control variables is at the investor level. To assess the potential effect of overall quality or reputation of the first-round syndicate members (Gu and Lu, 2014), we include the *share of past portfolio companies that were acquired, or held an Initial Public Offering (IPO)*. We also obtained the *venture capital reputation index* as calculated annually by Lee, Pollock and Jin (2011), but since that variable was not available for all the investors in our data, we exclude it from our models. Its inclusion does not affect our findings. In line with extant research (Podolny, 2001; Shipilov and Li, 2008), we computed eigenvector centrality to measure *investor status*. Since this variable is dependent on network size, we standardized it by total number of network actors (i.e., all syndicate members and their prior partners). We also include dummy variables for *angel investors* and *corporate venture capitalists*.

The third set of controls is at the level of the syndicate and its network. First, we include *syndicate size* since larger syndicates might have larger pools of resources which might positively affect the venture's chances of attracting a second round of funding (Lerner, 1994). Second, we include a measure for *network size*, without double-counting the contacts that multiple syndicate members have (i.e., both A and B are connected to E). In the examples in Figure 1, this variable takes the value 4 for the syndicate's relations to D, E, F, and G.

Estimation Method

To estimate the effect of syndication network properties on venture success, we employ three estimation techniques. First, we use standard logit regression techniques with the venture-investor combination as the unit of analysis. Although this method does not account for potential censoring issues, the lagged structure of our dependent variable means these should be minimized. Also, logit models are generally well-suited to estimating discrete time events (Allison, 2010). Setting our unit of analysis at the venture-investor level allows us to account accurately for the non-independence of observations that arises because ventures and investors occur multiple times in our dataset, by estimating robust standard errors and clustering them at the venture and investor levels simultaneously (Cameron, Gelbach, and Miller, 2011; Kleinbaum, Stuart, and Tushman, 2013).² We repeated all the estimations at the venture-syndicate level of analysis, which has the advantage that it gives equal sampling weight to each venture-syndicate observation regardless of syndicate size (rather than sampling N times each venture with syndicate size N). Our results are robust to shifting to the venture-syndicate unit of analysis. Likewise, adding sampling weights—the inverse of syndicate size—to the venture-investor-level analyses did not affect our estimates, suggesting that the sampling issue does not bias our findings. We prioritize the non-interdependence of observations at the investor level and report the venture-investor level analyses in the paper.

Second, we employ piecewise exponential regressions with occurrence of and time to second round funding as the dependent variable. Use of a standard Cox model was not possible because the proportionality assumption was violated. The piecewise exponential method allows accurate estimation of timing effects and censoring and truncation issues but, since these models are at the venture-syndicate level, they do not account for the possibility

² Given that syndicate size might have a major influence on the values of our network variables, we cluster standard errors also by syndicate size. Specifically, small syndicates are more likely to have either high or low values of closure or actor knowledge similarity, than intermediate values. Thus, the standard errors of network effects should be non-independent of syndicate size.

of investors influencing multiple observations through involvement in multiple syndicates. Logit models remain our preferred specification, partly also because it is ambiguous whether timing until further funding always signals success. For example, entrepreneurs may purposefully delay further funding to resolve uncertainties in a bid to achieve a higher valuation or to retain more equity in the next round (Hallen and Eisenhardt, 2012).

Third, we run Heckman probit selection models to account for the possibility that the ability of high social-capital investors to select more promising ventures is driving our results. We adopt the approach in Hallen (2008: 717) and match each syndicate that made a first-round investment in a particular venture to ten random alternative ventures that received first-round investment in the same year but from a different syndicate. After matching the venture-syndicate dyads, we expanded the database to the venture-investor level as in the main analysis. This makes for a better comparison and allows standard errors to be clustered at the venture, investor, and syndicate levels to account for the non-independence of observations. Our instrument is mean geographic distance between syndicate and venture. We believe that the proximity of a venture may make syndicate members more aware of some particular investment targets compared to others, and thus affects selection. However, we believe also that geographic distance has a negligible effect on the odds of successful further funding of a venture that already received first-round funding. In our sample, the difference in second funding success between firms at below-median levels of distance from their investors ($p=0.52$), and those at above-median levels ($p=0.49$) is marginal.

RESULTS

--- Insert Tables 1-3 and Figure 3 about here ---

The Interplay between Network Closure and Actor Knowledge Similarity

Table 1 provides summary statistics and correlations for all the variables included in the regressions. About half of the 2,371 ventures in the dataset that received first-round funding

attracted a second round of funding, with a mean of 575 days between rounds. First-round syndicates have a mean size of 2.8 members and collectively have a mean beyond-syndicate network size of 74 investors. Table 2 shows that all four network configurations we investigate occur frequently in the dataset.

Table 3 presents the logit regression analysis. Model 1 includes only the venture-level covariates. Investor-level and syndicate-level control variables are introduced in Models 2 and 3, respectively. Model 4 includes network closure and actor knowledge similarity, neither of which have significant independent effects on venture success. Model 5 includes the interaction term between network closure and actor knowledge similarity, which is negative and significant, providing support for our hypotheses.

This result holds in both alternative specifications of the full model: that is, taking account of timing and censoring effects (Model 7), and controlling for selection (Model 8). In this latter case, the marginally significant (at 10%) correlation between the error terms of the selection and venture success equations demonstrates that the selection process and the path to venture success are not completely independent. However, controlling for the determinants of selection, the sign and significance of the coefficients in the venture success part of the model are consistent with the findings from Model 5.

To gauge the nature of the interplay between network structure and actor knowledge similarity, and to illustrate the magnitude of the effects, Figure 3 plots the interactions for an example venture in the mobile communications sector in California which received first-round funding in 2005. We explored the use of simulation techniques suggested by Zelner (2009) to graph interaction effects and confidence intervals but this method does not support multiple clustering of standard errors. Graphs obtained by clustering at only one level show that the difference in the predicted probability associated with a change in actor knowledge similarity from -1.5 to 1.5 (as depicted in Figure 3) is statistically different from 0 (95%

confidence) at either end of the network closure range but not in the middle of the range where the lines intersect.

We also conducted a sample split at median values of actor knowledge similarity (Models 6a and 6b) and find consistent support for H1a and H1b. In line with H1a, Figure 3 shows that ventures have a higher probability of success if their syndicates have closed-diverse networks (A) rather than closed-specialized (C) or open-diverse networks (D). The higher probability of success of A relative to D is further supported in Model 6a which shows a positive association between network closure and venture success in diverse networks. In line with H1b, we find support also for our prediction that ventures benefit more from open-specialized syndication networks (B) than from closed-specialized networks (C) or open-diverse networks (D). The higher probability of venture success associated with B relative to C, is supported by a negative association between closure and venture success in specialized networks in Model 6b. These two findings taken together imply that, in line with Hypothesis 1a and 1b, there is a positive relationship between network closure and venture success if the actors are diverse, and a negative relationship between network closure and venture success if the network actors are specialized.

To further test the robustness of our results, we conducted several additional analyses, not included here for reasons of space. First, to check for potential multicollinearity issues, we estimated a variant of Model 5 which included only the investor social capital variables and the interaction term. The sign and significance level of the coefficients is largely unchanged, suggesting that multicollinearity is not a concern in our estimations. Second, we re-ran the logit models at the venture-syndicate rather than the venture-investor level of analysis, with investor-level covariates averaged across syndicate members. Although this setup does not allow us to control for investor-level interdependence, it enables a neater juxtaposition of the dependent variable at the venture level, and the network explanatory

variables at the syndicate level, and leads to more balanced sampling of venture outcomes independent of syndicate size. The results are consistent with those reported in the paper. Finally, although five-year time windows are common in syndication network research (Sorenson and Stuart, 2001, 2008), we reran the models with shorter (1 year and 3 year), and longer time spans (no tie decay) for our network variables. The results are consistent with those reported here.

--- Insert Table 4 and Figure 4 about here ---

Structural Holes, Structural Equivalence, and Industry Emergence

Ventures have the highest chance of success if their syndicates have either closed-diverse or open-specialized networks. These findings support our theoretical argument that these configurations capture the best of both worlds, combining non-redundancy of information which guarantees access to diverse information, and redundancy of information which eases its interpretation. To probe whether these mechanisms are indeed driving our results, we conducted four further analyses.

First, our argument is based in part on the theoretical assumption that open networks have more structural holes or bridging ties than closed ones. Although on average this is likely to be the case—the *count* of bridging ties and closure are correlated at -0.25—relatively open networks may have fewer structural holes if alter-alter ties are more widely distributed rather than being concentrated among selected groups of alters (see A and B in Figure 2). In fact, the positive correlation between *proportion* of bridging ties and closure suggests that the relation between closure and structural holes is not straightforward. In contexts such as ours, the distribution of bridging ties is skewed. Bridging ties are relatively rare since collaboration often takes places in larger groups which create closure. To gauge the direct effect of bridging ties as a measure of non-redundancy, in Models 9 and 10 of Table 4, we replaced our closure variable by the proportion of bridging ties. Figure 4A depicts the

results. Consistent with our earlier results, we find that networks with low levels of bridging (i.e., closed networks) are associated with higher levels of venture success if these networks are diverse, and that networks with high levels of bridging (i.e., open networks) are associated with higher levels of venture success if these networks are specialized. These results support our reasoning that structural holes are indeed an important mechanism driving our findings.

Second, another challenge to closure as a measure of redundancy relates to structural equivalence. Our argument is based on the notion that closure among a syndicate's alters is indicative of information redundancy in the network. Although this will hold on average, there may be cases where alters, despite being unconnected, have mostly the same information because they are tied to the same third parties, that is, they are structurally equivalent. Graphs C and D in Figure 2 illustrate this situation. Model 11 tests whether our results hold if we add structural equivalence to our original specification of Model 5. The model shows that controlling for redundancy based on structural equivalence does not affect our main result; the interaction effect between network closure and actor knowledge similarity is substantively unchanged. Overall, structural equivalence among alters has a positive and significant effect on venture success, suggesting that some overlap in the information that alters pass to the syndicate may be beneficial for its interpretation. This might be because overlap in the second network neighborhood increases the chances that certain bits of information reach the syndicate through different routes (and potentially in different versions), which allows the syndicate to interpret the information through triangulation.

However, the value of the structural equivalence of alters—that is, redundancy in the second network neighborhood—may just as well be contingent on the redundancy emanating from closure and actor knowledge similarity in the first network neighborhood. Models 12a

and 12b are sample split analyses which mimic the approach in Models 6a and 6b. There, we see how the value of closure in diverse or specialized networks may depend on the level of structural equivalence. One would expect that the value of closed-diverse networks to new ventures might be reduced if structural equivalence is high. If the syndicate's alters get their information largely from the same sources, information diversity might be less than one would conclude from only considering closure among the alters. Conversely, in open-diverse networks, problems of overloading due to excessive non-redundancy might be mitigated if structural equivalence among alters is high. Despite the alters not being directly connected, information diversity is limited because they rely on the same third-party sources. Model 12a and Figure 4B support these intuitions.

Similar reasoning can be applied to specialized networks. It could be argued that the value of open-specialized networks would be compromised if the syndicate's unconnected alters use the same third-party sources. The non-redundancy emanating from a sparse first neighborhood structure is limited if alters are structurally equivalent. Also, it might be expected that problems of overembeddedness are exacerbated if redundancy is also high in the second neighborhood of the network. However, Model 12b does not support this reasoning. Although the main effect of closure in specialized network remains negative—keeping our evidence for the value of open-specialized networks intact—the level of structural equivalence appears to neither reduce the advantages of open-specialized networks nor reinforce the disadvantages of closed-diverse ones.

Third, we have argued that the advantage of closure in closed-diverse networks, and the disadvantage of a lack of closure in open-diverse networks is based on two mechanisms: the known mechanism that cohesion of shared third parties around a tie pushes actors to put more effort in the exchange (Reagans and McEvily, 2003) and our newly proposed mechanism that closure among diverse actors enables triangulation of diverse interpretative

cues of the same information. Controlling for tie strength in Model 6a does not reduce the magnitude or significance of the positive effect of closure in diverse networks. Assuming the tie strength variable to be a more direct measure of augmented effort, we consider this result indirect evidence that the logic of triangulation we proposed indeed plays an important part in the advantages derived from closed-diverse networks and disadvantages of open-diverse networks.

Finally, we have so far portrayed the two ‘best-of-both-worlds’ network configurations—closed-diverse and open-specialized networks—as equally beneficial in terms of information advantages. To shed light on how the mechanisms driving advantage in both configurations differ, we explore whether the venture's level of technological uncertainty, a crucial external contingency (e.g., Khandwalla, 1977), influences the relative impact of these two network structures. We exploited a change in the classification in CrunchBase data to distinguish between ventures in established and emerging sectors. Up to the end of 2013, CrunchBase employed 11 classes to categorize IT and Internet industry subclasses. These related mostly to the technical underpinnings of IT and included fields such as hardware, network hosting, search, and security as well as relatively established areas of application such as e-commerce and video games. In 2014, CrunchBase introduced a more inclusive classification scheme including 32 sectors, and retrospectively recoded all the ventures in its database. The 21 additional sectors refer mostly to new IT application areas, notably mobile apps. We labeled the 11 original categories *established sectors* and the 21 new ones *emerging sectors*. The proportion of first-round investments in emerging sectors in our sample increased from around 15% in 2005, our earliest observation year, to more than 30% in 2011, the last year observed.

Table 4 Models 13a and 13b present the logit analysis for the sample split into ventures in established and emerging sectors. The interaction between network closure and

actor knowledge similarity is negative and significant in both models. However, Figures 4C and 4D show remarkable differences in the values for open-specialized and closed-diverse networks for ventures in emerging and established sectors respectively. New ventures in established sectors are most likely to be successful if their syndicates have closed-diverse networks, while ventures in emerging sectors benefit most from syndicates with open-specialized networks. To be clear, for both types of ventures, the nature of the interplay remains unchanged: as in the full sample, the relationship between closure and success is negative in specialized networks, and positive in diverse networks. However, there is a shift in the point where the lines describing the relationship between closure and venture success for specialized and diverse networks intersect.

The differences between the value of closed-diverse and open-specialized networks may be due to variety in the former configuration being based on diversity in insights from different domains, and the latter being limited to variation within domains. Between-domain variety in closed-diverse networks may be particularly valuable in settings where lock-in to established and taken-for-granted views is a potential risk (see Bruner, Goodnow, and Austin, 1956; Uzzi, 1997). At the same time, interpretation of between-domain variety would benefit from a collaborative approach with the involvement of shared third parties which are numerous in closed-diverse networks. In contrast, within-domain variety accessed via open-specialized networks may be better suited to settings where views have not yet become established (see Brown and Duguid, 1998). When there is little consensus about what might be good for firms within a particular field, a variety of views from experts with different experience within a particular field may be more valuable than different views from across field boundaries. Given that variety is mostly within-domain, independent interpretation without involvement of shared third parties may be sufficient. This might explain our finding that open-specialized networks are particularly beneficial for ventures in emerging sectors.

DISCUSSION

In this study, we have put forward the notion that the information advantages of social capital are embodied in the combination of non-redundant information which provides access to diverse insights, and redundant information which eases their interpretation. We suggested that these advantages can be derived from either closed networks among dissimilar actors, or open networks among similar actors. Our arguments are supported by the finding that that new ventures benefit most from the social capital of their investors, and thus, are more likely to be successful at attracting additional funding if their investors' networks are closed-diverse (Figure 1, upper right) or open-specialized (Figure 1, lower left). We found that these two best-of-both worlds' configurations were associated with higher levels of venture success compared to open-diverse networks (Figure 1, lower right) where investors have limited means to interpret the sheer diversity of information, and closed-specialized networks (Figure 1, upper left) where the diversity of information is too limited.

Redundancy, Non-redundancy, and Social Capital

With this study, we extend the discussion on the information advantages associated with social capital. In the literature on network structure, both redundancy and non-redundancy are considered pivotal to the information advantages derived from social capital, resulting in a longstanding debate over whether open structures with non-redundant information or closed structures with redundant information provide more valuable information (Ahuja, 2000; Burt, 2004). Our findings imply that to benefit from networks, actors need both redundancy *and* non-redundancy of information. Sole reliance on the dichotomy between open and closed structures cannot explain how these two properties are combined. By bringing actor knowledge similarity in the open versus closed networks debate, we argue that redundancy can stem from the similarity of actors' knowledge in open networks with non-redundant information, and that non-redundancy can come from dissimilarity of actors in closed

networks with high levels of ‘structural’ redundancy.

We thus establish that informational advantages associated with social capital may be maximized when redundancy and non-redundancy of information co-exist, since the former aids interpretation and the latter safeguards diversity. Actors may benefit from non-redundant information in open networks if they have some knowledge similarity with information providers which yields shared interpretative schema and creates redundancy between the received information and actors’ prior knowledge. Actors may benefit from non-redundant information in diverse networks if they can rely on joint third parties whose interpretation of the information from their perspective creates redundancy and enables triangulation. Conversely, combined non-redundancy from open networks and from actor dissimilarity can lead to problems of overloading in open-diverse networks, while combined redundancy from closed networks and from high similarity of actor knowledge leads to problems of overembeddedness (Uzzi, 1997).

Our findings add to the growing consensus that network structure is insufficient to explain the value of social capital (Kwon and Adler, 2014). Social capital research has a long tradition of ‘structuralist’ studies (Kilduff and Brass, 2010) which attribute much of the variance in performance outcomes to differences in network position and network structure but often do not sufficiently take into account explanations based on actor heterogeneity (Reagans and McEvily, 2003; Rodan and Galunic, 2004), network content (Chua, Ingram, and Morris, 2008; Sosa, 2011), or diversity in the information environment (Aral and Van Alstyne, 2011). We emphasize that the value actors obtain from the network is a function of the actors’ structural positions, the similarity of their knowledge, and the interplay between these two factors, which suggests that the effects of network structure (or content, for that matter) cannot be studied in isolation. Our study demonstrates that actor knowledge similarity is an important contingency in the value of network structure and sheds light on the boundary

conditions when structural holes and closure advantages apply.

Interpreting Diverse Information in Networks

We further contribute to social capital theorizing by proposing network actors' ability to interpret information as an integral component. Rather than assuming that actors in open or diverse networks are able to interpret all the information they access, we have highlighted two network-level mechanisms that facilitate effective interpretation of non-redundant or diverse information.

First, the relative similarity in knowledge profiles between actors in open-specialized networks creates potential overlap between the information they receive, and the information they may already have. This information redundancy makes it more straightforward to overcome potential interpretative barriers and surmount the limitations imposed by the lower information bandwidth typical of sparse network structures (Shannon and Weaver, 1948; Simon and Feigenbaum, 1964). Our argument offers new insights relative to extant research on structural holes in which the actors bridging such holes are often assumed to be able to combine and integrate knowledge and use it to their own advantage, regardless of their knowledge similarity to information providers. Although brokers may to some extent benefit from diverse information merely through the perspective broadening the effect it has on the 'engaged mind' (Burt, 2010), this strand of work treats the interpretative ability of network actors largely as a nodal property that is exogenous to the network, and thus usually falls short of theorizing it explicitly (Burt, 2004).

Although we need to be cautious about generalizing much beyond our specific setting, the results imply that structural holes can be expected to have negative effects in heterogeneous information environments, and positive effects in settings where the information environment is relatively homogeneous and the interpretation of relatively diverse information is less problematic. This is in line with earlier work (Burt, 2005) showing

that bankers can improve their performance by spanning structural holes in their professional context in which—in our words—actor diversity is low. We would encourage further research in different contexts to understand whether and how the value of structural holes is contingent on the level of actor knowledge similarity and the diversity of the information environment more generally.

Another mechanism facilitating the interpretation of diverse information highlighted in our study is triangulation via shared third parties. When the diversity of information stems from the dissimilarity of the actors in a network rather than from structural holes, shared third-party connections act as an important mechanism which helps actors to interpret information in the network. These arguments extend earlier work on actor knowledge similarity and diversity in closed networks. For example, Reagans and McEvily (2003) hint at the possibility that a combination of high network closure and diverse actors may be the optimal network structure, although they do not directly examine the interplay between these two factors, and do not point to the value of the combination of similar actors in networks with low levels of closure. Similar to Tortoriello and Krackhardt's (2010) findings for in the context of ties across intra-organizational boundaries, we find that the advantages of diversity from across domain boundaries are best realized in closed networks rich in shared connections.

The present study contributes to this line of research by highlighting the importance of triangulation. Shared third parties not only incentivize two connected actors to deepen the level of their exchange (Reagans & McEvily 2003), they also may contribute directly to corroborating the information by providing a platform for collective interpretation (Gavetti and Warglien, 2015). If a focal actor not only receives the information directly from the original source but also the interpreted and adapted version from a shared dissimilar alter, then that actor can triangulate the different versions of the same story and make inferences

about his or her own interpretation (Weick and Roberts, 1993). Tightly-knit groups of interconnected, dissimilar actors can function as a platform for distributed cognition allowing meaningful interpretation and application of even highly novel and unfamiliar information (Michel, 2007). This advantage from closure is specific to closed-diverse networks, since closed-specialized networks with homogeneous actors are unlikely to show major differences in the interpretation of the same information. In fact, the negative effect of closed-specialized networks on venture success may be driven in part by the risks of groupthink which emerge when the views of tightly interconnected groups achieve convergence without these views being challenged by relative outsiders (Janis, 1972). These findings relate directly to Uzzi's (1997) conceptualization of overembeddedness as a disadvantageous situation where inflowing novel perspectives are limited due to an emphasis on strong, embedded ties in dense network structures. We add that this lack of inflow of diverse information will be particularly salient if high levels of actor knowledge similarity and high levels of network closure coincide.

Sources of Diverse Information

Finally, in this study we have portrayed various sources of diverse information. In our framework, diverse information is derived either from embeddedness in open networks rich in structural holes, or from embeddedness in networks of heterogeneous actors. We build on a growing body of research on actor heterogeneity (Reagans and McEvily, 2003; Rodan and Galunic, 2004; Tortoriello, McEvily, and Krackhardt, 2015) and network content (Chua, Ingram, and Morris, 2008; Sosa, 2011) as *additional* sources of information diversity, and challenge the assumption that actor knowledge diversity typically coincides with low levels of network closure (Reagans, Zuckerman, and McEvily, 2004) while actor knowledge similarity coincides with high levels of network closure (Uzzi, 1997). In our context, we found these two sources of diversity to be substitutes rather than complements. Problems of

overloading occur when actors are faced with diverse information in both dimensions. This finding contrasts with Rodan and Galunic's (2004) study of managers' networks which suggests that actor heterogeneity and structural holes are mutually reinforcing sources of diversity.

Proposing network structure and actor knowledge similarity as distinct sources of information diversity raises questions about the extent to which structural holes and actor diversity capture the same type of information diversity. Despite finding network sparseness and actor heterogeneity to be mutually reinforcing, Rodan and Galunic (2004) find also that the main effect of structural holes on innovation disappears if a direct measure of diversity is included in the equation. This suggests that, in the context of their study, network sparseness functions as a proxy for diversity. However, in our setting, the frequent occurrence of closed-diverse networks and open-specialized networks suggests that neither network openness nor closure is necessarily indicative of the level of actor knowledge similarity. Also, post-hoc analysis contrasting established and emerging sectors shows that the two sources of diversity are not perfectly equivalent. Closed-diverse networks are most strongly associated to venture success in established IT sub-sectors because they can offer cross-domain diversity which can help challenge established assumptions and taken-for-granted views. Open-specialized networks have within-domain diversity which appears particularly beneficial for ventures in emerging sub-sectors where assumptions and views are still emerging. These findings complement those of Bellavitis and colleagues (2014) who show that extra-industry networks positively affect venture performance, while intra-industry networks have a negative effect unless these networks are complemented by strong extra-industry ties.

We also shed light on the different role of information diversity at different levels in the network. Although our story revolves mainly around the value of redundant and non-redundant information from the first neighborhood (syndicate members' prior partners) of the

syndication network, we have also demonstrated how the value of such (non-)redundancy can be enhanced or reduced by (non-)redundancy in the second neighborhood (the third parties that inform the syndicate's prior partners). We found that the advantages of closed-diverse networks are undermined if diversity is reduced by syndicate alters having highly overlapping third-party sources, while the problem of excess diversity in open-diverse networks are mitigated when equivalence is high. Accordingly, we suggest that the benefits of balance between structure and actor knowledge diversity documented for the first neighborhood network may also be attainable beyond that level. Future research could further investigate these tradeoffs.

Limitations and Suggestions for Future Research

Our study suffers from several shortcomings which suggest directions for future research. First, our findings relate to the indirect effect of network structure and actor knowledge similarity on desired performance outcomes. Although the mechanisms we describe have strong validity based on prior work on the effects of investors' social capital on venture performance (Hochberg, Ljungqvist, and Lu, 2007; Hallen, 2008), more work is needed to achieve a more fine-grained understanding of the type of advice syndicates bring to their portfolio companies and how it contributes to their success. For example, we provide indirect evidence of investor syndicates in closed-diverse networks benefitting from corroboration of diverse interpretative cues through triangulation, in the provision of advice to ventures. Qualitative and experimental research could provide more evidence of this mechanism as a crucial driver of information advantage in closed-diverse networks.

Second, there are various contextual factors which are not accounted for in this study but which have been highlighted in prior research on social capital as important contingencies in relation to the value of structural holes and network closure. There is a near consensus in the literature that structural holes are conducive to the processes of idea generation and

knowledge creation, and that network closure is beneficial for the implementation of ideas and innovation (Kilduff and Brass, 2010). It has also been suggested that closure and brokerage effects differ in relation to the time required for their manifestation (Soda, Usai, and Zaheer, 2004; Baum, McEvily, and Rowley, 2012). We do not make claims about the extent to which these explanations are compatible with our actor knowledge similarity approach. Future research might shed light on the extent to which the insights from the present study extend to networks in other contexts. Although we would predict that the value of closed-diverse and open-specialized networks and the dangers of open-diverse and closed-specialized networks will apply to other settings such as firms' innovation alliances, the testing of our hypotheses was confined to the specifics of syndication networks and their positive effect on ventures. In this context, it is worth noting that informational advantages transmitted through investor advice may be more important for to early-stage ventures than later-stage ventures. In particular, early-stage investments should have a much more formative impact on the venture itself, including its business model and organizational design, as opposed to later-stage investments which may focus more on growing an existing idea to reach a more refined technology development stage, new customers segments, or new geographic areas.

Third, actor knowledge similarity is not exogenous to the network structure. Both network structure and the actors' knowledge similarity are based on the set of investments in the five years prior to the focal investment. Thus, every syndicated co-investment creates a tie whilst also rendering the investors slightly more similar in their investment focus. Although this situation mimics reality—collaboration makes actors more similar over time (Cowan and Jonard, 2009)—the use of exogenously determined actor attributes might help to disentangle redundancy from network structural effects and redundancy related to actor attributes. Future research could use actor knowledge similarity measures based on, for example, text analysis

of documents that characterize the actors' knowledge profiles which are separate from network data sources. It could also help to unravel the complex theoretical interdependencies between network structures and actor knowledge attributes which drive the formation of closed-diverse, closed-specialized, open-diverse, and open-specialized networks.

Finally, although we tested for the alternative explanation that ventures with investor syndicates with the best-of-both-worlds networks are more successful because these networks allowed the syndicates to select more promising ventures in the first place, we acknowledge that our approach may not have ruled out endogeneity entirely.

Implications for Investors and Ventures

Our joint consideration of the structure and actor diversity of investors' past syndication networks sheds new light on how ventures can extract value from investors' social capital (Hochberg, Ljungqvist, and Lu, 2007; Hallen, 2008; Lungeanu and Zajac, 2015; Pahnke, Katila, and Eisenhardt, 2015). We showed that this value depends on the pattern of prior syndication relations as well as the respective investors' investment histories. Investors who 'dance with strangers' (Baum, et al., 2005) and collaborate with investors with whom few other members of the network have previously syndicated, or who have diverse industry portfolios, may be able to enrich their social capital to their own direct benefit, and also may increase the chances of success of the ventures in which they invest, ultimately boosting their own returns on investment. New ventures that need access to diverse but well-interpreted information can obtain it from open-specialized or closed-diverse investor syndication networks. These two networks both capture the best of both worlds by combining access to redundant information which helps interpretation, and non-redundant information which introduces diverse perspectives.

Our findings have implications for new ventures seeking to optimize their chances of success, and investors seeking the highest possible returns from their investment. Young

ventures are engaged in a continuous struggle for new funding for their long-term growth and survival, and thus are usually open to any type of venture capital investment. But how should ventures choose among similar offers? We show that the configuration of the network resources provided by the first-round syndicate has a substantial impact on the further course of the venture. It might seem logical that ventures exhibit a preference for syndicates which are strongly specialized in investments in their subsector, or syndicates of investors that have worked together extensively in the past. However, it might be worthwhile for the venture to consider that the advice to be obtained from the syndicate might be richer if the syndicate's network includes embedded connections to investors with 'diverse specializations' or if it includes investors with similar specializations but lower levels of past shared investment. Closely interlinked groups of highly specialized investors may give incomplete or biased advice if their views are not challenged by new insights and different perspectives.

Our results could be informative for investors who want to use syndication strategically to increase their social capital (see also Milanov and Shepherd, 2013). To achieve this, investors need to avoid both overembeddedness and overloading. For example, while involvement in the syndicate of 'non-local' investors, that is, investors with which they have never syndicated before or which have different portfolios of past investments, may be considered risky (Baum, et al., 2005), we show that such syndication relations are the basis for the two best-of-both-worlds configurations we have identified. Ties to new same-sector investors not shared by their current network are a critical component of open-specialized networks, and ties to investors with a dissimilar sectoral focus yet embedded in their network are critical to closed-diverse networks. Both types of ties enrich investor networks by providing a broader perspective on the knowledge already held, help both investors and ventures to obtain bigger returns, and provide investors with information helpful for future investment decisions.

REFERENCES

Ahuja, G.

2000 "Collaboration networks, structural holes, and innovation: A longitudinal study." *Administrative Science Quarterly*, 45: 425-455.

Alexy, O., J. Block, P. Sandner, and A. L. J. Ter Wal

2012 "Social capital of venture capitalists and start-up funding." *Small Business Economics*, 39: 835-851.

Allison, P. D.

2010 "Survival analysis." In G. R. Hancock, and R. O. Mueller (eds.), *The reviewer's guide to quantitative methods in the social sciences*: 413-425. New York: Routledge.

Aral, S., and M. Van Alstyne

2011 "The diversity-bandwidth trade-off." *American Journal of Sociology*, 117: 90-171.

Audretsch, D. B., W. Bönte, and P. Mahagaonkar

2012 "Financial signaling by innovative nascent ventures: The relevance of patents and prototypes." *Research Policy*, 41: 1407-1421.

Baum, J. A. C., B. McEvily, and T. J. Rowley

2012 "Better with age? Tie longevity and the performance implications of bridging and closure." *Organization Science*, 23: 529-546.

Baum, J. A. C., T. J. Rowley, A. V. Shipilov, and Y. T. Chuang

2005 "Dancing with strangers: Aspiration performance and the search for underwriting syndicate partners." *Administrative Science Quarterly*, 50: 536-575.

Baum, J. A. C., and B. S. Silverman

2004 "Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups." *Journal of Business Venturing*, 19: 411-436.

Bechky, B. A.

2003 "Sharing meaning across occupational communities: The transformation of understanding on a production floor." *Organization Science*, 14: 312-330.

Bellavitis, C., I. Filatotchev, and D. S. Kamuriwo

2014 "The effects of intra-industry and extra-industry networks on performance: A case of venture capital portfolio firms." *Managerial and Decision Economics*, 35: 129-144.

Block, J., and P. Sandner

2009 "What is the effect of the financial crisis on venture capital financing? Empirical evidence from US internet start-ups." *Venture Capital*, 11: 295-309.

- Block, J., De Vries, G., Schumann, J., and Sandner, P.
2014 "Trademarks and venture capital valuation". *Journal of Business Venturing*, 29(4), 453-484.
- Bonacich, P.
1972 "Techniques for analyzing overlapping memberships." In H. L. Costner (ed.), *Sociological methodology*. San Francisco: Jossey-Bass.
- Brewer, W. F., and G. V. Nakamura
1984 "The nature and functions of schemas."
- Brown, J. S., and P. Duguid
1998 "Organizing knowledge." *California Management Review*, 40: 90-111.
- Bruner, J. S., J. J. Goodnow, and G. A. Austin
1956 *A study of thinking*. New York: John Wiley & Sons.
- Burt, R. S.
1992 *Structural holes: The social structure of competition*. Cambridge, MA: Harvard University Press.
2004 "Structural holes and good ideas." *American Journal of Sociology*, 110: 349-399.
2005 *Brokerage and closure: An introduction to social capital*. Oxford: Oxford University Press.
2010 *Neighbor networks: Competitive advantage local and personal*. Oxford: Oxford University Press.
- Bygrave, W. D.
1987 "Syndicated investments by venture capital firms: A networking perspective." *Journal of Business Venturing*, 2: 139-154.
- Cameron, A. C., J. B. Gelbach, and D. L. Miller
2011 "Robust inference with multiway clustering." *Journal of Business & Economic Statistics*, 29: 238-249.
- Centola, D., and M. Macy
2007 "Complex contagions and the weakness of long ties." *American Journal of Sociology*, 113: 702-734.
- Chen, H., P. Gompers, A. Kovner, and J. Lerner
2010 "Buy local? The geography of venture capital." *Journal of Urban Economics*, 67: 90-102.
- Chua, R., P. Ingram, and M. Morris
2008 "From the head and the heart: Locating cognition-and affect-based trust in managers' professional networks." *Academy of Management Journal*, 51: 436-452.
- Coleman, J. S.

- 1990 Foundations of social theory. Cambridge, MA: Harvard University Press.
- Cowan, R., and N. Jonard
- 2009 "Knowledge portfolios and the organization of innovation networks." *Academy of Management Review*, 34: 320-342.
- Cumming, D., G. Fleming, and A. Schwienbacher
- 2005 "Liquidity risk and venture capital finance." *Financial Management*, 34: 77-105.
- De Clercq, D., V. H. Fried, O. Lehtonen, and H. J. Sapienza
- 2006 "An entrepreneur's guide to the venture capital galaxy." *Academy of Management Perspectives*, 20: 90-112.
- Dimov, D., and H. Milanov
- 2010 "The interplay of need and opportunity in venture capital investment syndication." *Journal of Business Venturing*, 25: 331-348.
- Dougherty, D.
- 1992 "Interpretive barriers to successful product innovation in large firms." *Organization Science*, 3: 179-202.
- Fitza, M., S. F. Matusik, and E. Mosakowski
- 2009 "Do VCs matter? The importance of owners on performance variance in start-up firms." *Strategic Management Journal*, 30: 387-404.
- Fleming, L., S. Mingo, and D. Chen
- 2007 "Collaborative brokerage, generative creativity and creative success." *Administrative Science Quarterly*, 52: 443-475.
- Fleming, L., and D. M. Waguespack
- 2007 "Brokerage, boundary spanning, and leadership in open innovation communities." *Organization Science*, 18: 165-180.
- Galunic, C., G. Ertug, and M. Gargiulo
- 2012 "The positive externalities of social capital: Benefitting from senior brokers." *Academy of Management Journal*, 55: 1213-1231.
- Gargiulo, M., and M. Benassi
- 2000 "Trapped in your own net? Network cohesion structural holes, and the adaptation of social capital." *Organization Science*, 11: 183-196.
- Gavetti, G., and M. Warglien
- 2015 "A model of collective interpretation." *Organization Science*, 26: 1263-1283.
- Ghosh, A., and L. Rosenkopf

- 2014 "Shrouded in structure: Challenges and opportunities for a friction-based view of network research." *Organization Science*, 26: 622-631.
- Gompers, P. A.
- 1995 "Optimal investment, monitoring, and the staging of venture capital." *Journal of Finance*: 1461-1489.
- Granovetter, M.
- 1992 "Problems of explanation in economic sociology." In N. Nohria, and R. G. Eccles (eds.), *Networks and organizations: Structure, form, and action*: 25-56. Boston: Harvard Business School Press.
- Grégoire, D. A., P. S. Barr, and D. A. Shepherd
- 2010 "Cognitive processes of opportunity recognition: The role of structural alignment." *Organization Science*, 21: 413-431.
- Gu, Q., and X. Lu
- 2014 "Unraveling the mechanisms of reputation and alliance formation: A study of venture capital syndication in China." *Strategic Management Journal*, 35: 739-750.
- Gulati, R., and M. Sytch
- 2008 "Does familiarity breed trust? Revisiting the antecedents of trust." *Managerial and Decision Economics*, 29: 165.
- Hallen, B. L.
- 2008 "The causes and consequences of the initial network positions of new organizations: From whom do entrepreneurs receive investments?" *Administrative Science Quarterly*, 53: 685-718.
- Hallen, B. L., and K. M. Eisenhardt
- 2012 "Catalyzing strategies and efficient tie formation: How entrepreneurial firms obtain investment ties." *Academy of Management Journal*, 55: 35-70.
- Hansen, M. T., and M. R. Haas
- 2001 "Competing for attention in knowledge markets: Electronic document dissemination in a management consulting company." *Administrative Science Quarterly*, 46: 1-28.
- Hargadon, A., and R. I. Sutton
- 1997 "Technology brokering and innovation in a product development firm." *Administrative Science Quarterly*, 42: 716-749.
- Harrison, D. A., and K. J. Klein
- 2007 "What's the difference? Diversity constructs as separation, variety, or disparity in organizations." *Academy of Management Review*, 32: 1199-1228.
- Hochberg, Y. V., L. A. Lindsey, and M. M. Westerfield
- 2015 "Resource accumulation through economic ties: Evidence from venture capital." *Journal of Financial Economics (JFE)*, Forthcoming.

Hochberg, Y. V., A. Ljungqvist, and Y. Lu

2007 "Whom you know matters: Venture capital networks and investment performance." *The Journal of Finance*, 62: 251-301.

Hsu, D. H.

2006 "Venture capitalists and cooperative start-up commercialization strategy." *Management Science*, 52: 204-219.

Hsu, D. H., and K. Lim

2014 "Knowledge brokering and organizational innovation: Founder imprinting effects." *Organization Science*, 25: 1134-1153.

Hwang, E. H., P. Singh, and L. Argote

2014 "Jack of all, master of some: The contingent effect of knowledge breadth on innovation." *International Conference on Information Systems: ICIS 2014 Proceedings*.

Jääskeläinen, M., and M. Maula

2014 "Do networks of financial intermediaries help reduce local bias? Evidence from cross-border venture capital exits." *Journal of Business Venturing*, 29: 704-721.

Janis, I. L.

1972 *Victims of groupthink: A psychological study of foreign-policy decisions and fiascoes*. Boston: Houghton Mifflin.

Khandwalla, P. N.

1977 *The design of organizations*. New York: Harcourt Brace Jovanovich.

Kilduff, M., and D. J. Brass

2010 "Organizational social network research: Core ideas and key debates." *The Academy of Management Annals*, 4: 317-357.

Kleinbaum, A. M., T. E. Stuart, and M. L. Tushman

2013 "Discretion within constraint: Homophily and structure in a formal organization." *Organization Science*, 24: 1316-1336.

Krackhardt, D.

1999 "The ties that torture: Simmelian tie analysis in organizations." In S. B. Andrews, and D. Knoke (eds.), *Research in the sociology of organizations*: 183-210. Greenwich, CT: JAI Press.

Kwon, S.-W., and P. S. Adler

2014 "Social capital: Maturation of a field of research." *Academy of Management Review*, 39: 412-422.

Lee, P. M., T. G. Pollock, and K. Jin

2011 "The contingent value of venture capitalist reputation." *Strategic Organization*, 9: 33-69.

Lerner, J.

1994 "The syndication of venture capital investments." *Financial Management*, 23: 16-27.

Lingo, E. L., and S. O'Mahony

2010 "Nexus work: Brokerage on creative projects." *Administrative Science Quarterly*, 55: 47.

Liu, Y., and M. Maula

2015 "Local partnering in foreign ventures: Uncertainty, experiential learning, and syndication in cross-border venture capital investments." *Academy of Management Journal*, forthcoming.

Lorraine, F. P., and H. C. White

1971 "Structural equivalence of individuals in social networks." *Journal of Mathematical Sociology*, 1: 49-80.

Lungeanu, R., and E. Zajac

2015 "Venture capital ownership as a contingent resource: How owner/firm fit influences IPO outcomes." *Academy of Management Journal*, forthcoming: amj. 2012.0871.

Mariotti, F., and R. Delbridge

2012 "Overcoming network overload and redundancy in interorganizational networks: The roles of potential and latent ties." *Organization Science*, 23: 511-528.

Michel, A. A.

2007 "A distributed cognition perspective on newcomers' change processes: The management of cognitive uncertainty in two investment banks." *Administrative Science Quarterly*, 52: 507-557.

Milanov, H., and D. A. Shepherd

2013 "The importance of the first relationship: The ongoing influence of initial network on future status." *Strategic Management Journal*, 34: 727-750.

Miller, D. J.

2006 "Technological diversity, related diversification, and firm performance." *Strategic Management Journal*, 27: 601-619.

Mors, M. L.

2010 "Innovation in a global consulting firm: When the problem is too much diversity." *Strategic Management Journal*, 31: 841-872.

Obstfeld, D.

2005 "Social networks, the tertius iungens and orientation involvement in innovation." *Administrative Science Quarterly*, 50: 100-130.

Oh, H., M.-H. Chung, and G. Labianca

2004 "Group social capital and group effectiveness: The role of informal socializing ties." *Academy of Management Journal*, 47: 860-875.

Pahnke, E. C., R. Katila, and K. M. Eisenhardt

2015 "Who takes you to the dance? How partners' institutional logics influence innovation in young firms." *Administrative Science Quarterly*, 60: 596-633.

Perry-Smith, J. E.

2006 "Social yet creative: The role of social relationships in facilitating individual creativity." *Academy of Management Journal*, 49: 85-101.

Podolny, J. M.

2001 "Networks as the pipes and prisms of the market." *American Journal of Sociology*, 107: 33-60.

Reagans, R., and B. McEvily

2003 "Network structure and knowledge transfer: The effects of cohesion and range." *Administrative Science Quarterly*, 48: 240-267.

2008 "Contradictory or compatible? Reconsidering the "trade-off" between brokerage and closure on knowledge sharing." In J. A. C. Baum, and T. J. Rowley (eds.), *Network strategy: Advances in strategic management*. Bingley, UK: Emerald.

Reagans, R., E. Zuckerman, and B. McEvily

2004 "How to make the team: Social networks vs. demography as criteria for designing effective teams." *Administrative Science Quarterly*, 49: 101-133.

Reagans, R., and E. W. Zuckerman

2001 "Networks, diversity, and productivity: The social capital of corporate R&D teams." *Organization Science*, 12: 502-517.

2008 "Why knowledge does not equal power: The network redundancy trade-off." *Industry Corporate Change*, 17: 903-944.

Rodan, S., and C. Galunic

2004 "More than network structure: How knowledge heterogeneity influences managerial performance and innovativeness." *Strategic Management Journal*, 25: 541-562.

Rosenbaum, S. M., S. Billinger, and N. Stieglitz

2014 "Let's be honest: A review of experimental evidence of honesty and truth-telling." *Journal of Economic Psychology*, 45: 181-196.

Rosenkopf, L., and A. Nerkar

2001 "Beyond local search: Boundary spanning, exploration, and impact in the optical disk industry." *Strategic Management Journal*, 22: 287-306.

Schilling, M. A., and C. Fang

2014 "When hubs forget, lie, and play favorites: Interpersonal network structure, information distortion, and organizational learning." *Strategic Management Journal*, 35: 974-994.

Schilling, M. A., and C. C. Phelps

2007 "Interfirm collaboration networks: The impact of large-scale network structure on firm innovation." *Management Science*, 53: 1113-1126.

Shane, S., and T. E. Stuart

2002 "Organizational endowments and the performance of university start-ups." *Management Science*, 48: 154-170.

Shannon, C. E., and W. Weaver

1948 "A mathematical theory of communication." *The Bell System Technical Journal*, 27: 379-423.

Shipilov, A. V., and S. X. Li

2008 "Can you have your cake and eat it too? Structural holes' influence on status accumulation and market performance in collaborative networks." *Administrative Science Quarterly*, 53: 73-108.

Simon, H. A.

1956 "Rational choice and the structure of the environment." *Psychological Review*, 63: 129-138.

1966 "Thinking by computers." In R. G. Colodny (ed.), *Mind and cosmos: Essays in contemporary science and philosophy*: 3-21. Pittsburgh, PA: University of Pittsburgh Press.

1974 "How big is a chunk?" *Science*, 183: 482-488.

Simon, H. A., and E. A. Feigenbaum

1964 "An information-processing theory of some effects of similarity, familiarization, and meaningfulness in verbal learning." *Journal of Verbal Learning and Verbal Behavior*, 3: 385-396.

Soda, G. S., A. Usai, and A. Zaheer

2004 "Network memory: The influence of past and current networks on performance." *Academy of Management Journal*, 47: 893-906.

Sorenson, O., and T. E. Stuart

2001 "Syndication networks and the spatial distribution of venture capital investments." *American Journal of Sociology*, 106: 1546-1588.

2008 "Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks." *Administrative Science Quarterly*, 53: 266-294.

Sosa, M. E.

2011 "Where do creative interactions come from? The role of tie content and social networks." *Organization Science*, 22: 1-21.

Stuart, T. E., H. Hoang, and R. C. Hybels

1999 "Interorganizational endorsements and the performance of entrepreneurial ventures." *Administrative Science Quarterly*, 44: 315-349.

Sweller, J.

1988 "Cognitive load during problem solving: Effects on learning." *Cognitive Science*, 12: 257-285.

Tortoriello, M., and D. Krackhardt

2010 "Activating cross-boundary knowledge: The role of simmelian ties in the generation of innovations." *Academy of Management Journal*, 53: 167-181.

Tortoriello, M., B. McEvily, and D. Krackhardt

2015 "Being a catalyst of innovation: The role of knowledge diversity and network closure." *Organization Science*, 26: 423-438.

Tortoriello, M., R. Reagans, and B. McEvily

2012 "Bridging the knowledge gap: The influence of strong ties, network cohesion, and network range on the transfer of knowledge between organizational units." *Organization Science*, 23: 1024-1039.

Tyebjee, T. T., and A. V. Bruno

1984 "A model of venture capitalist investment activity." *Management Science*, 30: 1051-1066.

Uzzi, B.

1996 "The sources and consequences of embeddedness for the economic performance of organizations: The network effect." *American Sociological Review*, 61: 674-698.

1997 "Social structure and competition in interfirm networks: The paradox of embeddedness." *Administrative Science Quarterly*, 42: 35-67.

Wadhwa, A., C. Phelps, K. Suresh

2016 "Corporate venture capital portfolios and firm innovation." *Journal of Business Venturing*, 31 (1): 95-112.

Walker, G., B. Kogut, and W. J. Shan

1997 "Social capital, structural holes and the formation of an industry network." *Organization Science*, 8: 109-125.

Wang, C., S. Rodan, M. Fruin, and X. Xu

2013 "Knowledge networks, collaboration networks, and exploratory innovation." *Academy of Management Journal*, 57: 484-514.

Weick, K. E., and K. H. Roberts

1993 "Collective mind in organizations: Heedful interrelating on flight decks." *Administrative science quarterly*: 357-381.

Zaheer, A., and G. Soda

2009 "Network evolution: The origins of structural holes." *Administrative Science Quarterly*, 54: 1-31.

Zelner, B. A.

2009 "Using simulation to interpret results from logit, probit, and other nonlinear models."
Strategic Management Journal, 30: 1335-1348.

Zukin, S., and P. DiMaggio

1990 Structures of capital: The social organization of the economy: Cambridge Univ Pr.

Table 1: Descriptive statistics and pairwise correlations

	Variable	N	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	
1	Venture	Second funding received	2371	0.51		0.00	1.00													
2		Raised amount first round (log)	2371	1.22	0.88	-1.39	2.30	0.04												
3		Number of patents	2371	0.87	5.07	0.00	112.00	-0.02	0.13											
4		Number of trademarks	2371	2.07	6.80	0.00	220.00	-0.07	0.11	0.29										
5	Investor	Past portfolio companies acquired	1646	0.02	0.07	0.00	1.00	0.03	-0.01	-0.05	-0.02									
6		Status (eigenvector centrality)	1646	0.00	0.00	0.00	0.02	0.05	0.15	0.02	0.00	0.06								
7		Corporate venture capitalist	1646	0.05		0.00	1.00	-0.02	-0.07	-0.01	0.00	0.02	-0.06							
8		Angel investor	1646	0.03		0.00	1.00	0.00	-0.24	-0.03	-0.02	0.01	-0.03	0.02						
9	Syndicate	Syndicate size	2371	2.84	1.21	2.00	13.00	-0.01	-0.11	0.08	0.02	0.00	-0.22	0.04	0.07					
10		Network size	2371	73.82	70.28	0.00	381.00	0.06	-0.04	-0.04	-0.02	0.26	-0.03	0.03	0.08	0.38				
11		Network closure ¹	2371	0.17	0.11	0.00	1.00	-0.03	-0.06	-0.03	-0.03	-0.06	0.07	0.00	-0.01	-0.25	-0.45			
12		Network specialization ¹	2371	0.11	0.07	0.00	1.00	0.02	0.19	0.06	0.01	-0.08	0.11	-0.03	-0.08	-0.06	-0.16	0.48		
13		Bridging ties (proportion) ¹	2371	0.03	0.08	0.00	1.00	-0.05	-0.06	-0.02	-0.01	-0.08	-0.01	-0.02	0.02	-0.13	-0.24	0.26	0.10	
14		Structural equivalence (of alters) ¹	2371	0.02	0.02	0.00	0.70	0.03	-0.09	-0.02	-0.04	0.07	0.10	0.03	0.01	-0.15	-0.10	0.40	0.00	0.02

Correlations above |0.03| are significant at 5% level

¹ Descriptive statistics show non-standardized variables, but variables were standardized before computation of correlations and inclusion in regression models.

Table 2: Co-occurrence of low and high levels of network closure and actor knowledge similarity

		<i>Actor knowledge similarity</i>		
		< mean (diverse networks)	>= mean (specialized networks)	Total
<i>Network closure</i>	< mean (open networks)	909	457	1,366
	>= mean (closed networks)	517	488	1,005
	Total	1,426	945	2,371

Table 3: Predicting probability of receiving second funding (network closure * actor knowledge specialization)

	Model 1 Logit Venture controls	Model 2 Logit Investor controls	Model 3 Logit Network controls	Model 4 Logit Main effects	Model 5 Full model (preferred specification)	Model 6a Sample split: diverse networks	Model 6b Sample split: specialized networks	Model 7 Piecewise exponential Full model	Model 8 part 1 Heckprobit Selection equation	Model 8 part 2 Heckman Probit Success equation
Venture	Mean distance to investors									
									-0.254 (0.020)***	
	0.117 (0.067)*	0.103 (0.057)*	0.072 (0.062)	0.073 (0.063)	0.066 (0.064)	0.151 (0.074)**	0.008 (0.194)	0.011 (0.035)	-0.006 (0.023)	0.044 (0.041)
	0.002 (0.010)	0.002 (0.011)	0.004 (0.011)	0.004 (0.011)	0.003 (0.012)	0.022 (0.019)	0.004 (0.011)	-0.008 (0.010)	0.005 (0.006)	0.002 (0.007)
	-0.044 (0.017)***	-0.044 (0.016)***	-0.043 (0.015)***	-0.043 (0.016)***	-0.043 (0.016)***	-0.016 (0.008)**	-0.071 (0.014)***	-0.023 (0.008)***	0.003 (0.003)	-0.025 (0.009)***
Investor	Share of past portfolio companies acquired/IPO									
		1.254 (0.565)**	0.969 (0.499)*	0.962 (0.498)*	0.956 (0.494)*	0.467 (0.557)	1.636 (0.647)**	1.706 (0.370)***	0.099 (0.064)	0.587 (0.304)*
		19.896 (6.250)***	9.496 (4.159)**	8.833 (4.700)*	3.959 (3.598)	14.930 (10.182)	-1.267 (5.873)	31.001 (10.327)***	-6.072 (1.235)***	2.975 (2.457)
		0.178 (0.351)	0.176 (0.332)	0.175 (0.330)	0.180 (0.322)	0.106 (0.306)	0.590 (0.574)	0.196 (0.237)	-0.017 (0.033)	0.112 (0.204)
		-0.232 (0.207)	-0.217 (0.210)	-0.219 (0.209)	-0.224 (0.210)	-0.039 (0.181)	-0.549 (0.294)*	-0.152 (0.159)	-0.058 (0.016)***	-0.135 (0.132)
Syndicate	Syndicate size									
			-0.077 (0.049)	-0.074 (0.049)	-0.077 (0.050)	0.014 (0.072)	-0.215 (0.056)***	-0.033 (0.027)	0.014 (0.006)**	-0.049 (0.030)
			0.002 (0.001)**	0.002 (0.001)***	0.002 (0.001)**	0.002 (0.001)*	0.001 (0.002)	0.001 (0.001)**	-0.000 (0.000)***	0.002 (0.001)***
				0.025 (0.063)	0.030 (0.064)	0.134 (0.057)**	-0.131 (0.062)**	-0.010 (0.016)	-0.020 (0.007)***	0.019 (0.038)
				0.003 (0.050)	0.061 (0.058)			0.044 (0.011)***	0.018 (0.007)**	0.035 (0.032)
					-0.035 (0.007)***			-0.023 (0.003)***	0.003 (0.002)*	-0.022 (0.004)***
	0.226 (0.241)	0.202 (0.247)	0.539 (0.225)**	0.520 (0.220)**	0.555 (0.230)**	-0.087 (0.557)	0.077 (1.023)	-7.994 (0.133)***	0.446 (0.165)***	0.476 (0.186)**
	6,744	6,744	6,744	6,744	6,744	3,374	3,370	9,149	74,184	6,744
	1,646	1,646	1,646	1,646	1,646	1,067	1,016	1,646	1,646	1,646
	2,371	2,371	2,371	2,371	2,371	1,111	1,260	2,371	2,371	2,371
	-4,446	-4,438	-4,424	-4,423	-4,417	-2,183	-2,169	-4,565		-24,575
	400.66	411.78	444.91	445.84	460.03	283.38	269.61			162.08
		16.62***	28.92***	0.86	11.93***					
										-0.088 (0.053)*

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Year dummies (2006-2011), location dummies (CA, MA, and NY), and dummies for the 32 IT sub-sectors included and jointly significant in all models. Time effects in Model 7 not shown. Unit of analysis is the venture-investor combination in all models, except Model 7 where it is the venture-syndicate combination. Sample split in Models 6a and 6b is at sample median values.

Standard errors (shown in parentheses) are clustered by investor, venture, and syndicate size in all models except Model 7 where standard errors are clustered on syndicate size only.

Sample includes firms that received first round investment between \$250,000 and \$10 million between 2005 and 2011. Second funding observed until the end of 2013.

LR-test assesses improvement in model fit relative to model in previous column and is based on log likelihood of model with clustered standard errors on investor and venture levels only.

Table 4: Logit models predicting probability of receiving second funding (structural holes, structural equivalence and industry emergence)

	Model 5 Full model For comparison	Model 9 Bridging ties Main effect	Model 10 Bridging ties Interaction	Model 11 Structural eqv	Model 12a Structural eqv diverse networks (compare 6a)	Model 12b Structural eqv specialized netw. (compare 6b)	Model 13a Sample split: established sectors	Model 13b Sample split: emerging sectors
Venture								
Raised amount 1 st round	0.066 (0.064)	0.047 (0.073)	0.054 (0.072)	0.062 (0.067)	0.114 (0.068)*	0.019 (0.185)	0.100 (0.058)*	-0.041 (0.097)
Number of patents	0.003 (0.012)	0.004 (0.011)	0.004 (0.011)	0.003 (0.012)	0.021 (0.019)	0.004 (0.011)	0.003 (0.011)	
Number of trademarks	-0.043 (0.016)***	-0.046 (0.018)***	-0.047 (0.018)***	-0.043 (0.016)***	-0.016 (0.008)**	-0.070 (0.015)***	-0.044 (0.015)***	
Investor								
Share of past portfolio companies acquired/IPO	0.956 (0.494)*	0.867 (0.475)*	0.854 (0.473)*	0.956 (0.501)*	0.387 (0.496)	1.653 (0.671)**	0.708 (0.384)*	1.322 (0.972)
Status (eigenvector centrality)	3.959 (3.598)	-1.448 (3.984)	-0.447 (4.185)	0.147 (2.413)	-9.325 (15.112)	-6.169 (7.078)	-0.291 (5.492)	20.852 (14.996)
Angel investor	0.180 (0.322)	0.175 (0.334)	0.190 (0.322)	0.187 (0.327)	0.132 (0.295)	0.660 (0.653)	0.050 (0.400)	0.700 (0.542)
Corporate venture capitalist	-0.224 (0.210)	-0.185 (0.188)	-0.186 (0.187)	-0.233 (0.203)	-0.067 (0.178)	-0.547 (0.286)*	-0.288 (0.244)	0.115 (0.208)
Syndicate								
Syndicate size	-0.077 (0.050)	-0.093 (0.053)*	-0.092 (0.053)*	-0.075 (0.054)	0.009 (0.073)	-0.212 (0.056)***	-0.070 (0.041)*	-0.070 (0.102)
Network size	0.002 (0.001)**	0.002 (0.001)*	0.002 (0.001)*	0.003 (0.001)***	0.003 (0.001)**	0.001 (0.002)	0.003 (0.001)**	-0.001 (0.002)
Network closure	0.030 (0.064)			-0.017 (0.074)	-0.054 (0.129)	-0.140 (0.064)**	0.072 (0.073)	-0.148 (0.045)***
Actor knowledge similarity	0.061 (0.058)	-0.064 (0.044)	-0.082 (0.039)**	0.063 (0.054)			-0.000 (0.061)	0.347 (0.089)***
Network closure * Actor knowledge similarity	-0.035 (0.007)***			-0.027 (0.009)***			-0.029 (0.011)***	-0.073 (0.042)*
Bridging ties		-0.092 (0.038)**	-0.106 (0.061)*					
Bridging ties * Actor knowledge similarity			0.060 (0.027)**					
Structural equivalence				0.100 (0.040)**	0.392 (0.159)**	0.150 (0.131)		
Network closure * Structural equivalence					-0.131 (0.025)***	-0.026 (0.036)		
Constant	0.555 (0.230)**	0.846 (0.298)***	0.834 (0.302)***	0.631 (0.206)***	0.520 (0.502)	1.452 (0.354)***	0.561 (0.194)***	-0.877 (1.030)
<i>N</i>	6,744	6,410 ²	6,410 ²	6,744	3,374	3,370	5,132	1,612
Unique investors	1,646	1,439	1,439	1,646	1,067	1,016	1,365	744
Unique ventures	2,371	2,229	2,229	2,371	1,111	1,260	1,805	566
Log pseudolikelihood	-4,417	-4,209	-4,205	-4,412	-2,159	-2,169	-3,359	-1,026
Wald χ^2	460.03	404.50	402.23	466.71	326.42	264.67	346.92	174.87

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Year dummies (2006-2011), location dummies (CA, MA, and NY), and dummies for the 32 IT sub-sectors included and jointly significant in all models. Unit of analysis is the venture-investor combination.

Standard errors (shown in parentheses) are clustered by investor, venture, and syndicate size in all models.

Sample includes firms that received first round investment between \$250,000 and \$10 million between 2005 and 2011. Second funding observed until the end of 2013.

¹ Ventures in emerging sectors in our sample have no patents or trademarks. ² Some observations were dropped, as proportion of bridging ties is undefined when all network relations are contained within the syndicate.

Figure 2: Structural holes and structural equivalence at equal levels of closure

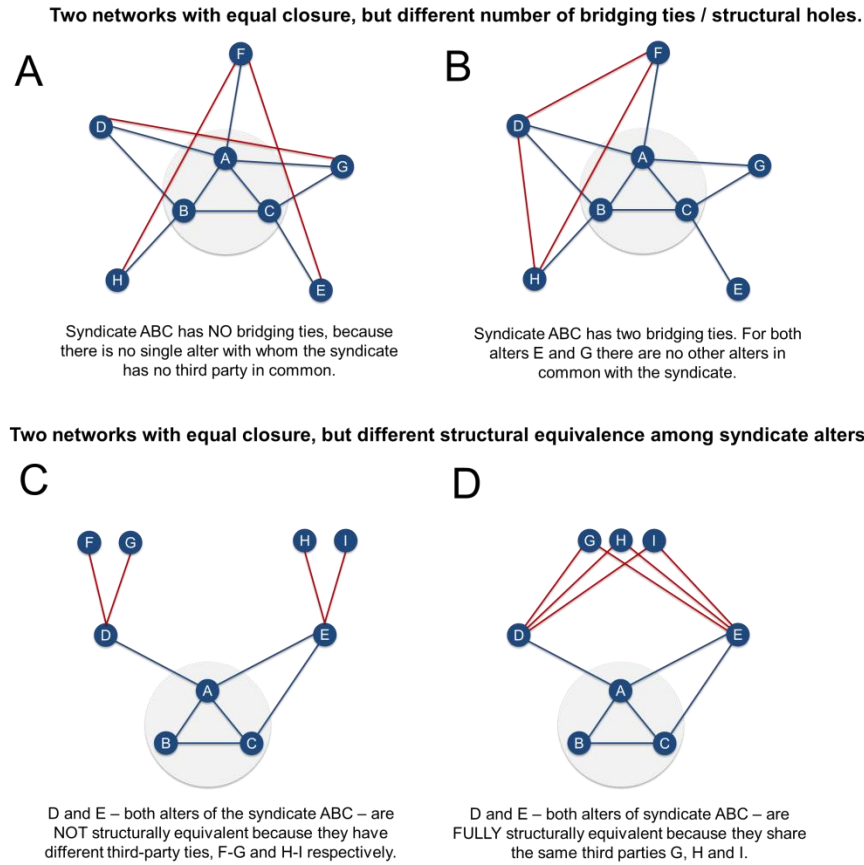


Figure 3: Interaction between network closure and actor knowledge similarity

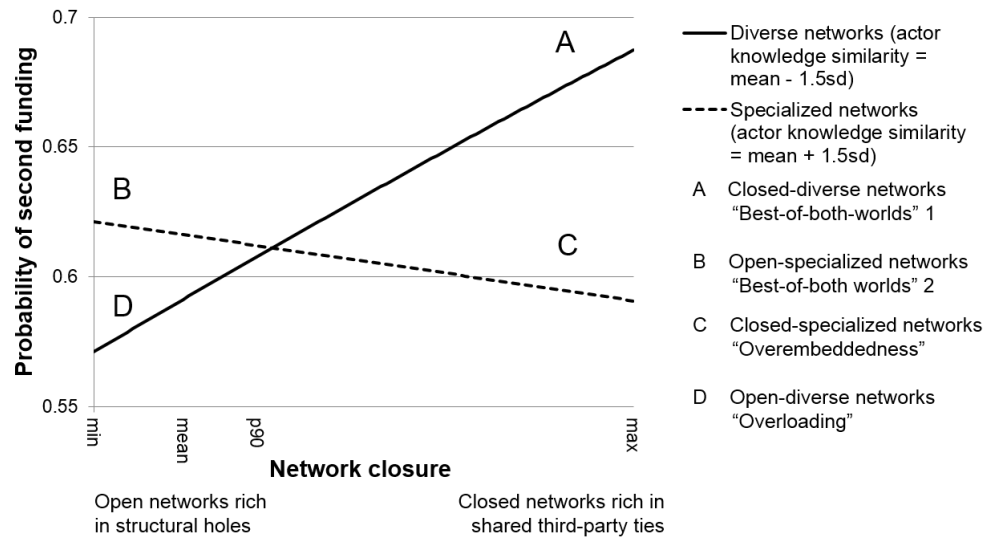
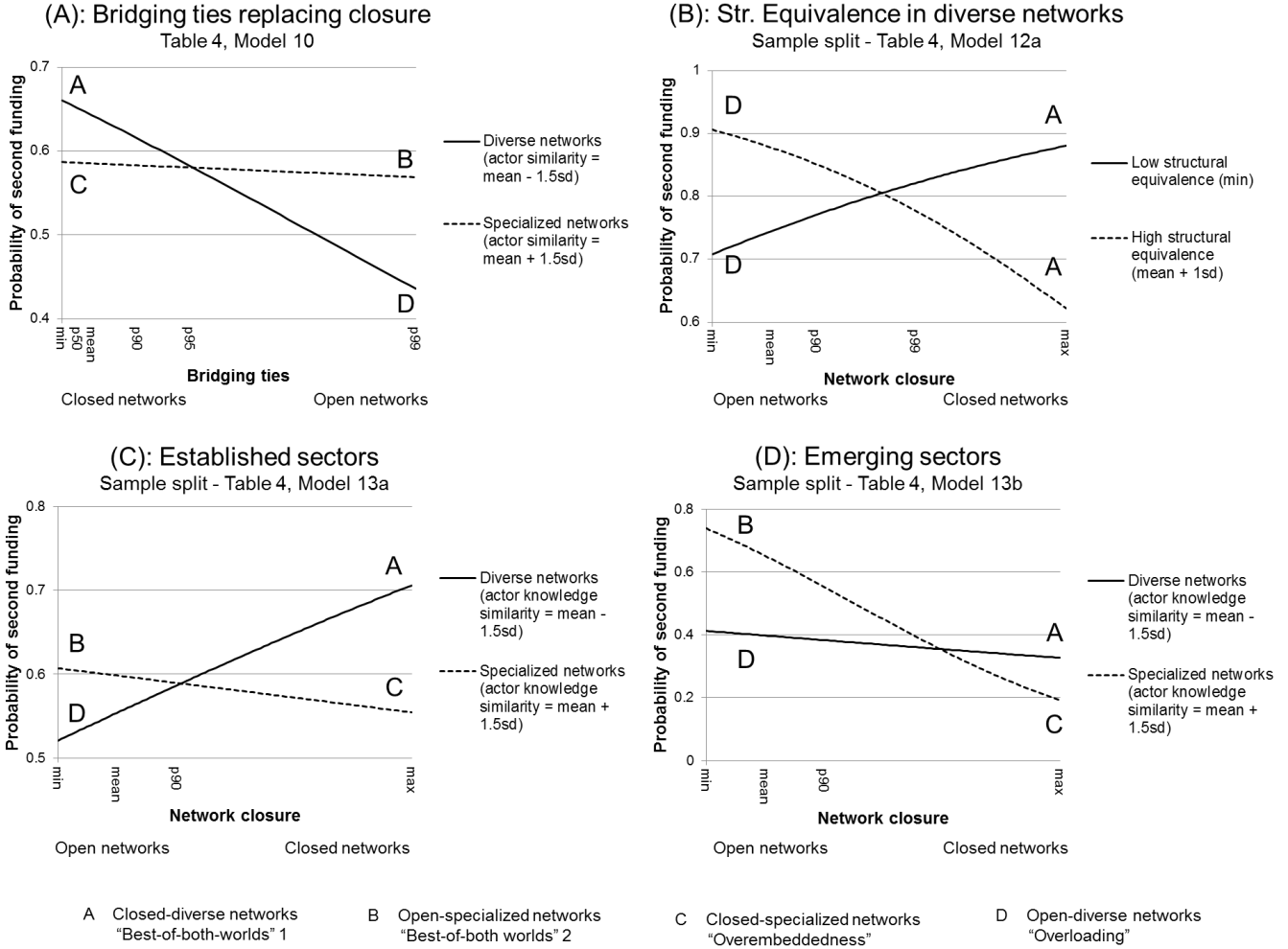


Figure 3 is based on the Heckprobit selection model, Model 8 in Table 3. Year is set to “2005”, sector to “mobile”, and location to “California”. All remaining variables are set to sample mean. Note that using different values for control variables would only shift the regression lines upwards or downwards. Graphs based on Models 5 (standard logit) and Models 7 (piecewise exp.) are highly consistent with graph shown.

Figure 4: Bridging ties, Structural Equivalence, and Industry Emergence



Year is set to "2005", sector to "mobile", and location to "California". All remaining variables are set to sample mean.
 Note that using different values for control variables would only shift the regression lines upwards or downwards.

Acknowledgements

The paper has greatly benefitted from the guidance and support of the associate editor Devereaux Jennings and three anonymous reviewers. The authors also thank Joel Baum, Paola Criscuolo, Hans Frankort, Adam Kleinbaum, Yuri Mishina, and Bill McEvily for providing comments on earlier drafts of this paper. Participants of the Innovation and Entrepreneurship (I&E) paper development workshop at Imperial College Business School, the brownbag seminar at the Strategy group of the Rotman School of Management, the Inter-organizational Networks Conference in 2014 in Kentucky, the 2013 DRUID conference, the 2013 Academy of Management conference and the 2012 UK-IRC workshop in Cambridge, and seminars at Oxford University and ESMT Berlin also provided valuable suggestions that helped the paper's development. An abstract of this article was published in the Best Paper Proceedings of the Academy of Management ([dx.doi.org/10.5465/AMBPP.2013.11425abstract](https://doi.org/10.5465/AMBPP.2013.11425abstract)). We thank the Leibniz Supercomputing Centre (LRZ) of the Bavarian Academy of Sciences and Humanities (BAdW) for the provisioning and support of Cloud computing infrastructure essential to this publication. Anne ter Wal gratefully acknowledges the support of the Economic and Social Research Council (ES/K001159/1) for its contribution to funding the research underpinning this article.