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Ties of survival: Specialization, inter-firm ties, and firm failure in the U.S. venture capital industry

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ABSTRACT

This study examines how firms' network ties interact with their level of specialization in affecting the risk of failure in the U.S. venture capital (VC) industry. Testing my hypotheses on data spanning 41 years, I find that there is an inverted J-shaped relationship between the degree of VC firms' specialization and the risk of failure and that this pattern is moderated by firms' portfolio homogeneity. I further find that VC firms depend on their network ties in avoiding failure, that this effect is stronger for generalist VC firms than specialist firms, and that ties to specialist VC firms reduce the risk of failure of generalist firms with heterogeneous portfolios the most. These results advance our understanding of the joint effects of specialization and network connections on firm survival and, more broadly, of the interdependence of generalist and specialist organizations.

1. Introduction

The burgeoning literature on inter-organizational networks shows that network ties are important conduits of resources, such as information, knowledge, legitimacy, and prestige that affect a multitude of organizational outcomes ranging from firm performance (Bellavitis, Filatotchev, & Souitaris, 2017; Gulati, 2007; Shipilov & Li, 2008) to market entry (Jensen, 2003; Tuschke, Sanders, & Hernandez, 2014) to financial returns (Rowley, Behrens, & Krackhardt, 2000) to learning (e.g., Peters, Pressey, & Johnston, 2016) and creation of innovation (e.g., Owen-Smith & Powell, 2004). Survival, a crucial organizational outcome, has also been linked to the pattern of network resource utilization by firms in different industries. For example, Baum and Oliver (1991) discovered that legitimation-granting ties to institutional actors enhanced survival chances of Toronto day care centers. Uzzi (1997) found that the right amount of network embeddedness is necessary for organizational survival in the New York garment industry whereas both under- and over-embeddedness hinder survival chances. Cattani, Ferriani, Negro, and Perretti (2008) showed that network ties between producer and distributor organizations played a key role in the survival of producers in the U.S. film industry. This prior research has thus established a link between network ties and organizational survival and advanced our understanding of the multitude of ways in which network resources affect organizations. Yet we lack an understanding of how firms' characteristics shape and mediate the effects of their network connections and of the utility that firms with different characteristics derive from network resources (Shipilov, 2006). Such understanding is necessary, however, for a nuanced and differentiated view of the role of network ties in firms' outcomes.

One of the most fundamental dimensions on which organizations differ, along with such demographic characteristics as size and age, is the degree of specialization. Specialist and generalist organizations pursue different competitive strategies, have different organizational structures and capabilities, and possess different types of resources. This heterogeneity has implications for their market survival (e.g., Carroll & Swaminathan, 2000; Hannan & Freeman, 1977). It also likely affects the type of network resources firms require, the pattern of utilization of such resources, and the benefits gained from them. Yet the question of how specialization and network ties interact to affect firms' outcomes is significantly understudied.

In this study, I first discuss how the degree of specialization affects survival chances of firms in the venture capital (VC) industry. I bring homogeneity of firms' market portfolios into the discussion of benefits of specialism and generalism as firms' market survival strategies. Prior research, while focusing on specialization (or firms' market "niche width"), often ignored the relatedness of resources within a firm's portfolios. Studies in corporate diversification demonstrate, by contrast, that the relatedness of firms' domains of operation affects a range of organizational outcomes (e.g., Sakhartov & Folta, 2014; Teece, Rumelt, Dosi, & Winter, 1994). Examining the role of portfolio homogeneity allows me to provide a more nuanced account of what determines specialists' and generalists' survival, compared to prior research in this area.

Building on this analysis, I then elaborate on the role of network ties in affecting survival chances of generalists and specialists of different degrees of portfolio homogeneity. In a study of how firm performance

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in open networks is affected by a firm's specialization, Shipilov (2006) argues that the "presence of generalists in multiple market segments, and specialists' deep expertise within select industry segments, represent differentiated resources that will be desired by other network members" and finds that in open networks both wide-niche generalists and specialists outperform firms with a medium degree of specialization. Shipilov argues that particular capabilities of specialists and wide-niche generalists make them more attractive network partners to all other organizations, which in turn positively affect their performance. My analysis is based on a similar premise, i.e., that the degree of specialization has direct implications for the network resources the organizations require and for the utility they derive from these resources. I consider, however, two different questions: 1) Does a firm's specialization affect the degree to which it depends on network ties in achieving survival? and 2) Under what conditions do the distinct capabilities of specialists and generalists make them more important partners to each other in achieving survival? To address these questions, I examine how specialization, portfolio homogeneity, and network ties separately and jointly affect the risk of firm failure. I situate my analysis in the context of the VC industry using data over a 41-year period as an ideal setting to study the interplay of specialization, portfolio homogeneity and network connections.

2. Theory and hypotheses

2.1. Specialization and the risk of failure in the VC industry

A firm's degree of specialization reflects its pattern of resource utilization (Dobrev, Kim, & Hannan, 2001; Hannan & Freeman, 1977). Generalist firms utilize a more diverse set of resources, whereas specialized firms focus on a limited resource set. In the venture capital (VC) industry – the empirical setting of this study – firms invest in companies (startups) in one or several domains (e.g., medical, telecommunications, energy, computer hardware). VC firms do not only provide financial resources, but – more importantly – act as "coaches" (Gompers & Lerner, 2001), mentors, advisors, and connectors to supported startup companies (Feld & Ramsinghani, 2013; Lerner, 1994; Li & Mahoney, 2011; Ma, Rhee, & Yang, 2013). In advising, coaching, monitoring, and guiding of startups, VC firms rely primarily on knowledge resources (Gompers & Lerner, 2001; Matusik & Fitza, 2012). The pattern of a firm's investments determines its degree of specialization and reflects one of two strategies that VC firms may pursue to deal with the risk inherent in the VC industry (Matusik & Fitza, 2012). Each of the strategies provides distinct but different survival advantages.

The specialization strategy leads VC firms to develop an in-depth knowledge of a limited number of market domains. Capitalizing on the depth of knowledge in a narrow segment of the market allows firms to cope with the risk of investing by both being better able to select investment targets and to better shepherd selected startups through developmental stages and unexpected circumstances. A narrower scope allows specialist VCs to develop expertise that includes an understanding of market domain trends, technology, regulation, human resources, competitive landscape, successful product development strategies used by other companies in a domain, etc. It also allows specialist VC firms to build up more fine-grained and nuanced domain-specific experience. This, in turn, increases specialists' performance and staying power in the market.

The generalist strategy, by contrast, comprises building a broad knowledge base, as opposed to a deep one (Matusik & Fitza, 2012; Shipilov, 2006). The value of generalist VC firms' knowledge comes from the breadth of exposure in a variety of domains. For example, a partner at Kleiner Perkins Caufield & Byers (KPCB), a prominent generalist VC, "invests in consumer and energy-related technologies and markets, including software, electronic commerce, Web services, semiconductors, consumer systems, media and telecommunications" (http://www.kpcb.com/team, accessed 03/2017). The involvement of generalist firms with startups in different domains facilitates intrafirm learning and the transfer of expertise, i.e., knowledge spillover (Kang, Burton, & Mitchell, 2011). As a result, generalist firms' stock of knowledge contains solutions applicable across a variety of different domains and what is learned in one domain can be used other domains. Knowledge spillover positively affects the generalist firms' performance as it allows them to find solutions by drawing on experiences from a variety of domains. This, in turn, increases VC firms' survival potential in the market.

Firms with a medium degree of specialization, on the other hand, likely experience neither the benefits of generalism nor those of specialization. These firms have neither the knowledge breadth of generalists that can sustain them in the market by relying on diversification and knowledge spillover across domains nor the in-depth expertise of specialist firms that can sustain them by achieving better performance in a narrow segment of the market. These firms likely suffer from the 'stuck-in-the-middle' phenomenon (Porter, 1985). Accordingly, the staying power of VC firms with medium degrees of specialization is likely lower than that of either generalist or highly specialized firms, which suggest a curvilinear relationship between specialization and failure in the VC industry:

H1. A VC firm's degree of specialization has an inverted U-shape relationship with its risk of failure so that generalist and specialist firms have a lower failure rate compared to firms with medium degrees of specialization.

2.2. VC firms' portfolio homogeneity and benefits of specialization

The survival of generalists and specialists depends not only on their capability to execute their chosen strategy but also on their ability to weather change in their environment (e.g., Freeman & Hannan, 1983). As a trade-off for their survival advantage in a narrow market, niche specialists accept the risk of a major (or "coarse-grained", Freeman & Hannan, 1983) environmental change to which they may not be able to adapt. In the VC industry, if the domains in which firms are specialized experience an upheaval due to e.g., change in governmental regulations, emergence of a disruptive technology, increased competition, specialist the VC firms' ability to respond to these new developments may be limited and result in an increased risk of firm failure. Generalists, on the other hand, trade off greater adaptability to the environment for lower exploitation capability in each of the domains in their market niche (Hannan & Freeman, 1977). The necessity to operate in a range of domains implies a lack of expertise in any of the domains (Hannan, Pólos, & Carroll, 2007; Hsu, 2006). In order to sustain themselves in a range of domains, generalists also have to carry excess capacity (i.e., 'organizational slack', e.g., Cyert & March, 1963; Penrose, 1959), which implies that generalism can be a costly strategy and negatively affect the firms' survival chances if the cost of slack becomes unbearable.

The ability of specialists and generalists to cope with changes in their environment likely not only depends on their degree of specialization (or 'niche width') but also on the relatedness of resources required to operate in different domains within their niche. The similarity of domains in firms' niches has implications for the generalists' and specialists' ability to weather environmental change and address their respective challenges. In particular, the greater similarity of domains comprising a specialist VC's niche (i.e., portfolio homogeneity) likely makes the firm's survival more susceptible to environmental change. The more similar domains A and B in a specialist's portfolio, the greater the chance that forces that produce a change in A will also produce a change in B and thus the firm may not be able to weather environmental change. By contrast, if domains A and B are dissimilar, the firm may rely on domain A to sustain itself in the market while domain B undergoes a drastic change to which the firm is unprepared. Thus specialists likely have a survival advantage when domains in their market niche are dissimilar.

Generalist VC firms, on the other hand, may benefit from greater homogeneity in their portfolios. Greater similarity of domains in a generalist's portfolio implies greater opportunities for knowledge and other resource spillover across domains, which helps to address the deficiency in the depth of the generalists' expertise. It also implies resource substitutability, which means that the generalist VCs will be able to more freely shift resources (e.g., personnel, expertise, external consultants, etc.) among domains in their portfolio and will thus need to maintain lower excess capacity and bear a lower overall cost. This likely results in increased survival chances of generalists with more homogeneous portfolios. Following this logic, I hypothesize that VC firms' portfolio homogeneity moderates the relationship between specialization and the risk of failure, so that:

H2a. Specialists with a low degree of portfolio homogeneity have a lower risk of failure than specialists with a high degree of portfolio homogeneity.

H2b. Generalists with a high degree of portfolio homogeneity have a lower risk of failure than generalists with a low degree of portfolio homogeneity.

2.3. The joint effects of specialization and co-investment ties on VC firms' risk of failure

Because inter-firm ties provide a way to tap knowledge, expertise, and capabilities that reside outside firms' boundaries, firms use them when they lack these in the market domains in which they operate (e.g., Chung, Singh, & Lee, 2000; Grant & Baden-Fuller, 2004; Gulati, 1995). In the VC industry, ties to other venture capital firms established through co-investment provide a focal firm with access to the knowledge resources and competencies of its alliance partners. Resources transferred through co-investment ties, e.g., information about investment opportunities, syndicate partners' prior experiences with similar projects, domain-specific knowledge and expertise, and access to external experts that partners engage in a focal venture, contribute to the development of the firms' own knowledge resources and capabilities (Matusik & Fitza, 2012). The value of collaborative ties to other firms likely differs, however, between generalist and specialist VC firms, for several reasons.

The literature on organizational learning shows that learning occurs differently in specialized and generalist firms. Specialist and generalist firms exhibit different types of absorptive capacity (Cohen & Levinthal, 1990). The routines and processes of generalist firms make them better positioned to recognize, value, and absorb external knowledge (Lane & Lubatkin, 1998). While specialists also have a capacity to learn in their domain of specialization from external sources (Barnett, Greve, & Park, 1994), research suggests that they benefit relatively less from the experience of others (Ingram & Baum, 1997) and the environment (Haunschild & Sullivan, 2002). Because specialists' survival critically depends on their ability to succeed in their niche, they are “more motivated to learn from their own experience” (Ingram & Baum, 1997) rather than outside sources and develop routines and processes that facilitate such learning. As a result, inputs of knowledge from external sources have a relatively smaller effect on them, compared to generalists. Based on these prior findings, I expect that the value derived by specialist and generalist firms from their network ties differs. Compared to specialists focused on learning from experience, generalists can be expected to derive a greater survival advantage from external sources accessed through inter-firm ties:

H3. VC firms' network ties reduce the risk of firm failure and this effect is greater for generalist VC firms than for specialist VC firms.

2.4. Generalist-specialist capabilities complementarity and portfolio homogeneity

Starting with Penrose (1959), a vast amount of literature on organizational interdependence and strategic alliances has documented the benefits of resource complementarity in organizational partnerships. Prior studies have established that resource complementarity is a major reason for firms to enter alliances with each other in the first place (Chung et al., 2000; Doz, 1988; Nohria & Garcia-Pont, 1991; Shan & Hamilton, 1991). After an alliance is created, firms that access resources that are beneficial to but are not possessed by them obtain superior outcomes, such as the timely introduction of products to the market (Teece, 1986) or mutual value creation (Hamel, Doz, & Prahalad, 1989). The absorptive capacity literature has shown that knowledge transfer between alliance partners is maximized when they share a common knowledge base that provides a common language and facilitates the assimilation of new knowledge, but possess different additional knowledge (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998; Zahra & George, 2002). Generalist and specialist VC firms active in the same domain share a common knowledge base pertaining to that domain. They possess, however, different additional types of knowledge. Both generalist and specialist firms have distinct competencies that the other group lacks. By tapping into the generalists' competencies, specialists can leverage their focused, specialized knowledge; by tapping into the specialists' competencies, generalists can leverage their broad, extensive knowledge. Successfully accessing each other's stock of knowledge will likely enhance generalist and specialist firms' own knowledge resources and reduce the risk of failure.

The value of complementary resources of generalists and specialists to each other, however, likely depends on the degree of homogeneity of their portfolios. The value of specialized VC firms' expertise stems from their fine-grained and nuanced understanding of their domain of specialization. The depth of specialists' expertise is likely to be especially valuable to those generalists who have heterogeneous portfolios. Portfolio heterogeneity implies distinctiveness of resources required to operate in portfolio domains, which limits knowledge spillover within a VC firm and likely makes the input of external expertise in each of the domains especially valuable. According to a partner at a leading generalist Silicon Valley VC firm I interviewed,

> [A co-investment partner] *in an industry that he is an expert* [in] *is by far better … and has a lot more added value than someone who is not specialized in the industry…* (private correspondence).

High portfolio homogeneity, by contrast, facilitates internal expertise flows and likely makes VC firms relatively less dependent on inputs from partners. Following this reasoning, I put forward:

H4a. Ties to specialist VC firms reduce the risk of failure for generalist VC firms with a low degree of portfolio homogeneity more than for generalist firms with a high degree of portfolio homogeneity.

The value of generalist VC firms' knowledge comes from the breadth of exposure in a variety of domains. They are less likely to be bound by idiosyncratic conditions in a particular domain while searching for solutions to complex problems that comprise VC firms' activity (Feld & Ramsinghani, 2013; Gompers & Lerner, 2001). The breadth of their knowledge bases predisposes generalists to apply solutions effective across a number of different domains. This kind of expertise is likely to be especially valuable to specialist VC firms with a high degree of portfolio homogeneity. The similarity of domains in a specialist's portfolio implies that the firm's expertise is very narrowly focused and that these firms especially lack the breadth of expertise, compared to specialists with more diverse portfolios. Accordingly, I hypothesize that:

H4b. Ties to generalist VC firms reduce the risk of failure for specialist VC firms with a high degree of portfolio homogeneity more than for specialist firms with a low degree of portfolio homogeneity.

3. Data and method

3.1. Data

The data for this analysis come from the VentureXpert Database compiled by Thompson Reuters. I use the sample of dedicated VC firms, which I refer to as "firms", and exclude other organizations making venture investments (e.g., banks, hedge funds, pension funds) as their motivations and purposes may differ. I use the data on investments made by firms located in the U.S. between 1961 (the year of the first syndicated VC investment) and 2002.

I take advantage of the detailed data in the VentureXpert dataset to construct both the life-histories and co-investment networks of VC firms. I constructed the firms' life-histories based on the dates of the investments they made using the calendar year as the unit of time. Firms enter the risk set in the year in which they first make a venture investment and exit in the year their last investment is recorded. From the data on individual investment rounds, I constructed yearly venture capital co-investment networks. Following prior studies (e.g., Zhelyazkov & Gulati, 2016), a tie between two firms is established if both firms invested in the same company in the same year.

3.2. Model and variables

I use survival analysis to estimate the instantaneous risk, $\mu_k(t)$, of a venture capital firm exiting the industry. Assuming a constant hazard rate throughout the 41 year period in my analysis may not be warranted, because a number of environmental and temporal factors may affect it during this wide time window. Accordingly, I split the entire period into 5-year spells and included corresponding time period variables in all my models. I thus use piece-wise exponential models which assume a constant baseline hazard rate within each 5-year time period but allow the rate to vary flexibly across time periods (Blossfeld, Golsch, & Rohwer, 2007). These models usually provide a better fit to the organizational survival data compared to parametric models, e.g., Gompertz or Weibull (Carroll & Hannan, 2000). The models are described by this formula:

$$\mu_k(t) = \lim_{\Delta t \to 0} \frac{\Pr(t < T \leq t + \Delta t \mid T > t)}{\Delta t}$$

where T is a random variable for the time of firm failure, t is the time that firm k has spent in the market, and $Pr(.)$ is the probability of market exit over the interval $[t, t + \Delta t]$ given that the firm was in the market at the beginning of the interval.

3.3. Explanatory variables

3.3.1. Degree of specialization

I operationalize specialization of a VC firm by the number of domains in which it is active and the number of companies it invests in. In the VentureXpert database, start-ups in which VC firms invest are classified by the Venture Economics Industry Codes (VEIC), a proprietary code schema developed by Thomson Reuters. Following prior research (e.g., Dimov & Martin de Holan, 2010; Dushnitsky & Lenox, 2006), I use the schema to classify the industry domains and to calculate both the specialization and portfolio homogeneity variables (see below). The VEIC classification contains 69 domain categories that include specific technology and product domains such as "Industrial Automation," "Oil & Gas Exploration," "Consumer Services," and "Biotech Research." My measure of the degree of specialization (S) of firm k in year i is based on the Hirschman-Herfindahl Index and defined as follows:

$$S_{ik} = 1 - \sum_j \left(\frac{n_{ijk}}{N_{ik}}\right)^2,$$

where n_{ijk} is the number of supported startups in domain j, in which firm k invested in years (i-5) to (i-1), and N_{ik} is the total number of the startup companies in which firm k invested in the same period of time. It ranges in the interval (0,1), with lower values indicating greater specialization. One important advantage of this measure is that it accounts for both the number of market domains in which firms invest and the number of companies in which they invest in each of the domains. As a result, it facilitates the correct comparison of the levels of specialization of firms that differ both in the number of domains in which they operate and the number of companies in which they invest.

3.3.2. Portfolio homogeneity

I relied on prior theoretical work on corporate diversification (Lien & Klein, 2009; Teece et al., 1994) and its empirical applications in the VC industry (e.g., Dimov & Martin de Holan, 2010) and operationalized portfolio homogeneity using the survivor-based method. Firms are more likely to operate (survive) in domains that are similar because they capitalize on their expertise gained in one domain in another. Consequently, the domains that firms combine in their portfolios provide an indication of domain relatedness (Teece et al., 1994). The survivor-based approach compares the actual co-occurrence of domains in firms' portfolios to the co-occurrences expected under a random diversification process (Lien & Klein, 2009). To account for the changing nature of the relatedness of investment markets over time, similar to Dimov and Martin de Holan (2010), I made this variable time-variant. In line with the operationalization of my other variables, I used a 5-year moving window to capture the variation over time. First, I computed domain-to-domain relatedness as follows:

$$r_{ijt} = (J_{ij(t-5)} - \mu_{ij(t-5)})/\sigma_{ij(t-5)}$$

where $J_{ij(t-5)}$ represents the observed number of firms operating in both domains i and j in the previous 5 years (t-5), and $\mu_{ij(t-5)}$ and $\sigma_{ij(t-5)}$ represent, respectively, the mean and standard deviation of the number of firms operating in domains i and j based on a random diversification process (Teece et al., 1994). Then I calculated the average domain-to-domain relatedness in a firm's portfolio to arrive at a measure of portfolio-level homogeneity:

$$H_{kt} = \frac{\sum_t r_{ijt}}{M_{(t-5)}},$$

where H_{kt} is the homogeneity of firm k's portfolio in year t, r_{ijt} is defined as above, and $M_{(t-5)}$ is the total number of domains in which firm k invested in the previous 5 years. Larger values of this variable indicate greater homogeneity.

3.3.3. Number of ties to specialist partners and number of ties to generalist partners

I designate every organization with the S value of 0 as being specialist and organizations with a value of S above 0 as being generalist.[1] Using this classification and based on 5-year co-investment networks, I determine the specialization of all the syndicate partners of a focal organization. I calculate the number of ties to specialist and generalist partners a focal firm had in the past five years as the sum of the unique partners designated as specialist and generalist firms, respectively, across all domains a firm operated in, weighted by the size of each domain in the firm's portfolio. Formally, the variables are produced according to these formulas:

$$Nsp_{ik} = \sum_j \left(Nsp_{ijk} \times \frac{n_{ijk}}{N_{ik}}\right),\ Ngen_{ik} = \sum_j \left(Ng_{ijk} \times \frac{n_{ijk}}{N_{ik}}\right)$$

[1] For details of a sensitivity analysis of this operationalization, see Section 4.1 below.

where Nsp_{ijk} is the number of unique partners firm k co-invested within domain j in years (i-5) to (i-1), and n_{ijk} and N_{ik} are defined as above. I assume that the benefits derived from ties to a co-investment partner are partner- and domain-specific, not venture-specific so that the benefit is derived the first time a firm co-invests with a partner in a given domain. For this reason, I calculated the number of unique specialist and generalist syndicate partners and not the number of times a focal firm co-invested with specialist and generalist partners.

3.4. Control variables

My analysis includes the following three blocks of controls: organizational demography, network, and industry-specific variables. Demography controls are included to account for the organizational and population-level forces emphasized by organizational ecologists (Carroll & Hannan, 2000; Hannan & Freeman, 1984) that may affect firm failure. I include network controls to ensure that the effects of my primary variables of interest – the number of ties to generalist and specialist partners – do not simply reflect the network effects associated with the partners' network positions. I control for a firm's location in the network and the overall network structure using *Bonacich centrality*, *structural holes*, and *network connectivity* variables. I control for *repeat interaction with partners* to account for trust and familiarity (Zaheer, McEvily, & Perrone, 1998; Zhang, Gupta, & Hallen, 2016) that may affect the transfer of knowledge across ties. Industry-specific controls include *Silicon Valley location,* a dummy for *early-stage investment preference,* and three variables capturing different growth phases of the VC industry.

Table 1 presents the descriptive statistics and correlations for all the variables in the analysis. None of the independent variables are correlated to the extent that would result in a multicollinearity problem. Even though the correlation between the number of repeat ties and the number of generalist partners is high (0.79), it may inflate the standard errors of point estimates but will not bias the estimates (Kennedy, 1992).

4. Results

Table 2 reports the results from the models of VC firms' failure rates. I used likelihood-ratio (LR) tests to compare nested models and Akaike's Information Criterion (AIC) to compare non-nested models. AIC indicates the loss of precision when the maximum likelihood estimate is substituted for the true parametric estimate in the likelihood function, with smaller AIC values indicating better fitting models.

Model 1 includes just control variables and establishes a baseline model. To check if the effect of specialization has an inverted-U shape, I split the specialization variable ranging from 0 to 1 into five dummy variables with 0.2, 0.4, 0.6, and 0.8 cut-off points and included these dummy variables (with the first dummy as the reference category) in Model 2. Model 2 indicates that coefficients on the categorical specialization variables first rise and then decline, compared to the reference category, suggesting a concave relationship. This indicates that modeling the effects of specialization with the continuous specialization variable and its squared terms is appropriate, which I do in Model 3. The coefficient for the main effect of specialization is positive and highly statistically significant ($p < 0.05$) and the coefficient for the squared term is negative and also highly statistically significant ($p < 0.001$), confirming a curvilinear effect of specialization on the risk of firm failure.

The coefficient on the portfolio homogeneity variable included in Model 4 is negative and high statistically significant ($p < 0.001$), indicating that, on average, greater homogeneity of market domains in VC firms' portfolios decreases their survival chances. Model 5 includes an interaction term between specialization and portfolio homogeneity. The coefficient is positive and significant, indicating that the effects of specialization on survival depend on how similar domains in a firm's portfolio are. Fig. 1 visualizes this interaction and makes clear that specialists (firms with specialization below approximately 0.45) with homogenous portfolios have a higher risk of failure than specialists with a low degree of portfolio homogeneity, whereas the reverse is true for generalist firms (i.e., firms with specialization above approximately 0.45). Combined, Model 5 and Fig. 1 lend strong support to Hypotheses 1, 2a and 2b: specialization has a curvilinear relationship with the risk of failure and portfolio homogeneity moderates this relationship.

Models 6 and 7 add variables for the number of specialist and generalist co-investment partners to the baseline specification of Model 5, respectively. Model 8 includes these variables simultaneously. Both variables are, independently and jointly, negative and statistically significant ($p < 0.01$), which indicates that co-investment ties reduce the risk of firms' failure. LR tests against Model 5 reveal that both Models 6 and 7 improve on Model 5 significantly ($\chi^2(L_6–L_5) = 8.13$, $p < 0.01$ and $\chi^2(L_7–L_5) = 4.56$, $p < 0.05$ for 1 d.f.) Firms connected to generalist or specialist partners translate the benefit of these partnerships into increased survival chances.

Models 9 and 10 test whether the effect of network ties on failure risk reduction depends on the degree of firms' specialization. The (specialization × generalist partners) and (specialization × specialist partners) interaction terms are both highly statistically significant ($p < 0.001$). Models 9 and 10 significantly improve on Model 8, which does not include the interaction terms ($\chi^2(L_9–L_8) = 6.05$, $p < 0.05$ for 1 d.f. and $\chi^2(L_{10}–L_8) = 13.64$, $p < 0.001$ for 1 d.f., see Table 2 for results of LR tests). Model 11 includes the two interaction terms simultaneously. LR tests and AIC values indicate that Model 11 provides a better fit to the data than either Model 9 or 10 (or any of the Models 1–8). In Model 11, both the interaction coefficients are negative, which indicates that both specialist and generalist partners reduce the risk of firm failure. The larger (in absolute terms) coefficient on the (specialization × specialist partners) term compared to the (specialization × generalist partners) term indicates that ties to specialized firms reduce the risk of failure for generalist firms more than ties to other generalist firms. This lends support to Hypothesis 3. Testing Hypothesis 3 rigorously, however, calls for a formal test of difference in the coefficients. I, therefore, perform a Wald test for the equality of coefficients, contrasting (specialization × specialist partners) and (specialization × generalist partners) interaction terms. With a chi-square value of 5.29 on 1 degree of freedom, the test is highly statistically significant ($p < 0.05$), which indicates that there is a substantial difference in the degree to which ties to specialized partners affect VC firms' risk of failure, as compared to ties to generalist partners.

Finally, to test whether the interaction between specialization and network ties further depends on firms' portfolio homogeneity, I include the following three-way interactions: (specialization × specialist partners × portfolio homogeneity) and (specialization × generalist partners × portfolio homogeneity) in Models 12 and 13, respectively. (I also include the necessary two-way interaction term between portfolio homogeneity and network ties). In Model 12, the coefficient on the three-way interaction term is positive and highly significant ($p < 0.05$), indicating that the value of network ties to specialist partners indeed depends on firms' portfolio homogeneity. In Model 13, the coefficient on the interaction term is also positive but fails to reach statistical significance. Thus I conclude that the joint effect of specialization and ties to specialist partners depends on portfolio homogeneity, but that of specialization and generalist ties does not. Fig. 2 illustrates the interaction of specialization and portfolio homogeneity in the effect of ties to specialists.

Fig. 2 presents graphically the relationship between specialization, portfolio homogeneity, network ties, and the risk of failure. The graphs on the left depict the relationship for VC firms with a low degree of portfolio homogeneity (mean homogeneity – 2 S.D.), while the graphs on the right – for VC firms with a high degree of portfolio homogeneity (mean homogeneity + 2 S.D.). In each of the graphs, the relationship between specialization and the risk of failure is plotted for firms with no

Table 1
Variables in the analysis: descriptive statistics and correlation matrix.

	Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	9	10
1	Firm age	9.05	0.08									
2	Firm size × 10^{-3}	0.36	0.01	0.20								
3	Density of generalist organizations	0.83	0.00	−0.03	0.16							
4	Density of generalist organizations^2 × 10^{-3}	0.88	0.01	−0.03	0.15	0.99						
5	Density of specialist organizations	0.25	0.00	0.00	0.18	0.78	0.76					
6	Density delay × 10^{-3}	0.64	0.01	−0.57	−0.07	0.56	0.54	0.33				
7	Market concentration	0.40	0.00	0.04	−0.14	−0.90	−0.83	−0.71	−0.51			
8	Firm experience	40.54	0.66	0.68	0.38	0.02	0.02	0.02	−0.38	−0.01		
9	Number of repeat network ties	13.40	0.27	0.30	0.19	−0.08	−0.08	−0.09	−0.31	0.05		
10	Structural holes	0.38	0.00	−0.19	−0.16	−0.02	−0.03	−0.07	0.18	0.01	−0.45	
11	Bonacich centrality	−0.11	0.01	0.01	−0.01	0.02	0.02	−0.01	0.01	−0.01	0.00	−0.01
12	Network connectivity	0.76	0.00	−0.16	−0.05	−0.21	−0.19	−0.24	−0.18	0.19	0.19	−0.03
13	Silicon valley	0.15	0.00	0.06	0.02	0.00	0.00	0.00	−0.04	0.01	0.25	−0.19
14	Start-up stage preference	0.48	0.01	0.05	−0.06	0.03	0.03	0.01	0.05	−0.02	0.13	−0.20
15	Legitimation period (1961–1979)	0.05	0.00	−0.09	−0.05	−0.32	−0.21	−0.28	−0.24	0.62	−0.09	0.13
16	Growth period (1980–1992)	0.38	0.01	−0.12	−0.13	−0.66	−0.62	−0.65	−0.41	0.62	0.17	0.00
17	Explosive growth period (1993–2002)	0.62	0.01	0.12	0.13	0.66	0.62	0.65	0.41	−0.62	−0.17	0.00
18	Specialization 0 ≤ n < 0.25	0.07	0.00	−0.08	−0.07	−0.05	−0.05	−0.02	0.03	0.05	−0.13	0.32
19	Specialization 0.25 ≤ n < 0.5	0.12	0.00	−0.16	−0.08	0.01	0.01	0.02	0.14	−0.02	−0.18	0.31
20	Specialization 0.5 ≤ × n < 0.75	0.27	0.00	−0.18	−0.08	0.12	0.11	0.10	0.21	−0.11	−0.24	0.16
21	Specialization 0.75 ≤ × n < 1	0.54	0.01	0.30	0.15	−0.09	−0.08	−0.09	−0.29	0.08	0.40	−0.50
22	Specialization	0.71	0.00	0.24	0.14	0.00	0.00	−0.02	−0.18	0.00	0.33	−0.54
23	Portfolio homogeneity	0.15	0.00	−0.28	−0.09	0.01	0.01	0.07	0.21	−0.02	−0.23	0.30
24	Number of ties to generalists	21.02	10.29	0.26	0.27	0.00	0.01	0.06	−0.27	0.00	0.79	−0.56
25	Number of ties to specialists	1.15	1.02	0.16	0.17	−0.12	−0.11	0.00	−0.24	0.12	0.61	−0.38

	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1														
2														
3														
4														
5														
6														
7														
8														
9														
10														
11														
12	0.01													
13	−0.02	−0.04												
14	0.00	−0.07	0.19											
15	−0.01	−0.56	0.03	−0.02										
16	0.00	0.76	−0.02	−0.06	−1.00									
17	0.00	−0.76	0.02	0.06	−1.00	−1.00								
18	0.00	0.02	−0.06	−0.08	0.05	0.03	−0.03							
19	0.00	−0.04	−0.07	−0.05	0.01	−0.04	0.04	−0.10						
20	−0.01	−0.06	−0.06	−0.04	0.01	−0.11	0.11	−0.16	−0.23					
21	0.00	0.08	0.13	0.11	−0.05	0.11	−0.11	−0.29	−0.41	−0.66				
22	0.00	0.03	0.12	0.11	−0.06	0.03	−0.03	−0.85	−0.35	−0.01	0.67			
23	−0.02	0.00	−0.07	−0.08	−0.01	−0.01	0.01	0.42	0.31	−0.01	−0.41	−0.56		
24	0.00	0.18	0.25	0.14	−0.11	0.11	−0.11	−0.17	−0.21	−0.23	0.43	0.38	−0.22	
25	−0.01	0.11	0.17	0.08	0.01	0.13	−0.13	−0.11	−0.14	−0.16	0.29	0.25	−0.13	0.58

Table 2
Survival analysis: piece-wise exponential regression models of firm failure in the U.S. venture capital industry, 1961–2002.

Variable	Model 1		Model 2		Model 3		Model 4		Model 5			Model 7
5-year time period dummies	yes		yes		yes		yes		yes			yes
Constant	−0.264		−0.210		−0.205		−0.207		−0.137			−0.367
	(1.180)		(1.148)		(1.143)		(1.851)		(1.854)			(1.855)
Firm age	0.053	***	0.040	***	0.039	***	0.035	**	0.034	**	**	0.034
	(0.009)		(0.009)		(0.009)		(0.011)		(0.011)			(0.011)
Firm size	−1.144	***	−0.774	***	−0.763	***	−0.942	***	−0.947	***	***	−0.879
	(0.251)		(0.226)		(0.223)		(0.287)		(0.288)			(0.280)
Density of generalist organizations/10^3	−2.211	***	−1.208		−1.163		−1.141		−0.988			−1.210
	(0.811)		(0.807)		(0.804)		(2.213)		(2.219)			(2.218)
Density of generalist organizations^2/10^6	1.814	***	1.505	***	1.497	***	1.723	*	1.666	*	*	1.744
	(0.353)		(0.351)		(0.350)		(0.875)		(0.877)			(0.877)
Density of specialist organizations	0.230		−0.614		−0.685		−0.672		−0.740			−0.637
	(0.428)		(0.430)		(0.430)		(0.615)		(0.618)			(0.620)
Density delay	0.102		−0.055		−0.074		−0.185		−0.201			−0.197
	(0.105)		(0.108)		(0.109)		(0.151)		(0.151)			(0.151)
Market concentration	−0.814		−0.689		−0.703		−0.622		−0.590			−0.744
	(0.497)		(0.478)		(0.474)		(1.551)		(1.554)			(1.553)
Firm experience	−0.020	***	−0.007	**	−0.007	*	−0.007	*	−0.007	*	*	−0.007
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)			(0.003)
Number of repeat network ties	−0.080	***	−0.055	***	−0.057	***	−0.056	***	−0.055	***	***	−0.035
	(0.015)		(0.013)		(0.013)		(0.014)		(0.014)			(0.017)
Structural holes	1.280	***	0.771	***	0.740	***	0.867	***	0.879	***	***	0.717
	(0.119)		(0.126)		(0.127)		(0.158)		(0.158)			(0.175)
Bonacich centrality	0.030		0.025		0.023		0.042		0.044			0.045
	(0.030)		(0.030)		(0.031)		(0.041)		(0.041)			(0.041)
Network connectivity	−1.281		−1.159		−1.150		−3.492	*	−3.528	*	**	−3.374
	(1.069)		(1.056)		(1.053)		(1.623)		(1.626)			(1.631)
Silicon valley	−0.170		−0.204		−0.197		−0.176		−0.191			−0.179
	(0.143)		(0.143)		(0.143)		(0.173)		(0.174)			(0.174)
Start-up stage preference	−0.767	***	−0.717	***	−0.715	***	−0.450	***	−0.448	***	***	−0.448
	(0.085)		(0.085)		(0.085)		(0.101)		(0.101)			(0.101)
Growth period (1980–1992)	0.844	**	0.740	*	0.726		1.382	***	1.386	***	***	1.402
	(0.396)		(0.394)		(0.393)		(0.395)		(0.396)			(0.396)
Explosive growth period (1993–2002)	−0.052		−0.172		−0.181		−0.182		−0.186			−0.102
	(0.456)		(0.450)		(0.448)		(0.365)		(0.357)			(0.318)
Specialization $0.2 \leq n < 0.4$			0.280	*								
			(0.153)									
Specialization $0.4 \leq n < 0.6$			0.303	***								
			(0.002)									
Specialization $0.6 \leq n < 0.8$			−0.967	***								
			(0.097)									
Specialization $0.8 \leq \mathrm{n} < 1$			−2.149	***								
			(0.231)									
Specialization					0.828	*	0.880	†	0.855			0.929
					(0.375)		(0.529)		(0.646)			(0.646)
Specialization^2					−1.214	***	−1.233	***	−1.287	***	***	−1.308
					(0.626)		(0.705)		(0.777)			(0.777)
Portfolio homogeneity							−0.085	***	−0.271			−0.276
							(0.012)		(0.182)			(0.182)
Specialization × Portfolio homogeneity									0.575	**	**	0.642
									(0.294)			(0.315)
Specialist partners											**	
Generalist partners												−0.022
												(0.011)

Table 2 *(continued)*

Variable	Model 1		Model 2		Model 3		Model 4		Model 5			Model 7
Specialization × Specialist partners (Ț)												
Specialization × Generalist partners (ȚȚ)												
Portfolio homogeneity × Specialist partners												
Specialization × Portfolio homogeneity × Specialist partners												
Portfolio homogeneity × Generalist partners												
Specialization × Portfolio homogeneity × Generalist partners												
Log-likelihood	409.3		412.5		413.0		413.9		414.9			417.1
Chi-square	970.28	***	981.75	***	986.56	***	994.18	***	996.09	***	***	1000.64
Chi-square vs. model 5											**	4.56
Chi-square vs. model 11												
Wald test												(Ț = Ț-Ț) 5.29
AIC	−762.6		−772.1		−774.9		−789.8		−789.7			−792.3
N (firm/year spells)	11,844		11,844		11,844		11,844		11,844			11,844

Variable		Model 8		Model 9		Model 10		Model 11		Model 12		Model 13	
5-year time period dummies		yes		yes		yes		yes		yes		yes	
Constant		−0.539		−0.320		−0.308		−0.210		−0.225		−0.122	
		(1.850)		(1.854)		(1.847)		(1.849)		(1.850)		(1.851)	
Firm age	**	0.034	**	0.034	**	0.034	**	0.034	**	0.034	**	0.034	**
		(0.011)		(0.011)		(0.011)		(0.011)		(0.011)		(0.011)	
Firm size	**	−0.888	**	−0.889	**	−0.841	**	−0.849	**	−0.850	**	−0.855	**
		(0.281)		(0.281)		(0.273)		(0.274)		(0.274)		(0.275)	
Density of generalist organizations/10^3		−1.319		−1.240		−1.246		−1.200		−1.236		−1.216	
		(2.211)		(2.212)		(2.206)		(2.208)		(2.210)		(2.209)	
Density of generalist organizations^2/10^6	*	1.775	*	1.748	*	1.769	**	1.750	**	1.765	**	1.754	**
		(0.875)		(0.875)		(0.873)		(0.874)		(0.875)		(0.874)	
Density of specialist organizations		−0.570		−0.567		−0.516		−0.518		−0.512		−0.527	
		(0.622)		(0.620)		(0.622)		(0.621)		(0.622)		(0.621)	
Density delay		−0.194		−0.193		−0.194		−0.194		−0.196		−0.193	
		(0.151)		(0.152)		(0.151)		(0.151)		(0.151)		(0.151)	
Market concentration		−0.773		−0.683		−0.627		−0.586		−0.608		−0.580	
		(1.542)		(1.546)		(1.537)		(1.540)		(1.542)		(1.541)	
Firm experience	*	−0.007	*	−0.007	*	−0.007	*	−0.007	*	−0.007	*	−0.007	*
		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
Number of repeat network ties	**	−0.035	**	−0.035	**	−0.025		−0.027	*	−0.028	†	−0.031	†
		(0.017)		(0.017)		(0.016)		(0.016)		(0.017)		(0.018)	
Structural holes	***	0.691	***	0.698	***	0.682	***	0.683	***	0.686	***	0.678	***
		(0.175)		(0.175)		(0.173)		(0.174)		(0.174)		(0.174)	
Bonacich centrality		0.041		0.042		0.039		0.040		0.039		0.039	
		(0.041)		(0.042)		(0.042)		(0.042)		(0.042)		(0.042)	
Network connectivity	**	−3.493	**	−3.380	**	−3.728	**	−3.635	**	−3.639	**	−3.581	**
		(1.633)		(1.630)		(1.640)		(1.638)		(1.638)		(1.636)	
Silicon valley		−0.193		−0.193		−0.194		−0.194		−0.194		−0.203	
		(0.174)		(0.174)		(0.174)		(0.174)		(0.174)		(0.175)	
Start-up stage preference	***	−0.453	***	−0.446	***	−0.451	***	−0.448	***	−0.448	***	−0.447	***
		(0.101)		(0.101)		(0.101)		(0.101)		(0.101)		(0.101)	
Growth period (1980–1992)	***	1.413	***	1.389	***	1.425	***	1.410	***	1.412	***	1.403	***
		(0.396)		(0.395)		(0.398)		(0.397)		(0.397)		(0.396)	

Table 2 *(continued)*

Variable		Model 8	Model 9		Model 10	Model 11	Model 12	Model 13
Explosive growth period (1993–2002)		−0.128	−0.189		−0.125	−0.110	−0.112	−0.103
		(0.329)	(0.396)		(0.380)	(0.395)	(0.319)	(0.323)
Specialization 0.2 ≤ n < 0.4								
Specialization 0.4 ≤ n < 0.6								
Specialization 0.6 ≤ n < 0.8								
Specialization 0.8 ≤ n < 1								
Specialization		0.906	0.934		0.947	0.946	0.925	0.956
		(0.647)	(0.647)		(0.650)	(0.649)	(0.651)	(0.657)
Specialization^2	***	−1.277 ***	−1.266 ***		−1.230 **	−1.285 **	−1.290 **	−1.294 **
		(0.777)	(0.777)	(0.780)		(0.780)	(0.780)	(0.781)
Portfolio homogeneity		−0.247	−0.294		−0.226	−0.260	−0.234	−0.085
		(0.182)	(0.184)		(0.182)	(0.184)	(0.199)	(0.243)
Specialization × Portfolio homogeneity	**	0.617 *	0.716 *		0.637 *	0.698 †	0.624 †	0.374
		(0.366)	(0.417)		(0.414)	(0.415)	(0.451)	(0.546)
Specialist partners		−0.172 **	0.088 **		−0.168 **	0.001	0.063	0.001
		(0.075)	(0.115)		(0.075)	(0.123)	(0.236)	(0.125)
Generalist partners	**	−0.016 *	−0.014 *		0.046 **	0.039 **	0.038 **	0.052 **
		(0.091)	(0.071)		(0.018)	(0.018)	(0.018)	(0.022)
Specialization × Specialist partners (Ț)			−0.541 **			−0.360 **	−0.469	−0.361
			(0.212)			(0.123)	(0.367)	(0.228)
Specialization × Generalist partners (ȚȚ)					−0.106 ***	−0.091 ***	−0.089 ***	−0.108 ***
					(0.026)	(0.026)	(0.027)	(0.028)
Portfolio homogeneity × Specialist partners							−0.090	
							(0.276)	
Specialization × Portfolio homogeneity × Specialist partners							0.227 *	
							(0.111)	
Portfolio homogeneity × Generalist partners								−0.038
								(0.035)
Specialization × Portfolio homogeneity × Generalist partners								0.063
								(0.064)
Log-likelihood		420.1	423.1		426.9	428.1	431.2	428.7
Chi-square	***	1006.5 ***	1012.5 ***		1020.1 ***	1022.57 ***	1026.48 ***	1023.77 ***
Chi-square vs. model 5	*							
Chi-square vs. model 11							3.91 *	1.19
Wald test	**							
AIC		−796.1	−800.2		−807.8	−808.2	−810.4	−805.4
N (firm/year spells)		11,844	11,844		11,844	11,844	11,844	11,844

Note: Standard errors in parentheses.
† $p < 0.10$, two-tailed *t*-tests.
* $p < 0.05$, two-tailed *t*-tests.
** $p < 0.01$, two-tailed *t*-tests.
*** $p < 0.001$, two-tailed *t*-tests.

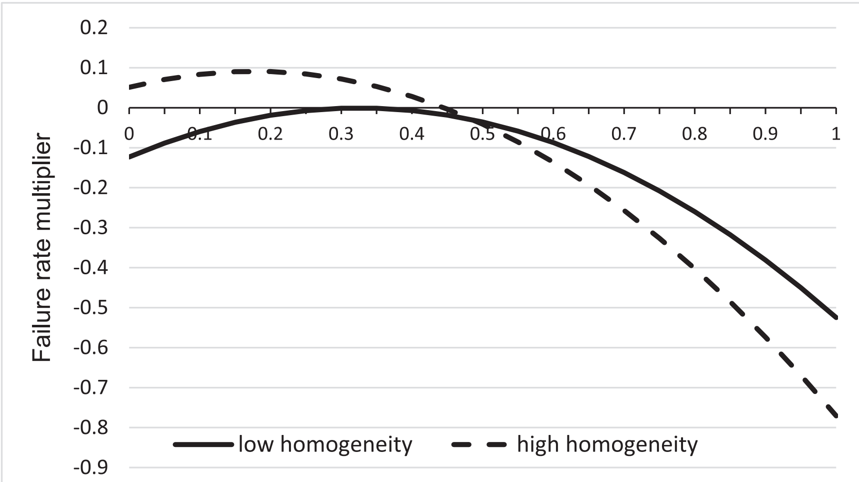

Fig. 1. The effect of specialization on the multiplier of the failure rate for U.S. VC firms with high (mean + 1SD) and low (minimum value) portfolio homogeneity.

network ties and for those who have a large number of ties (mean + 2S.D.). Graphs at the top of Fig. 2 plot the effects of ties to specialist partners, while those at the bottom to generalist partners. Overall, across all four graphs, the lines representing the risk of failure for firms with a large number of ties are below the lines representing that for firms with no partners, indicating that network ties (whether to specialist or generalist partners) reduce the risk of failure for VC firms. Also, the difference between these lines at a given level of specialization is, overall, greater for firms with higher degrees of generalism. Combined, these effects illustrate the significance of the Wald test contrasting the (specialization × specialist partners) and (specialization × generalist partners) interactions in Model 11. Both network ties to specialist and generalist partners reduce the risk of failure for both specialist and generalists VC firms and this effect is especially pronounced for generalists firms, as predicted by Hypothesis 3.

Fig. 2 also indicates that as the degree of generalism increases, network ties to specialist partners reduce the risk of failure more for generalists with heterogeneous portfolios than for those with homogeneous portfolios (compare two graphs at the top of Fig. 2). The greater vertical distance between the lines representing the risk of failure for firms with no ties to specialists and many such ties in the low homogeneity graph (compared to that in the high homogeneity graph)

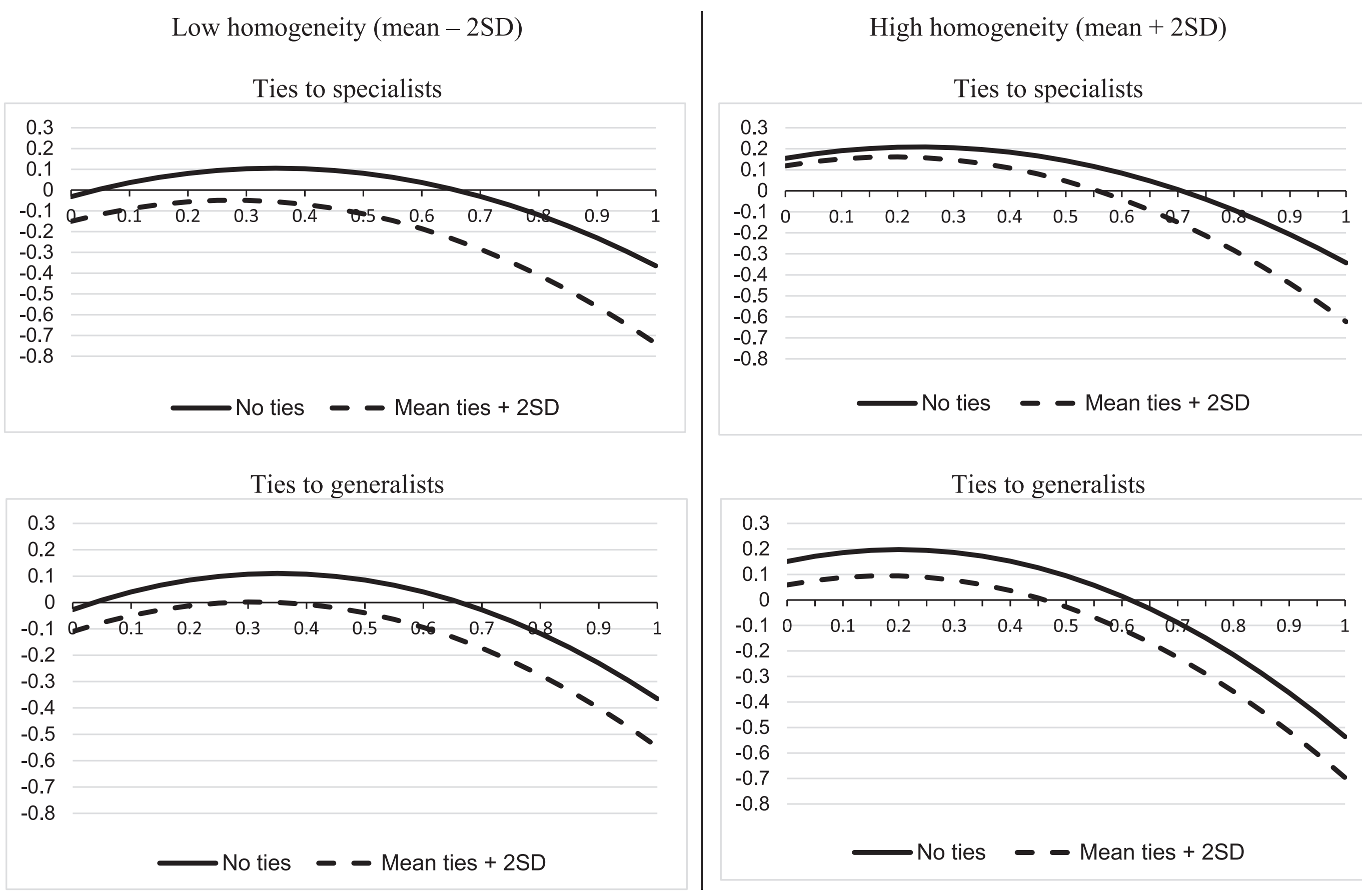

Fig. 2. The joint effects of specialization and network ties to specialist and generalist partners on the multiplier of the failure rate for U.S. VC firms. (Note: Failure rate multiplier on the vertical axis).

illustrate this effect. For example, in the low homogeneity graph, the failure rate multiplier for a VC firm with the degree of specialization of 0.8 (generalist) diminished by approximately 0.3 if the firms go from having no ties to many ties to specialist partners, whereas in the high homogeneity graph the failure rate multiplier for a comparable firm only diminishes by approximately 0.2. This lends support to Hypothesis 4a. Ties to specialists are especially important to generalists who lack expertise and knowledge spillover due to the dissimilarity of domains in their portfolios. The effect of ties to generalists, on the other hand, while more important to the specialist rather than generalist firms (per Hypothesis 3) does not similarly depend on firms' portfolio homogeneity, i.e., the effect of failure risk reduction provided by ties to generalists is not different for specialists with homogenous and heterogeneous portfolios. This is illustrated by similar vertical distances between lines in the two bottom graphs in Fig. 2. Overall, I find support for Hypothesis 4a but not for 4b.

4.1. Post-hoc analyses

To ensure robustness of my results I performed the following post-estimation analyses.

4.1.1. Diversification measure

I performed sensitivity analyses of my measure of specialization to ensure that changes in its operationalization did not affect my results. First, firms with a specialization *S* of 0 may be considered 'strict specialists' as they invested in exactly one industry in the previous 5 years. A more inclusive definition of a specialist may allow the value to take some small values close to 0 (as when a VC firm invests in a small number of companies that are not in its primary industry of specialization). To examine the robustness of my results compared to alternative definitions of specialism, I reran my analyses by designating firms with specialization values of up to 0.3 as specialists. As expected, the interaction effects became somewhat weaker, but retained their statistical significance and produced, substantively, the same picture. I present models with specialization values of 0 here; alternative results are available upon request.

4.1.2. Distribution effects

To check the robustness of (specialization × generalist partners) and (specialization × specialist partners) effects and to make sure they are not entirely driven by differences in the relative value of the ties at the low end of the specialization variable distribution, I estimated Model 11 for firms with a specialization level of above the mean value of 0.71 and performed a Wald test for the equality of coefficients. This test indicated that the interaction is also highly statistically significant at the upper end of the diversification distribution, where the majority of generalist firms are positioned.

4.1.3. Curvilinear effects of independent variables

To ensure that the results of my analyses are not biased by the non-linear effects that network ties may exhibit on firms' survival rate due to under- or over-embeddedness (Uzzi, 1997), I ran models that included the squared terms for specialist and generalist network ties. If the effects of the squared terms were significant, having too few or too many network ties is worse for avoiding firm failure than a medium number of ties. The coefficients on both variables were, however, insignificant and, according to LR tests and the AIC statistics (not reported here), failed to improve on models without curvilinear effects of ties.

Finally, I also tested a curvilinear effect of the Portfolio homogeneity variable by including the squared term of this variable in my analyses. LR test and AIC statistics indicated, however, that the term was not statistically significant and thus was omitted from my models.

5. Discussion

This paper studied how VC firms' degree of specialization and the degree of specialization of their syndicate partners affect firms' survival chances. The results of my analysis reveal a J-shaped relationship between specialization and VC firm failure. Specialist and generalist firms have a survival advantage, compared to firms with a medium-low degree of specialization, and generalism provides greater survival benefits than specialization. This result generally confirms my hypothesis about the relationship between diversification and failure. If the effects were of equal strength for generalists and specialists, the relationship would have an inverted U-shape. Capitalizing on a broad knowledge base and knowledge spillovers in an inherently risky industry such as VC, however, provides generalists with an additional benefit, compared to specialists. This explains the shorter tail of the inverted U-shape and the relationship between specialization and the risk of failure can thus be described as an inverted J-shape.

Further, I find that this effect is moderated by the firms' portfolio homogeneity. I relied on the concept of domain relatedness in firms' portfolios from the literature on corporate diversification to inform my discussion of effects of specialization on survival. My results suggest that homogeneity of firms' portfolios hinders the survival chances of highly specialized firms while it increases the survival chances of wide-niche generalists. Assessing how the relatedness of domains in firms' portfolios affects the dynamics of survival of specialist and generalists organizations – something that has often been neglected in prior studies on effects of specialization on survival – adds a new insight and provides for a more nuanced understanding of the effects of specialization.

The results of this study suggest that the value of network ties for organizational outcomes changes with both the degree of specialization of the focal firm and the degree of specialization of its network partners. Generalist VC firms need access to expertise, knowledge, and capabilities in each of the market segments that constitute their market niche. Because the level of expertise and the amount of resources the generalist organizations can develop internally in each of the market segments are lower compared to specialist firms, generalists rely more on network ties for the provision of these assets than do specialists. Ties to other firms provide a way to tap into lacking resources and, as such, become an important factor in outcomes for generalists. Ties to firms of any degree of specialization are more important to generalists than they are to specialists in achieving survival. But ties to specialized organizations are more important the wider the organization's niche and the more heterogeneous its portfolio, compared to ties to other generalists. In addition to the benefits of partnerships that other generalists can provide, specialists possess in-depth expertise and market segment-specific capabilities that generalists do not. This makes specialists particularly valuable partners for generalists with heterogeneous portfolios who especially lack a capability to develop in-depth expertise in their niche domains and to benefit from knowledge spillovers within their portfolios.

Specialist firms rely more on their highly developed competencies and capabilities in particular segments of the market. Their competitive advantage stems to a greater extent from their internal resources than from their external environment. Specialists also, however, depend on ties to other firms in achieving survival. The resources they need from their environment are, however, different in nature from what generalists require. To leverage their in-depth expertise and narrowly focused capabilities, specialists benefit most from access to broad, market-wide competencies. Generalist VC firms possess such competencies by virtue of engagement in multiple market segments, which makes them particularly valuable partners to specialists. Overall, this study shows that in inter-organizational exchange, specialists and generalists can benefit from the conditions of complementarity that their differentiated resources and capabilities create. Those generalists who manage to access specialists' competencies and expertise by establishing alliances with them experience lower risks of failure, and vice versa.

This study contributes to the literature that focuses on firm-level factors in outcomes of inter-organizational collaboration. Even though studies employing resource-based perspectives on inter-organizational alliances yielded valuable insights (e.g., Eisenhardt & Schoonhoven, 1996), this strand of research is underdeveloped with the majority of studies focusing on factors external to organizations in analyses of the propensity of organizations to enter alliances or outcomes of inter-organizational collaboration (Shipilov, 2006). By focusing on a fundamental organizational characteristic – the degree of specialization – this study further develops our understanding of how organizational resources and capabilities shape organizational outcomes resulting from participation in inter-organizational alliances and partnerships. It suggests that resources and capabilities that organizations possess which are reflected in their degree of specialization affect the utility obtained from collaboration with other organizations.

This study sheds more light on the consequences of the ecological segregation process (Carroll & Swaminathan, 2000) on which the discussion of generalist and specialist interdependences in the ecological tradition (e.g., Hannan & Freeman, 1977) is based. This analysis in this study reveals that the generalists-specialists interdependence is not confined to the level of common resource base but is also enacted through direct exchanges between organizations. The same ecological process of segregation that results in the emergence of specialists and generalists in the market creates conditions for their interdependence. By pursuing either a specialist or generalist strategy to mitigate market competition and increase survival chances, generalist and specialist firms develop capabilities that are valuable to but not possessed by the other population, which creates conditions of interdependence. By tapping into complementary resources and capabilities of the other population through inter-organizational ties, organizations are able to increase their survival chances.

The results of this study contribute to the growing literature on optimal configuration of interorganizational alliances and partnerships (Baum, Calabrese, & Silverman, 2000; Vissa & Chacar, 2009) and managing them (Davis, 2007; Gulati, Sytch, & Merhotra, 2008) and have practical managerial implications. First, the study makes clear that since generalism implies greater reliance on external resources that can be procured through ties to other firms, alliance building needs to be a core capability of generalist firms, especially wide-niche generalists with heterogeneous portfolios. The ability of generalist organizations to enter alliances with partners that possess necessary resources and capabilities will be reflected in a multitude of organizational outcomes, including survival. Second, this study implies that the choice of alliance partners needs to change with the degree of specialization of the organization. Diversification has been a central mantra in strategy endorsed by academic researchers (Grant, 2004; Porter, 1980) and practitioners alike. Following it, most organizations occupy a narrow niche when they first enter a market and then increase their product offering to cover a wider niche. This study suggests that as this process unfolds, organizations may need to reshape their alliances: selecting partners based, among other things, on their degree of specialization to achieve complementarity that leads to positive outcomes.

6. Limitations and directions for further research

This study, like most other research, has limitations. While my data allow me to establish the presence of ties between VC firms, they do not provide information on the content of the exchanges that happen in those ties. Our understanding of the content of the interactions in VC networks is shaped by the prior literature produced by industry insiders and outside observers (e.g., Feld & Mendelson, 2011; Gompers & Lerner, 2004), and provides a description of the syndication process at a general level. Further research, whenever possible, would do well to incorporate information about network exchanges at a more micro, operational level. With regard to the complementarity of generalists and specialists, it would be instructive to evaluate to what extent a firm's degree of specialization plays a role in its selection as a syndicate partner in the first place and how it shapes the way the firm's partners structure their exchanges with it. Are generalists more prone to syndicate with a specialist when the perceived lack of expertise in a given technology area is greatest? Are specialists' opinions allotted a greater weight in the decision-making process by generalists, and vice versa? Do generalists' partnerships with specialists focus more on expertise transfer (as opposed to fund pooling and risk sharing) than their partnerships with other generalists? Answering these questions would give us a more detailed understanding of how the interdependence of generalists and specialists operates and the mechanisms through which their complementarity is translated into increased survival chances.

Further research would also do well to evaluate the findings of this study in other contexts and industries. An evaluation of the interplay between the degree of specialization, portfolio homogeneity, inter-firm network ties, and outcomes in other settings would broaden our understanding of the interactions analyzed in this study.

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